2023

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13th ECNDT
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European Congress of Radiology
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Reliability, Maintenance & Managing Risk Conference
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17th International Symposium on Nondestructive Characterization of Materials
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8th Railway Forum
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railwayforum.eu

60th Annual British Conference on NDT
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National Pavement Preservation Conference
18–21 September, Indianapolis, IN
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ME

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ASNT Learn Webinar*
12 JULY
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Speaker: Lennart Schulenburg
Time: 3:00 p.m. (ET)

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17–19 JULY
Time: 8:00 a.m. to 5:00 p.m. (ET)
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PT Exam Prep Course
20–21 JULY
Time: 8:00 a.m. to 5:00 p.m. (ET)
Deadline to register/ transfer/cancel: 6 July

VT Exam Prep Course
24–26 JULY
Time: 8:00 a.m. to 5:00 p.m. (ET)
Deadline to register/ transfer/cancel: 10 July

ISQ – UT Thickness Prep Course
24–26 JULY
Time: 8:00 a.m. to 5:00 p.m. (ET)

Membership Mondays*
31 JULY
Topic: Researching NDT
Time: 7:00 a.m. and 4:00 p.m. (ET)

ET Exam Prep Course
31 JULY–2 AUGUST
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BENEFITS AND CONCERNS

of Using Emerging Artificial Intelligence Chatbots With Work in NDT

BY JOHN C. ALDRIN

While most of the papers in this special issue explore the use of artificial intelligence and machine learning (AI/ML) to support the evaluation of nondestructive testing (NDT) data and assist with the classification of NDT indications, there are other important ways that emerging AI tools may impact how we work in NDT. The article discusses the recent emergence of AI chatbots, also referred to as generative artificial intelligence agents or large language models (LLMs), and highlights the potential benefits and risks as part of work in the NDT field.

Introduction

ChatGPT, launched in late 2022, has been getting a lot of attention due to its ability to generate human-like text responses to various tasks such as answering questions or generating summaries of content (Molla 2023). For many of us who have been working with computer algorithms since the 1990s, the idea of developing computer-assisted tools, like expert systems, has been around for a long time. What makes these systems different today? Recent breakthroughs in the AI field are enabling such tools to be much more useful than past generations (Wolfram 2023). To start, these models are very large. The GPT-3 architecture is from OpenAI, and the language model ChatGPT has been reportedly trained on around 45 terabytes of text data,


48%
79%
95%

which is roughly one quarter the size of the Library of Congress. Second, these models also operate differently than models of the past. ChatGPT and other LLMs are trying to produce a reasonable continuation of the text that was initially provided. Some people refer to this as a "next word guessing engine." Based on input phrases, these LLMs are essentially evaluating the probability of what the next word should be. What is interesting is the latest generation of models don't always choose the highest-ranked word. Because some randomness is involved in the model response, these AI chatbots appear to produce much more variety and interesting content. For more details on how ChatGPT works, see Wolfram (2023).

Potential Benefits

Let's ask ChatGPT about how it might help NDT professionals with their job. (Note: my prompts are in blue and ChatGPT's responses are in red.)

ChatGPT Q&A Part I

What are the benefits or positives of using emerging AI chatbots like ChatGPT with work in nondestructive testing?

There are several potential benefits to using emerging AI chatbots like ChatGPT in nondestructive testing (NDT) applications. Some of these benefits include:

1. Improved speed and efficiency: AI chatbots can perform tasks much faster than humans, and can work around the clock without breaks. This means that NDT tasks can be completed more quickly and efficiently, which can lead to cost savings and improved productivity.
2. Increased accuracy: AI chatbots can be trained to perform NDT tasks with a high degree of accuracy, which can reduce the risk of errors and improve the reliability of test results.
3. Enhanced safety: NDT tasks can often be dangerous or involve exposure to hazardous materials. By using AI chatbots to perform these tasks, human workers can be kept out of harm's way, reducing the risk of accidents and injuries.
4. Scalability: AI chatbots can be easily scaled up or down depending on the needs of the project, making it easier to handle large volumes of work or adjust to changes in demand.
5. Better data analysis: AI chatbots can process large amounts of data quickly and accurately, allowing for more detailed analysis of test results and better insights into the health of the materials being tested.

Overall, the use of emerging AI chatbots like ChatGPT has the potential to significantly improve NDT processes, making them faster, more accurate, and safer for workers.

This reads pretty well. I must admit I'm skeptical of some of these points, but I do feel there are clear opportunities for AI chatbots to assist humans to be more efficient with some laborious tasks.

Jill Ross, the ASNT Director of Publications, wrote about the potential impact of ChatGPT on editing in the February 2023 issue of *Materials Evaluation*, using ChatGPT: "AI has the potential to revolutionize the editing and publishing industry by automating various tasks that are traditionally done by human editors and publishers" (Ross 2023). For example, one application is writing summaries and abstracts. AI can take a longer piece of writing and summarize it into a shorter version in seconds, which can be particularly useful for editors and publishers who need to quickly grasp the main ideas of a piece of writing. Another one of the most promising aspects of the latest AI agents is improved language editing for non-English speakers (Kim 2023). Such tools, currently free to everyone around the world, can produce generally good-quality, edited paragraphs in seconds. Coupling this feature with existing AI-based text translation tools, the quality and accessibility of published materials is being positively impacted throughout the world.

Taking this one step further, Ripi Singh has been one of the leading early investigators of the potential of collaborative writing with AI agents. In 2021, Singh and Garg created their own interface script to engage with GPT-3 and collaborated with it to research human factors in decision-making for NDE 4.0. The result was published in the *Journal of Nondestructive Evaluation* (Singh et al. 2021) and was the first NDT paper having an AI agent as a co-author. The article and a more recent blog post (Vrana et al. 2023) provide evidence of the opportunities for practical human-machine co-working at the linguistic and cognitive levels. (Also, see the NDE Outlook article in this issue on page 17 [Singh and Garg 2023].)

Beyond just technical writing, AI agents like ChatGPT can also be a valuable tool for programmers in several practical ways (Timothy 2023). ChatGPT is best used as a companion tool, generating efficient algorithms for specific tasks, answering coding questions, and providing help with ideas. It can also translate code to another language and in certain instances help debug your code. Tyler Lesthaeghe at the University of Dayton Research Institute has been experimenting with the potential use of AI tools to accelerate NDT research. "I presented ChatGPT with a request to develop a Python script that would tackle an old challenge in automated geometry generation for finite element modeling. It generated a script that, with some minor tweaks, was functional; but it, unfortunately, did not actually solve the fundamental problem. However, it did make me aware of a library that I was previously unfamiliar. I later tested ChatGPT with a more general task—plot the dispersion curves for a generic isotropic material. It set up the script reasonably well, produced material property values for the material I requested, and generated functional code producing the correct kind of plot. However, the actual calculation, and thus the resulting curves themselves, were complete nonsense. ChatGPT can, however, be 'coached.' So, with a knowledge of how to properly solve the problem, you can provide it with that explanation, and it will ultimately generate the right output. While I think there is real potential value in accelerating the more trivial parts of code development for NDE applications, and it may be useful in providing new perspectives or potential solution paths for more challenging kinds of problems, it performs best with a human in the loop."

Risk and Concerns

Let's now ask ChatGPT about risks and concerns with NDT professionals using it.

ChatGPT Q&A Part II

What are the risks or potential issues using emerging AI chatbots with work in nondestructive testing?

While there are potential benefits to using emerging AI chatbots like ChatGPT in nondestructive testing (NDT), there are also some risks and potential issues that need to be considered. Some of these include:

1. Lack of human judgment: AI chatbots may not have the same level of judgment or intuition as a human worker, which could lead to errors or misinterpretations of data.
2. Limited flexibility: AI chatbots are only able to perform tasks that they have been specifically programmed to do, which could limit their usefulness in certain NDT applications.
3. Data bias: AI chatbots may be trained on biased or incomplete data, which could lead to inaccurate or unreliable test results.
4. Cybersecurity risks: AI chatbots are vulnerable to cybersecurity threats like hacking or data breaches, which could compromise sensitive NDT data.
5. Ethical concerns: The use of AI chatbots in NDT raises ethical questions about the role of technology in the workplace, and the potential impact on human workers.

It is important to carefully evaluate these risks and potential issues when considering the use of AI chatbots in NDT applications, and to take steps to mitigate these risks through careful planning, rigorous testing, and ongoing monitoring and maintenance.

What sources did you use to provide these responses on the benefits and risk for using AI for NDT?

As an AI language model, I have been trained on a large corpus of text data that includes a wide range of sources on the topic of artificial intelligence and nondestructive testing. Some of the sources that may have contributed to my response include:

1. Research articles and publications from academic journals, conferences, and industry experts on AI and NDT.
2. Online articles and reports from reputable sources such as industry publications, news outlets, and research organizations.
3. White papers and case studies from companies and organizations that are involved in developing or using AI for NDT applications.
4. Technical documentation and specifications for AI technologies and tools that are relevant to NDT.

It is important to note that my responses are generated based on patterns and associations in the data I have been trained on, and may not always reflect the most current or accurate information on the topic. It is always a good idea to consult multiple sources and consult with subject matter experts when making decisions about the use of AI in NDT.

Humans are required to cite their specific sources when writing. It is a common courtesy to recognize one's peers. But more important, citation of sources is a critical part of referencing where ideas come from and validating the foundations of their work. Can you please provide articles you are leveraging to respond to my questions on artificial intelligence and nondestructive testing above?

As an AI language model, I don't have access to a list of specific articles or sources that have contributed to my response. This is because my responses are generated based on patterns and associations in the data I have been trained on, which includes a vast amount of text data from a wide range of sources.

However, I can suggest some relevant articles and sources related to artificial intelligence and nondestructive testing that you may find useful:

1. "Applications of artificial intelligence and machine learning in non-destructive testing" by A. T. Arulrajah, P. R. W. Nadeeka, and M. A. Ali. This is an academic research paper that provides an overview of the applications of AI and machine learning in NDT.
2. "Non-Destructive Testing and Inspection Market - Growth, Trends, COVID-19 Impact, and Forecasts (2021 - 2026)" by Mordor Intelligence. This is a market research report that provides insights into the trends and drivers in the NDT market, including the role of AI and machine learning.
3. "Artificial Intelligence in Nondestructive Testing: A Review" by M. Elsafi, S. Saeed, and S. M. Zubair. This is another academic research paper that provides a comprehensive review of the use of AI in NDT, including the benefits and challenges.
4. "Nondestructive Testing Using Artificial Intelligence: Trends and Opportunities" by S. K. Tiwari and R. K. Jain. This is a research article that discusses the use of AI in NDT, with a focus on the potential benefits and challenges.

I hope you find these resources helpful in your research on AI and NDT.

At first, this series of responses appears appropriate and honestly impressive. However, there is one major issue if you dig deeper; none of these suggested references in the last response are actually real publications. They are all fabrications.

Why does this happen? GPT-3 is a language model that uses deep neural networks to predict the next word in a sequence of text based on the context provided by the previous words. Sometimes, when the predicted prompt responses are not precisely matched, the LLM will still do its best to string together the most plausible text response. Unfortunately, for some instances where precise responses are expected, sometimes they turn out to be nonsense.

Besides fake references, poor logic and unexpected responses are an issue for AI agents in 2023. The term *hallucinations* has been given to such fabricated responses (Alkaissi and McFarlane 2023). This issue becomes more critical when such tools are applied to technical and scientific work, like NDT, where specific details are of the utmost importance and where we can't afford to have such errors and fabrications. On NDT.net, there is a thread highlighting the bad idea of "ChatGPT3 writing your inspection procedure" (Bisle 2023). Clearly, AI agents are not ready to be given large complicated technical writing tasks and be expected to produce error-free content. From my perspective, this is OK. NDT technicians, engineers, and researchers should be leading and responsible for the quality of written procedures, reports, and scientific publications.

The other issue that the aforementioned interchange tried to highlight is the lack of any means to reference and verify where such content originated. I've written about the benefits and risks of AI for NDT in the past and was curious where ChatGPT was getting its material. While it is impressive that such AI agents can generate articulate responses to such questions, I do see an ethical issue. If these language models are being trained using material on the order of the content of the Library of Congress, shouldn't they do a better job of providing the source material for their response? To some degree, the current versions of these AI tools operate like efficient plagiarism agents, which is the antithesis of quality technical and scientific writing that depends on collegial citation.

The Future

These tools have come a long way in recent years and will only get better. While ChatGPT is based on GPT-3, OpenAI recently released GPT-4, which has received many positive reviews (Metz and Collins 2023). (While there is a monthly charge to access GPT-4 directly, Microsoft Bing Chat does provide free limited access to GPT-4 today.) There are also a number of other promising AI tools to explore today like Google's Bard, DeepMind Sparrow, and Amazon Titan. In terms of knowledge capability, GPT-4 has been trained to be more precise and OpenAI claims it can score a 1300 (out of 1600) on the SAT. So, training on a wider depth of material and taking more care with the content selection will help. But, to some degree, if these AI agents are trained using the broad history of human writing, all of the positives and the negatives of our writing will be baked into these algorithms. The current black-box architecture will make it challenging to eliminate false or offensive responses.

Going forward, the most effective way of using such tools will be in a collaborative way. This will follow our general experience with the application of AI/ML for evaluating NDT data, where maintaining a critical role for human inspectors ensures NDT data quality and helps compensate for instances of poor AI performance. (See Lindgren 2023 on page 35 in this issue for more discussion on this topic.) Workers are already finding ways to leverage these tools effectively while doing their job. In a recent survey, over 40% of Americans said they were using generative AI technology at work

(Molla 2023). While new technologies certainly can cause disruptions, they may ultimately lead to more and better-quality work, much like the impact of the personal computer or the internet. University instruction is already striving to rethink how to integrate such tools into their curriculum and promote best practices (Yang 2023). It is critical to understand how to create appropriate prompts for getting the best information, while also understanding the risk and quality issues of the output.

One of the biggest issues going forward concerns plagiarism, copyright concerns for human content providers, and how this technology could be better regulated. Artists and writers are beginning to take action to defend their intellectual property from so-called "fair use" (DelSignore 2023). Daniel Gervais, a professor at Vanderbilt Law School who specializes in intellectual property law states that it hinges on the following: "What's the purpose or nature of the use and what's the impact on the market" (DelSignore 2023). Basically, it comes down to how you are using the output. Is it for research or commercial purposes? If commercial, one needs to be extremely careful. These questions and concerns are going to greatly impact the future of this technology, and how widely and rapidly it will be used.

The regulation of AI is expected to evolve rapidly and must address the safe application of this technology. To date, regulation is being led by the EU and China, while the US response has been fairly limited in scope. The White House's *Blueprint for an AI Bill of Rights* highlights the need for better decision-making including explanations: "Automated systems should provide explanations that are technically valid, meaningful, and useful to you and to any operators or others who need to understand the system, and calibrated to the level of risk based on the context" (Klein 2023). But experts generally agree we have made almost no progress on explaining what is happening inside these LLMs (Klein 2023). There is a clear need to be able to comprehensively validate AI performance, but this appears to be greatly complicated by how complex these algorithms have become. Work on Explainable AI—a set of tools that help one understand and interpret the outputs generated by ML algorithms—is progressing, but it will take time to get there.

One consideration for our community: What if we created our own NDT Chatbot, let's say residing behind the ASNT login, trained using ASNT-copyrighted materials, for example back issues of *Materials Evaluation*, and maybe even handbooks? Based on what GPT-4 is doing, it is clear such a tool could pass a Level III exam. If done right, this could be a valuable resource for the community. Of course, we'd have to first ensure that the answers are consistently correct, just as we have reviewers ensure our handbooks and publications are as error-free as possible. I feel the technology would also need to produce the source(s) for its answer to the user, so we have a record to check and verify that the answer is correct. If poor responses are discovered, we must also have the means of correcting it.

While we can imagine all of the positive uses for such AI agents, they can just as easily be deployed for nefarious causes today. For example, these tools will likely improve the social engineering that is being used to fleece people of personal information and money through predatory emails, robocalls, and social media. It is critical to consider the trade-offs of organizing our body of knowledge into one easily accessible place. Ripi Singh has some very important insight on this going forward: "The 'Vulnerable World Hypothesis' is a topic that deserves our undivided attention at every ASNT conference as a single body of professionals committed to Creating a Safer World!® We can start with Generative AI as the first item on the list to be addressed, now" (Singh and Garg 2023).

While I don't have all the answers and definitely can't predict the future, I do want to encourage more discussion and feedback on this important topic within ASNT. This topic has been brought up in the ASNT AI/ML Committee recently and we plan to explore possible guidance for the use of generative AI in NDT going forward. (As well, please feel free to share your thoughts with me at aldrin@computationaltools.com or get involved with the ASNT AI/ML Committee.) ME

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VALIDATED AND DEPLOYABLE AI/ML FOR NDT DATA DIAGNOSTICS

BY ERIC LINDGREN

While artificial intelligence/machine learning (AI/ML) methods have shown promise for the analysis of image and signal data, applications using nondestructive testing (NDT) for managing the safety of systems must meet a high level of quantified capability. Engineering decisions require technique validation with statistical bounds on performance to enable integration into critical analyses, such as life management and risk analysis. The Air Force Research Laboratory (AFRL) has pursued several projects to apply a hybrid approach that integrates AI/ML methods with heuristic and model-based algorithms to assist inspectors in accomplishing complex NDT evaluations. Three such examples are described in this article, including a method that was validated through a probability of detection (POD) study and deployed by the Department of the Air Force (DAF) in 2004 (Lindgren et al. 2005). Key lessons learned include the importance of considering the wide variability present in NDT applications upfront and maintaining a critical role for human inspectors to ensure NDT data quality and address outlier indications.

Introduction

There is a growing increase in interest and attention in AI/ML, which are statistical methods for data analysis. The promise of AI/ML is to use statistical methods to self-extract attributes in the data, such as relationships and/or trends in data that are not as quickly and reliably made through typical human observation. The DAF has embraced the use of these tools for applications where it can accelerate decision-making in representative campaigns, as shown in Figure 1. The objective defined for one of these efforts is summarized as: "The Air Force aims to harness and wield the most optimal forms of artificial intelligence to accomplish all mission-sets of the service with greater speed and accuracy" (USAF n.d.).

With the potential to secure more NDT data through the transformation to fully digital instruments connected as envisioned by the Internet of Things (IoT) and NDE 4.0, there is an increased interest to use AI/ML methods as the diagnostic tool to determine if a flaw is present in NDT data. Justification for the use of AI/ML includes improved accuracy, improved reliability, and faster disposition time by decreasing or eliminating dependence on human interpretation and analysis of NDT data. The initial focus for the use of AI/ML addresses the detection of flaw indications, although there is exploration in the use of AI/ML to provide additional information on characterizing the size and location of discontinuities.

When considering the applicability of AI/ML for flaw detection, it is important to recall that these technical approaches are based on statistical methods, namely regression or classification of data. The concept includes the use of multiple statistical methods in parallel combined with multiple layers of analysis to extract statistical trends in the data to enable decisions that are not readily detectable through more classical methods. These multidimensional data analysis methods frequently are called neural networks. These approaches can either be trained using data with known ground truths called supervised AL/ML, or be allowed to form the statistical relationships without training data, called unsupervised AI/ML. As these methods rely on

Figure 1. The Department of the Air Force artificial intelligence/machine learning campaign illustration.

US AIR FORCE GRAPHIC BY TRAVIS BURCHAM

data, critical attributes of the data must be considered for their use. This includes the amount of available data, the accuracy of the data, and noise present in the data.

The intent of this article is to discuss some of the challenges of using AI/ML exclusively for the analysis of NDT data through a representative outcome when considering noise and data quantity. The approach being used by the researchers at the AFRL to enhance manual interpretation of NDT data is discussed, and several representative examples that integrate attributes of AI/ML into diagnostic capability are presented. The intent is to highlight the capabilities and opportunities within the NDT community to facilitate and accelerate the analysis of NDT data.

AI/ML Requirements for Engineering Decisions

The detection of flaws using NDT capabilities is an engineering decision that requires a statistical metric of capability to ensure the safety of systems. In aviation, the capability is frequently validated by a POD study that follows the guidance provided in MIL-HDBK-1823A (US DOD 2009). To make these types of assessments possible, it is necessary to have metrics on the data that include such factors as quantity, quality, and fidelity, which includes such relatively simple factors as signal-to-noise ratios (SNRs). The outcome of a POD study that follows the guidelines of MIL-HDBK-1823A will be appropriate statistical metrics for risk calculations, ensuring the safety of systems. In the DAF, this is part of the Aircraft Structural Integrity Program (ASIP) (US DOD 2016) and the Propulsion Systems Integrity Program (PSIP) (US DOD 2008).

Similar to POD studies, the same factors of the data affect the use of AI/ML. These factors become more critical as a function of the risk to a system if a flaw is not detected during an inspection cycle. Therefore, detailed understanding of the data being used is important to enable proper use of the AI/ML algorithms when using them to extract information from this data. Recent work has illustrated the impact of data quantity and SNR on the ability of a supervised neural network–based classifier (Lindgren 2022). The study used a synthetic dataset and introduced Gaussian noise at different percent levels while varying the number of data points used to train the AI/ML algorithm. The neural network used for this study was a multilayered perceptron with four layers and 50 layers in each hidden layer. The results of this evaluation are shown in Figure 2. The plot illustrates the log of the mean square error of the neural network as a function of SNR for varying the number of data points in each dataset. The SNR varies from an infinite value to one that is poor of only 10 to 1. The number of data points in each dataset varies from 50 up to 14 000. The outcomes are presented in standard box plots showing the interquartile region (IQR) and whiskers based on the 1.5 IQR value, and the outliers are indicated by red indices for each set of numbered data points.

It is clear from this study that the improved SNR and larger datasets result in a lower value for the mean squared error. This outcome is intuitively anticipated as it is expected that more data with higher fidelity will result in improved model outcomes. However, this example highlights some of the challenges of using AI/ML for NDT data analysis. Even with the highest level of SNR, using smaller datasets for training will produce outliers that are considerably deviant for the mean values. When considering the impact on safety of systems, these outliers are the equivalent of a large, missed

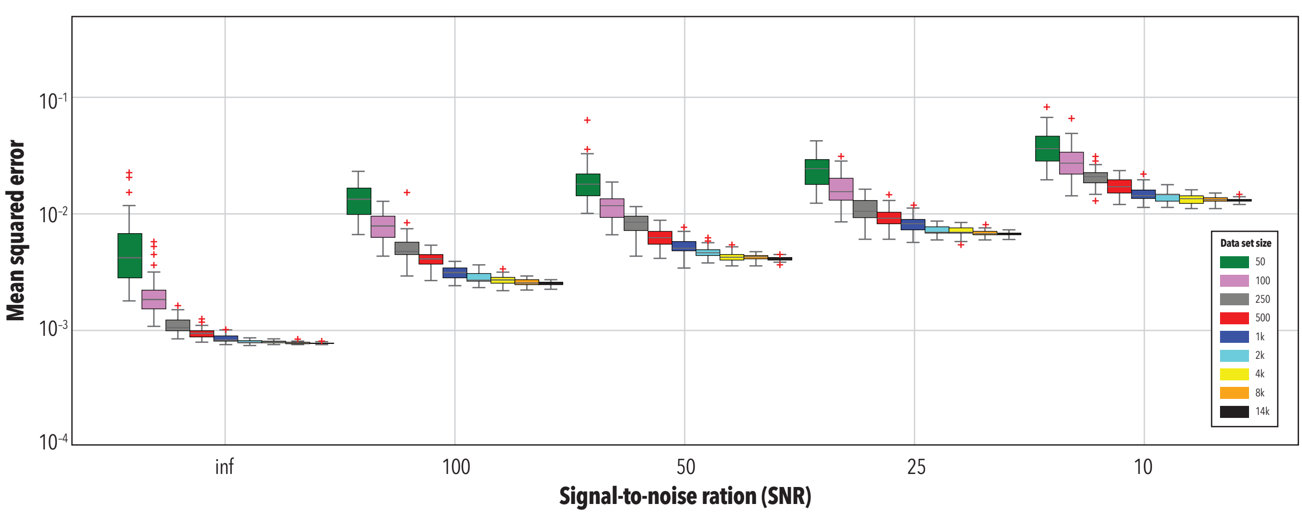

Figure 2. Multilayer perceptron results illustrating mean square error as a function of data quantity and signal-to-noise ratio.

flaw that could lead to an increased risk of a catastrophic outcome. It is important to recall that it is not the smallest flaw that can be detected, but the largest flaw that could be missed that impacts the safety of a system. This is especially true in aviation where single-load path structures are expected to have an extraordinarily low risk of failure when risk is managed by damage tolerance (US DOD 2016).

This data sensitivity study demonstrates two critical issues that need to be considered when applying AI/ML algorithms to NDT data. The first is the number of data points required to achieve improved performance of AI/ML methods. Large training sets of actual flaws are hard to generate due to the time and cost of preparing such samples. A common complaint of POD studies that follow the guidance of MIL-HDBK-1823A is the high cost to prepare samples with characterized flaws. The minimum number of flaws for a versus a-hat (i.e., flaw size versus magnitude of the signal response from the measurement system) assessments is 40 and for hit-miss assessments is 60. Large datasets of flaw responses in NDT data are difficult to find from service since the engineering response to the detection of a growing number of flaws is either to modify or replace the structural element of concern before a large population of flaws is present. An option that has been pursued includes the use of simulation to generate the required datasets for training. However, the challenge is to create simulations that are representative of the flaws found in actual structures. This approach would require a validation process with a good amount of empirical data covering the wide range of test conditions expected from an engineering perspective.

The second issue is the ability to address outliers and nuances in data that can be indicators of flaws. The concern is the tendency of statistical methods to ignore such features when using large datasets. Unless the attributes of the outlier and nuance change in data are included in sufficient large quantities in training, the approach would tend to dismiss such features in the data, which could result in missed flaws. Conversely, if the AI/ML is sensitive to outliers, then the concern becomes that a large number of false calls could decrease the value of implementing the AI/ML algorithm.

Thus, the lessons learned from the analysis of representative data includes the need to have the right data for training, including multiple flaws that are independent from each other. It is extremely important to recall that resampling the same data is not acceptable unless proper statistical methods to address correlated data are included in the analysis. Similarly, it is not acceptable to test AI/ML methods using the same data that was used for training. Another aspect is to ensure factors that can affect the statistical analysis of data (such as SNR) are included in the training datasets. In addition, if simulation data is used in training, it must be from validated models that capture all the anticipated variances found in the NDT data for the inspection. Lastly, the desired precision and accuracy of the diagnostics to be performed by AI/ML must be defined to ensure the amount of available data is sufficient to meet these objectives. This last consideration is especially true if unsupervised methods are being considered.

Challenges for AI/ML in NDT

As indicated by the sensitivity studies in the previous section, a significant challenge for the use of AI/ML in NDT data is to capture the effect of all the factors that can influence the capability to detect the flaws of interest. Figure 3 is a representation of these factors that the author has used extensively to illustrate the additional challenges when migrating from a laboratory to an operational environment. The three general classes of challenges can be summarized as equipment variability, structural complexity and variability, plus flaw complexity and variability. In addition, these parameters can change as a function of the life of a system, which increases the capability validation difficulty of the NDT system when integrated into system life management.

Equipment variability is the easiest of the three sources of variability to address from a research and development perspective. The variability in equipment settings can be defined and managed, but the unknown that frequently needs to be quantified is sensor variability and its impact on the diagnostics of flaws. Common NDT procedures address this with calibration processes, which alleviate many of these

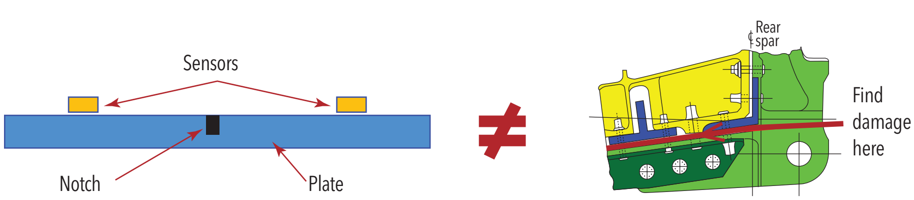

Figure 3. Representative increase in challenges when migrating from a laboratory environment (left) to an operational environment (right).

concerns. However, small changes in sensor configuration, such as coil tilt within eddy current sensors or slight depolarization of well-used ultrasonic transducers, can influence the flaw detection response.

Flaw-to-flaw variability can have a much greater impact on the NDT response. Previous studies have illustrated that the same size flaw can vary in amplitude response from an eddy current inspection by over 20% of a full screen height reading (Forsyth et al. 2015). Similar results can occur in ultrasonic testing as well as other NDT techniques. For ultrasound, fatigue crack morphology and tortuosity can affect a response. Local stress considerations from a fit-up of assemblies and changes due to use can vary crack closure, which, in turn, affects the magnitude of the ultrasonic signal. The variability can be addressed in simulation provided all the attributes of the flaw that affect detection are included in the simulation studies. This includes their interaction, which can become a very large study, especially when considering engineering level validation of the simulation.

While flaw-to-flaw variability can be broadly categorized as a function of the type of flaw, structural variability can become much more challenging in the analysis of NDT data. This is largely due to the extensive range of structures evaluated by NDT, which includes power generation, infrastructure, and transportation, the latter which can be segmented into ground, aviation, and space categories. In addition, other considerations include the materials being used, including metals, polymers, ceramics, and composites; the manufacturing process being used, for example, automation, partial automation, or hand assembly; plus, the assembly process used to join components, such as welding, fastening, and bonding. With all these parameters, it becomes very clear why NDT is the ultimate multidisciplinary engineering domain!

A significant challenge is how to evaluate the effect all these parameters, both individually and through important interactions, have on the NDT response. Consider the simple fastened joint between two metal surfaces, where up to 22 factors addressing equipment, flaws, and structure need to be included in a sensitivity study (Lindgren et al. 2007). Structural considerations include such things as composition of each layer; the possibility of shims and their composition; assembly quality, such as fastener hole tilt or skewed fasteners; and fit-up stresses as a function of what type of fastener is used and how it is installed. In addition, how these factors change as a function of time due to maintenance, repairs, modifications, and even use need to be included.

Using AI/ML techniques for these applications can become very daunting when considering all the parameters that need to be addressed to make diagnostic decisions using automated processes. This includes how the statistical processes adjust to account for changes that occur as a function of time. In addition, how these affect the diagnostic capability of the NDT data must be validated to enable their use in system risk and life management. Therefore, the proper capturing of these factors in statistically representative methods presents itself as a significant challenge, but also a significant research and development opportunity.

DAF Approach to AI/ML for NDT Data

AFRL has been leading the development of algorithms to assist in the diagnostics of NDT data, including one of the first implementations for an aviation NDT application (Lindgren et al. 2005). Attributes that have made this approach successful include the use of multiple approaches to develop algorithms for the diagnostic capability combined with the approach that the algorithms will not replace all human interpretation of NDT data. The algorithms are used as a capability to facilitate and guide the interpretation to make the workload on an inspector easier and focused on the critical elements of the diagnostic process that do not easily lend themselves for automation. AFRL has called this approach intelligence augmentation (IA), but an alternative term being used in the scientific community is collaborative intelligence (CI) (Epstein 2015). This reflects how software tools and capabilities can be used to assist in the analysis of NDT data, which AFRL has named assisted data analysis (ADA).

ADA algorithms combine multiple approaches to provide an optimized method to facilitate NDT diagnostics. These algorithms can be grouped into three general categories. The first uses heuristic-based methods that incorporate "rules of the road" that closely mimic the procedures by which inspectors interpret data. The second is a model-based inversion algorithm that uses simulation to represent the measurement response and iteratively solve for the unknown flaw or material state in the presence of variability. The third uses AI/ML methods trained using NDT data and as much diagnostics information as possible from available datasets. Frequently, the amount of well understood NDT data is much smaller than what would be required for robust AI/ML analysis, and likely requires supplementation from simulated data or transfer learning.

Successful application of ADA has frequently included at least two of these approaches into an integrated diagnostic algorithm for the specific

NDT application being addressed. This includes the use of test data to ensure the intent of the application is being met and that the available data meets the needs of the application before a comprehensive validation study is accomplished. The output of the ADA diagnostic is not the final disposition of an indication. Depending on the application, the output enables inspectors to focus their attention on portions of the inspection data that have features of possible indications by screening data with no attributes of a possible flaw. Alternatively, the output can be used to provide guidance on the nature of an indication so the proper disposition process can be rapidly identified and implemented, minimizing the time a system is in the inspection stage of a maintenance process. The key attribute of this approach is the human inspector remains in the loop. The inspector functions to ensure data quality, data fidelity, and can review any ADA outputs to make the final determination regarding an indication.

Representative DAF Successes

The following represents several examples developed by AFRL and transitioned to the DAF. The ADA capabilities are presented as a function of increasing complexity from the perspective of combining the three technical approaches outlined in the previous section. However, this order should not be considered a listing of increasing complexity as each application had its unique degrees of complexity and used different approaches to tailor to the need and to the desired outcome of the inspection.

A representative application that emphasizes the use of heuristics occurs in the manufacturing of aerospace composite structures, especially primary load carrying structures such as wing and fuselage skins. These parts require 100% ultrasonic inspection to detect delaminations and porosity where common rejection criteria are for delaminations greater than 6.35 mm (0.25 in.) in diameter or porosity that exceeds 2%. When considering the large areas to be inspected at manufacturing (note: this is not a requirement once a system is fielded), a bottleneck in the production flow can occur with the large volume of data to be assessed by inspectors. To minimize this bottleneck, a heuristic-based algorithm was developed to closely mimic the steps taken by an inspector to review data collected from these inspections (Aldrin et al. 2016).

The ADA algorithm leverages the available A-scan and B-scan data that accompanies the C-scan data. Multiple steps are taken in each of the three data representations to determine if an indication has features associated with delaminations that exceed the reject criteria. The representative result is shown in Figure 4 where C-scan features are identified as suspected defects and others are identified as benign. Though both may appear similar in the C-scan, attributes of the front wall, back wall, and volumetric gating can be used to distinguish between acceptable and rejectable features. The rejectable features are highlighted to the trained inspector who makes the final determination regarding the indication. With this approach, inspection processes have been greatly accelerated, though exact metrics are not available for publication.

Another representative case study includes the use of both simulation and heuristics to identify defects and discriminate between types of defects. The specific application is for rotating turbine engine components evaluated by an automated inspection system that can provide highly registered data. Using a combination of model-based assessments and heuristic analysis methods, the response from data with varying probe conditions can be evaluated and provide guidance on what features are from suspected indications and what are due to the probe variability (Aldrin et al. 2019b). A representative illustration of this approach is the experimental response from a subsurface nonmetallic inclusion in the presence of probe variation

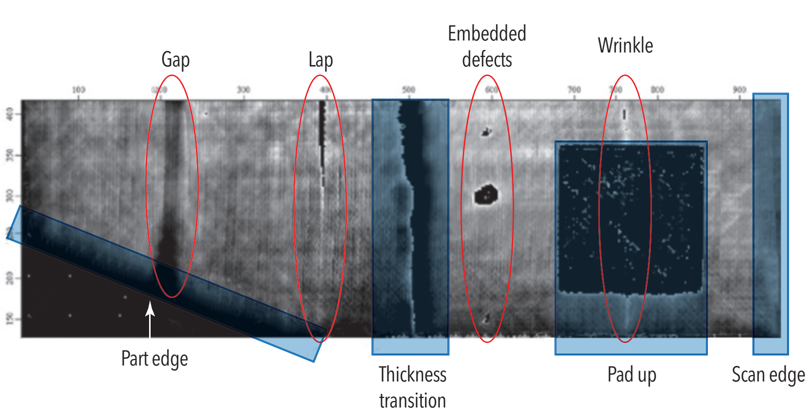

Figure 4. Ultrasonic C-scan of a composite test article indicating regions identified by the assisted data analysis algorithms as potential defects.

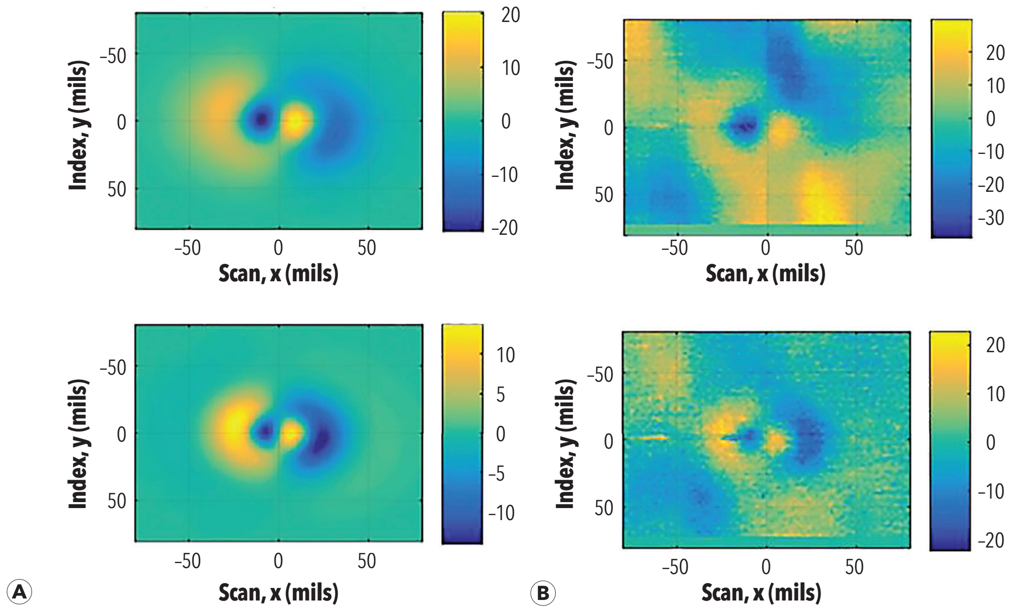

Figure 5. Model fit (a) to experimental data (b) for the vertical (top) and horizontal (bottom) representations of eddy current scans from a sub-surface nonmetallic particle with differences due to probe and material variability.

and material noise. Final results from iterative comparison and adjustments of the model data, being compared in impedance planes, are shown in Figure 5 and highlight the ability to evaluate the buried nonmetallic inclusion size and depth. Additional steps in the development process resulted in the ADA algorithms providing guidance to the inspectors when features in the data indicate when a fatigue crack is emanating from a nonmetallic inclusion. The ADA being developed for this application is in its final stages of refinement before it will be evaluated by a formal validation process.

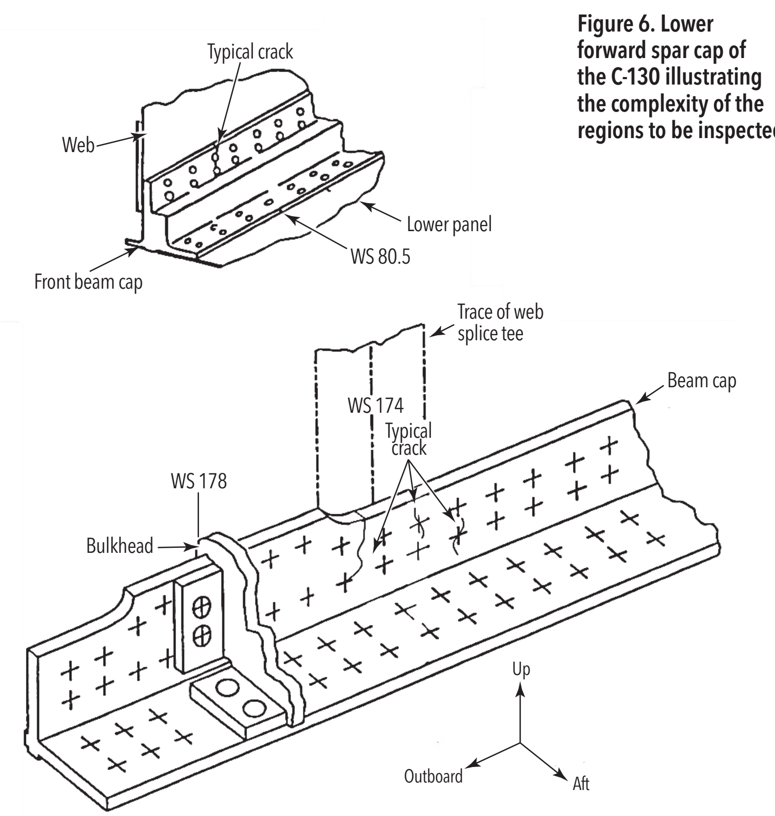

Figure 6. Lower forward spar cap of the C-130 illustrating the complexity of the regions to be inspected.

The third example combines elements of heuristics, simulations, and large dataset analysis to realize a successful outcome on a very complex inspection. The application addresses the lower forward spar cap on C-130 aircraft (Lindgren et al. 2005), as shown in Figure 6. The approach leverages development at the academic level for both the generation and detection of ultrasonic creeping waves (Nagy et al. 1994), plus the use of algorithms to discern the presence of cracks in a less complex, but still challenging, application (Aldrin et al. 2001). As described in Lindgren et al. (2005), the solution included the use of analytical methods to fully represent the propagation paths within the structure; simulation tools to explore various attributes of the inspection data as it propagates in the structure; plus, the use of advanced processing methods, namely echo dynamics and local correlation functions, to discriminate between responses from potential flaws to those from other geometric reflectors found intermittently in the structure. In addition, over 2000 representative inspection opportunities from both harvested and mock-up test articles were used to refine the decision-making process for the ADA algorithms.

The inspection process was fully validated by a comprehensive POD study before being deployed. The inspections were accomplished by contractor field teams that would collect the data and ensure it had sufficient quality to be evaluated by the ADA. Suspected indications identified by the ADA were sent to an NDT engineer to make a final determination if the indication was confirmed and needed to be sent to engineering for disposition.

The next generation of ADA will expand the capability of algorithms to facilitate the identification of defects to the capability to characterize the defects in ways that are not available today. While inspectors can use methods to approximate defect size, attributes like fatigue crack depth are especially challenging. However, using a combination of heuristics, simulations, and data-driven analytical methods, the use of ADA to determine the depth of a fatigue crack from a bolt-hole eddy current inspection was shown to have an average accuracy of 8.5% for fastener holes with minimal variability (Aldrin et al. 2019a). The next steps in the development process are to use this integrated approach to address fastener hole variability, such as skew and out-of-round attributes, to provide a crack depth estimated with a statistical bounds on accuracy, to enable rapid disposition of these defects in aerospace structures.

Summary

There is a continued potential for AI/ML methods to enhance data analysis and diagnostics for NDT data. However, there needs to be a realistic approach that includes evaluation of the data quantity, quality, and fidelity. This ensures it has the desired attributes that enable the AI/ML techniques to provide outcomes with sufficient statistical metrics for the results to be used in engineering decisions. In addition, these outcomes require rigorous validation of the diagnostic capability before they can be trusted to help ensure the integrity, or safety, of systems.

A representative example illustrated the challenges in using AI/ML techniques for smaller and noisy datasets, highlighting how this can lead to outliers that would imply potentially missed defects if this approach was used for NDT datasets. Additional challenges exist in data variability from equipment, defects, and structure that impact the amount of quality data required for AI/ML approaches. While data for defects can be augmented by simulations, these must contain all the anticipated variability and complexity of the NDT evaluation technique to represent nuances and outliers that are challenging for AI/ML, but critical for high-accuracy flaw detection.

The challenges of AI/ML when used for NDT data has led AFRL to pursue a hybrid approach that integrates AI/ML with heuristic- and model-based diagnostic algorithms to facilitate and reduce the workload of inspectors while not taking them completely out of the loop. Representative examples for several DAF-related applications have demonstrated the power of combining at least two of these methods to enable complex inspections and diagnostics of NDT data. The ADA algorithms are combined with human analysis to maximize the value of the algorithms by reducing the workload of inspectors so they can focus on the critical data that could be indications of defects being present. Future work includes plans to expand the capabilities of ADA algorithms to characterize defects with statistical metrics of accuracy. Initial development efforts have shown the potential of this capability, which would decrease the disposition time of indications and increase availability of the system to the end user. ME

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TIPS FOR EFFECTIVE MACHINE LEARNING IN NDT/E

BY JOEL B. HARLEY, SUHAIB ZAFAR, AND CHARLIE TRAN

The proliferation of machine learning (ML) advances will have long-lasting effects on the nondestructive testing/evaluation (NDT/E) community. As these advances impact the field and as new datasets are created to support these methods, it is important for researchers and practitioners to understand the associated challenges. This article provides basic definitions from the ML literature and tips for nondestructive researchers and practitioners to choose an ML architecture and to understand its relationships with the associated data. By the conclusion of this article, the reader will be able to identify the type of ML architecture needed for a given problem, be aware of how characteristics of the data affect the architecture's training, and understand how to evaluate the ML performance based on properties of the dataset.

Introduction

Advances in ML have consistently generated headlines in the past few years. These developments can be attributed to sophisticated algorithms, faster hardware, and reduced costs for data storage. The natural consequence of such advancements is the deluge of datasets, often known as the age of big data. ML algorithms, especially deep learning, capitalize on these foundations, finding applications in speech recognition and object detection while opening up new possibilities through innovations such as ChatGPT (OpenAI 2023). These applications vary considerably from one another, yet the main task in each case is to recognize patterns in datasets.

Pattern recognition is arguably the primary driving force behind new scientific and engineering discoveries. For instance, Kepler utilized the observations of Tycho Brahe in astronomy to derive the laws governing planetary motion, which formed the basis for classical mechanics (Bishop 2006). However, data was not a driving force behind scientific inquiry until recently (Brunton et al. 2020), and these trends have also impacted NDT/E (Taheri et al. 2022), with recent advances such as crack detection in concrete using neural networks (Saleem and Gutierrez 2021) or identifying damage modes in composite structures via clustering algorithms (Xu et al. 2020). Neural networks are one of the most widely used algorithms today and can be understood as a class of mathematical models inspired by the structure of the human brain.

However, utilizing neural networks, or ML in general, for tasks such as defect detection or aiding data interpretation is a familiar trend in NDT/E. Martín et al. (2007) published a study in 2007 to interpret ultrasonic oscillograms obtained via the pulse-echo method with the aid of neural networks. Even earlier, in the 1990s, Mann et al. (1992) presented the use of neural networks to classify ultrasonic signals obtained from microfiber cracking in a specimen built using a metal matrix composite. These examples demonstrate that the NDT/E community has long recognized the need to augment human judgment with pattern recognition algorithms.

Despite these advances, limitations of ML in NDT/E have mitigated its impact on the field when compared with other disciplines. A widely acknowledged problem is the limited amounts of data available, which is the driving force behind the success of ML in many applications. Even if the lack of training data is not an issue with data-intensive applications, such as acoustic emission testing (Sikorska and Mba 2008), acquiring data with a high signal-to-noise ratio (SNR) is a significant hurdle. Finally, an adequate level of understanding and experience in ML techniques is required to ensure the accurate performance of algorithms, which currently needs improvement (Vejdannik et al. 2019).

In this article, we address important challenges in applying ML to NDT/E by providing guidelines for practitioners and researchers on building high-quality datasets and using appropriate algorithms to ensure high performance from trained ML models. The desired outcome of this effort is to encourage progress in realizing the full potential of ML in NDT/E, leading to more accurate and efficient testing methods in the future. Note that the focus of this article is on how to assess datasets and results. Detailed descriptions of the ML algorithms can be found in other papers (Taheri and Zafar 2023).

Forms of Machine Learning

ML can be divided into various learning paradigms, each with its characteristics and uses. Below are descriptions for two of these paradigms: supervised learning and unsupervised learning. Examples of supervised learning and unsupervised learning are illustrated in Figure 1.

Supervised learning: An ML paradigm that trains the parameters (often numerical weights) of a model from input data (features) and known output data (labels). Supervised learning is the most popular ML paradigm due to the ease at which model training can be directly translated to the target task. The key element of supervised learning is the availability of labeled data. Yet in

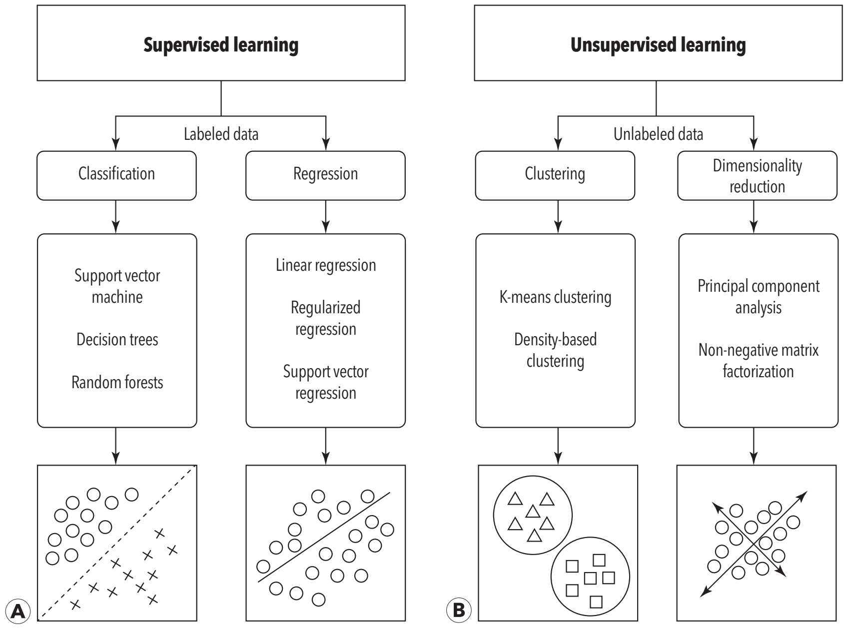

Figure 1. Learning paradigms of machine learning: (a) supervised learning algorithms utilize labeled data, which allows algorithms to be trained directly on the downstream task (classification and regression); (b) unsupervised algorithms utilize unlabeled data, which are primarily used for clustering and dimensionality reduction. Semi-supervised learning algorithms incorporate characteristics of both of these paradigms.

NDT/E, obtaining reliable labels is a specialized and time-consuming task, which is further complicated as manual delineation of discontinuities introduces user subjectivity. In turn, mislabeled data can be counteractive to the learning process of supervised learning ML models (Taheri and Zafar 2023; Lever et al. 2017).

Unsupervised learning: An ML paradigm from which an ML model is trained from the input data features, but without known data labels. Clustering is one of the most well-known forms of unsupervised learning, wherein data is divided into discrete groups. Furthermore, dimensionality reduction and manifold learning methods such as principal component analysis (PCA) (Lever et al. 2017; Yang et al. 2022) and t-distributed stochastic neighbor embedding (tSNE) (van der Maaten and Hinton 2008) are forms of unsupervised learning. Unsupervised learning is useful in NDT/E due to the challenges of obtaining labels.

Tips: If dependable labels can be obtained for a dataset, a supervised learning paradigm is often the simplest and most accurate. Assuming no labels are known, unsupervised learning is powerful but requires domain-specific insights from the user. Unsupervised learning also generally lacks metrics for standardized evaluation.

Types of Learning Tasks

Each ML paradigm can take on different tasks. In this subsection, we subdivide supervised learning into its two most common tasks (classification and regression) and subdivide unsupervised learning into its two most common tasks (clustering and dimensionality reduction). These subgroups are illustrated in Figure 1.

Classification: A supervised ML model performs classification when it determines if the input data belongs to one of a discrete set of "classes," or categories. For example, different defect types (e.g., delamination, crack, no defect) may represent different classes that we may observe.

Regression: A supervised ML machine model performs regression when estimating the value of a continuous dependent variable from an input independent variable. For example, an ML model may process imaging NDT/E data to estimate the size of a defect.

Clustering: The clustering task aims to classify data without known information by identifying groups, or clusters, of data that are similar to each other in some manner. Clustering can be valuable for identifying unknown relationships between the data, such as the presence of outlier data that could correspond to a discontinuity.

Dimensionality reduction: The aim of dimensionality reduction is to reduce the data into its essential features. Many compression and denoising algorithms can be considered forms of dimensionality reduction (Yang et al. 2022). It can separate components (e.g., multiple reflections from an ultrasonic B-scan) that reconstruct the data when added together (Liu et al. 2015). This is sometimes referred to as blind source separation.

Tips: It is important to determine the appropriate learning task for a given problem as it dictates the choice of an ML model and the associated challenges. Figure 1 describes the most common ML models used for each task.

Characteristics of Machine Learning Datasets and Architectures

Most ML architectures learn only from the provided data. As a result, ML model performance is highly dependent on the dataset quality. The classic bias-variance tradeoff is one of the most common challenges we must consider when building a dataset and choosing an architecture.

Bias: One of the most significant issues that one must consider when creating a dataset is to consider the inherent bias that the dataset exhibits and how it affects the ML model. That is, a dataset will be biased if the training data (i.e., the input data and labels that are used to initially train the model) tends to better represent one scenario over another (Mehrabi et al. 2022). Note that bias is not inherently bad since you may want to focus on a particular scenario (Miceli et al. 2022), but it is important to acknowledge that bias. For example, an ML model trained

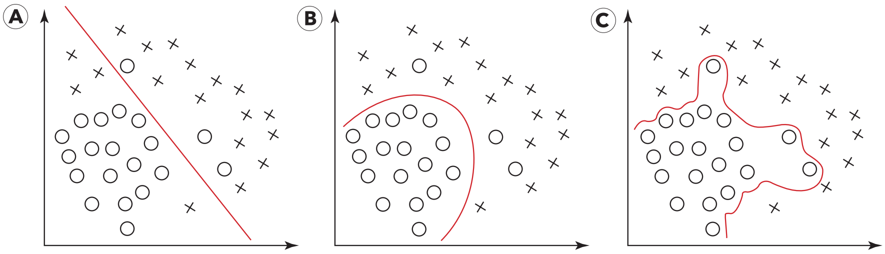

Figure 2. Model fitting: (a) underfitting; (b) ideal fitting; and (c) overfitting. An underfitting model characteristically suffers from poor performance in the training data, being unable to learn the relationships within the data. On the other hand, an overfitting model characteristically suffers from over-performing on the training data (often viewed as "memorization") and fails to generalize onto new data samples. Thus, a fundamental goal of machine learning algorithms is to find an ideal fitting.

on simulated data (for which we can produce an abundance of labeled data) will learn the specific characteristics of the simulated data, but it may not also represent experimentally measured data. If the labels are imbalanced (e.g., there are twice as many cracks as delaminations), then the data will be inherently more likely to predict the larger class. In short, if a characteristic of our data is imbalanced (e.g., twice as many measurements originate from aircraft wings than bridges), then the predictions will be more accurate for those dominant characteristics. An underfit ML model is created when trained with a biased dataset or when the ML model has too few parameters (Figure 2). Such a model fails to learn specific characteristics from the data, leading to poor performance (the classic bias-variance tradeoff is illustrated in Figure 3).

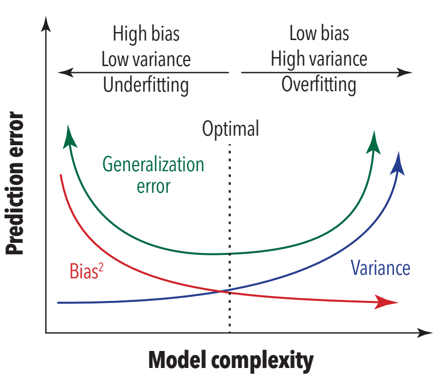

Figure 3. Bias-variance tradeoff curve. Machine learning models strive to balance bias and variance. Simple machine learning models typically have fewer parameters, wherein the high bias and low variance are characteristic of model underfitting. On the other hand, complex machine learning models have a large number of parameters, wherein the low bias and high variance are characteristic of model overfitting.

Variance: The effects of data imbalances are difficult to gauge in part due to the variance in the dataset, another factor that must be considered when building data. A common question posed by non-ML practitioners is often "How much data do you need?" The answer is usually "it depends" due to the inherent variance in the input data. For example, if a crack looks identical in every single measurement, then the dataset has very low variance. In this scenario, you may not need a learning system because one datum of a crack sufficiently describes all other examples (although some pattern recognition is still necessary). In contrast, if there are a million different and unique permutations of how a crack is represented, then the ML model will need at least a million examples to correctly classify cracks. In reality, there are usually complex relationships between all data corresponding to cracks, which the ML model can learn. A highly variable dataset with too few training examples and too many parameters to learn can yield an overfit ML model (Figure 2). Such a model may find uninformative relationships in noise, leading to poor performance (Figure 3) (Belkin et al. 2019).

Interpretability: One should also consider the interpretability of an ML architecture. An interpretable ML model is one from which humans can comprehend how a decision is made (Du et al. 2019). In general, there is a negative correlation between accuracy and model interpretability (Figure 4). Gaining interpretability is a difficult problem due to the nature of black-box models, non-linearities, and high-dimensional data visualizations. Deep neural networks are the prime example, being the most accurate models but with little to no interpretability of the model decision-making. On the other hand, linear models (e.g., linear regression) are very interpretable, yet often less accurate.

Tips: Misunderstanding bias and variance is a significant pitfall for early ML practitioners. For example, novice deep learning practitioners often default toward increasing the number of layers in a neural network, thereby increasing the model complexity. However, such an architecture is not only more computationally demanding but can in some cases be less effective (due to overfitting) and less interpretable than a simpler architecture. For this reason, deep neural networks are unfavorable in situations with limited data samples of potentially high variance and situations where interpretability and accountability are important. In such a scenario, users may often analyze their problem using conventional ML models, such as support vector machines or linear regression

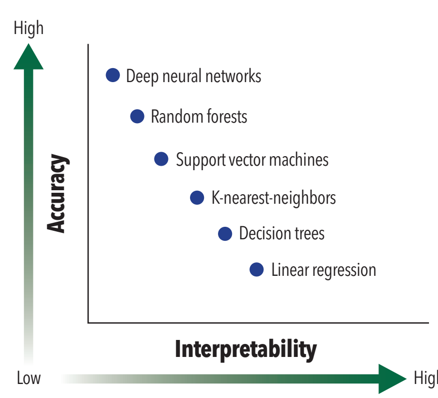

Figure 4. Model accuracy versus interpretability. In machine learning, increased accuracy has a natural consequence of decreased interpretability. Accurate models tend to capture nonlinear and non-smooth relationships, while interpretable models tend to capture linear and smooth relationships.

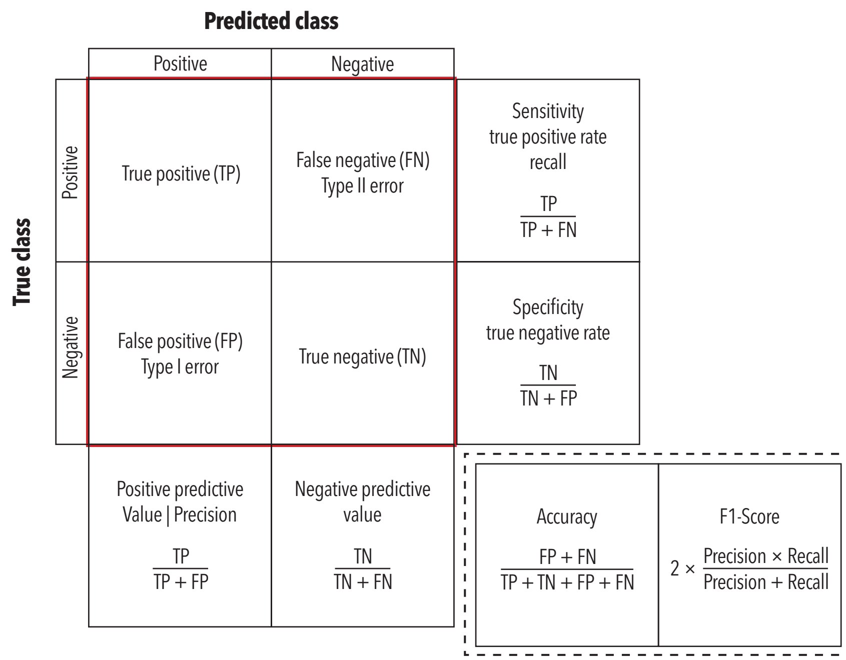

Figure 5. A confusion matrix is used to evaluate the performance of a classifier, summarizing the information between true and predicted classifications. The confusion matrix entails the number of true positives, false negatives, false positives, and true negatives. Further classification metrics may be extracted (e.g., sensitivity, specificity, accuracy, etc.) to measure different aspects of the classifier.

models, which are generally more interpretable (Figure 4). In essence, applying a model architecture should be inspired by the data and underlying factors at hand, especially for new datasets that have not been utilized for ML in the past.

Metrics for Evaluation

Evaluation metrics are performance measures for comparing ML models and understanding specific characteristics of the data or task. This is in part due to the bias and variance within the data. In particular, different evaluation metrics can be used to attain either a holistic performance or a class-specific measure. Here we review several of the most widely used metrics for evaluating the performance of ML models.

Confusion matrix: The confusion matrix visualizes the predicted values against the true values. Elements on the diagonal of the matrix indicate the number of true predictions of the model to the true class (true positives and true negatives). The off-diagonal elements indicate incorrect predictions. Reading the confusion matrix tends to give further insight as to what types of errors are made for a model and allows a holistic set of evaluation metrics. We provide a typical illustration in Figure 5, together with the common name of such evaluation metrics. The confusion matrix need not be binary but can be conducted in a multi-class fashion. However, in the multi-class scenario, summarizing the model performance may be cumbersome, and traditionally each class is evaluated in a one-versus-all manner.

Accuracy: Accuracy is often the most common evaluation metric. The accuracy is the proportion of the model predictions correct relative to the true class. From the perspective of the confusion matrix, this is equivalent to the sum of the diagonal divided by the sum of all of the values. Accuracy is an easy value to understand. However, for imbalanced datasets, the accuracy can be uninformative. For example, a common scenario in NDT/E might be that 99% of the data is from a normal material and 1% of the data is a material with a discontinuity. If 100% of the data is classified as normal, then the accuracy is 99%. This is often considered a good result until you recognize that none of the discontinuities are identified.

Recall: Also known as sensitivity or the true positive rate (TPR), the recall is the proportion of true positive cases that are correctly predicted. In binary classification, notice that if 99% of the labels do not correspond to the class of interest, and 100% of the predictions correspond to those classes, then the recall will be 0. Hence, recall can be suitable when data is imbalanced.

Precision: Also known as the positive predictive value (PPV), measures the proportion of correct positive predictions made. Observe, if 99% of the labels do not correspond to the class of interest, and 100% of the predictions correspond to those classes, then the precision will be 0. Therefore, precision can be advantageous when data is imbalanced.

F1 score: The F1 score is a metric designed to summarize both precision and recall. It is defined as the harmonic mean of precision and recall. The harmonic mean, as opposed to the arithmetic mean, addresses large deviations between precision and recall. For example, if the precision for a class is 0, and the recall is 1, then the arithmetic mean evaluates to 0.5, which may naively indicate a random classifier. On the other hand, the harmonic mean in this scenario equates to 0, revealing the classifier is predicting only one class.

Receiver operating characteristic curve: The receiver operating characteristic (ROC) curve can be generated when the confusion matrix varies as a function of a set call criterion (Figure 6). This metric originates from traditional statistical hypothesis testing in which a binary classifier is based upon the premise that some statistic is above or below a threshold. In a binary classification scenario, the ROC curve shows the false positive rate versus the true positive rate for all threshold values. To summarize the ROC, the area under the ROC curve (AUC) is often reported, where a perfect classifier attains a value of 1 and a random classifier attains an AUC of 0.5. The AUC metric is valuable as it is invariant of the chosen threshold

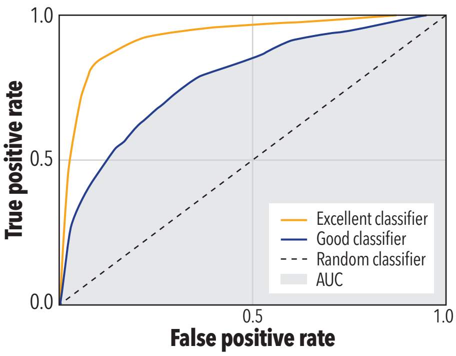

Figure 6. Receiver operating characteristic (ROC) curve. The ROC curve is achieved by plotting the false positive rate versus the true positive rate at each classification threshold. The quality of the ROC curve can be summarized by the area under the curve (AUC) shaded in gray.

and therefore evaluates the overall classifier rather than some user-chosen value. The AUC is also a feasible metric for imbalanced data.

Tips: Careful choice of evaluation metrics should be selected based upon the bias and variance of the dataset. For an unbiased, well-balanced dataset, accuracy is often the most characteristic of the model performance. In NDT/E, we are often concerned with the true positive rate, which is also known as the probability of (defect) detection or the recall of a defect. In other NDT/E scenarios, we may want to ensure that normal materials are not predicted as material defects (e.g., delaminations), in which case, the false call rate (also known as the false negative rate) or the precision score may be more valuable. Note the true positive and false positive rates are utilized in traditional NDT/E probability of detection assessment (Cherry and Knott 2022). In the cases where we want a balance between the recall and precision scores, the F1 score becomes a valuable metric.

Conclusion

ML has a significant potential to contribute to the NDT/E community. However, successful usage of ML algorithms demands greater insight into their capabilities and intricacies. This sentiment is also true for those in the community building new datasets for ML practices. Understanding the basic capabilities of ML paradigms, navigating how bias and variance within the data affect the ML model, and establishing how performance will be measured will help the community create datasets that have the greatest impact.

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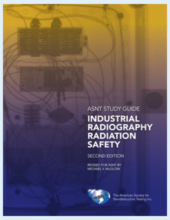

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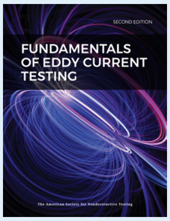

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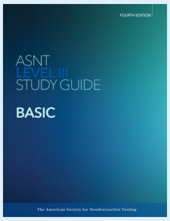

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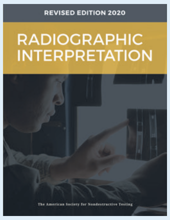

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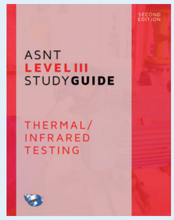

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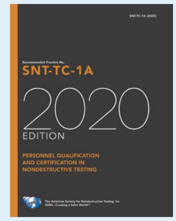

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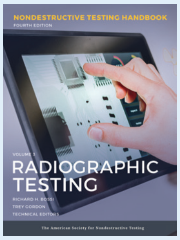

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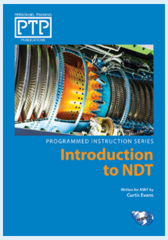

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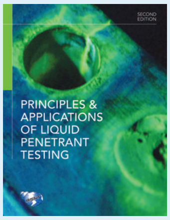

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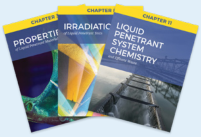

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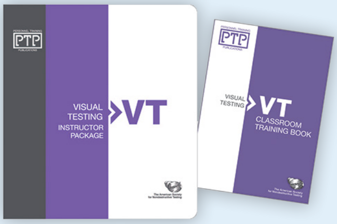

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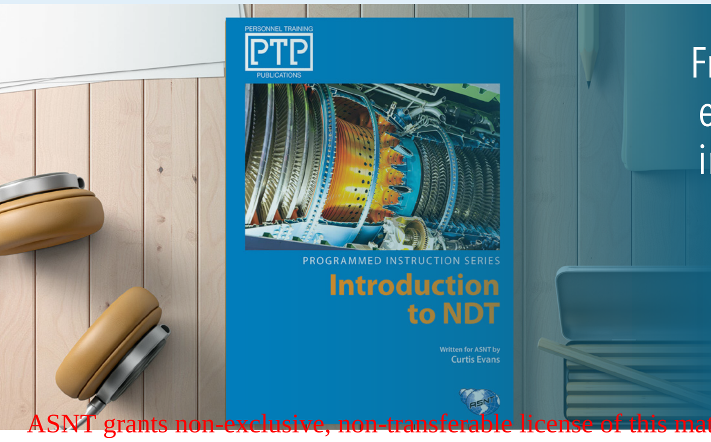

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MACHINE LEARNING TECHNIQUES FOR ACOUSTIC DATA PROCESSING IN ADDITIVE MANUFACTURING IN SITU PROCESS MONITORING A REVIEW

HOSSEIN TAHERI* AND SUHAIB ZAFAR†

ABSTRACT

There have been numerous efforts in the metrology, manufacturing, and nondestructive evaluation communities to investigate various methods for effective in situ monitoring of additive manufacturing processes. Researchers have investigated the use of a variety of techniques and sensors and found that each has its own unique capabilities as well as limitations. Among all measurement techniques, acoustic-based in situ measurements of additive manufacturing processes provide remarkable data and advantages for process and part quality assessment. Acoustic signals contain crucial information about the manufacturing processes and fabricated components with a sufficient sampling rate. Like any other measurement technique, acoustic-based methods have specific challenges regarding applications and data interpretation. The enormous size and complexity of the data structure are significant challenges when dealing with acoustic data for in situ process monitoring. To address this issue, researchers have explored and investigated various data and signal processing techniques empowered by artificial intelligence and machine learning methods to extract practical information from acoustic signals. This paper aims to survey recent and innovative machine learning techniques and approaches for acoustic data processing in additive manufacturing in situ monitoring.

KEYWORDS: additive manufacturing, in situ monitoring, acoustic, machine learning, data processing

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Introduction

Various additive manufacturing (AM) methods are utilized for manufacturing parts with complex geometries and complicated features that are either unfeasible or highly challenging to produce via traditional manufacturing techniques. This outstanding capability of AM provides substantial design flexibility and facilitates the production of complex parts with marginal added cost compared to subtractive and traditional manufacturing methods (Calta et al. 2018). Laser powder bed fusion (LPBF), directed energy deposition (DED), and wire arc additive manufacturing (WAAM) are among the most popular methods of metal AM (Koester et al. 2018). Fused deposition modeling (FDM), stereolithography (SLA), direct ink writing (DIW), and selective laser sintering (SLS) are the most common AM techniques for polymers (Baechle-Clayton et al. 2022; Lee et al. 2020).

The AM processes not only can cause different mechanical properties for the parts manufactured, but also lead to the potential generation of specific types of discontinuities and defects in AM parts (Koester et al. 2018, 2019b; Taheri et al. 2017). The types of defects in AM parts significantly depend on manufacturing process conditions and type of materials. A summary of defect types, causes of defect generation, and their potential effect on AM parts is presented in Table 1.

Although inspection and quality assessment for the manufactured parts can be done after the production is finished (ex situ), there are several significant challenges in traditional ex situ inspection methods. One of the major challenges of traditional inspection of AM parts is due to the capability of AM techniques to produce complex-geometry components. This is an outstanding capability for AM but makes traditional inspection of AM parts extremely challenging since many available nondestructive testing (NDT) techniques have been developed for simpler geometries (Bond et al. 2019). Another primary concern in post-production or ex situ inspection of AM parts is that AM techniques are used to manufacture many critical, high-valued, or exotic parts. Possible rejection of such unique parts due to unacceptable quality causes a significant loss of time and cost and is not a desirable outcome for industries (Koester et al. 2018c; Taheri 2018). Despite the complexity of the processes in AM, the layer-by-layer deposition of materials allows the measurement and recording of large amounts of data on each layer for statistical process monitoring and quality assessment (Grasso and Colosimo 2017; Koester et al. 2018b).

TABLE 1

A summary of common process-induced defects, their causes, and potential effects on part quality in laser metal additive manufacturing (Herzog et al. 2023)

Defect type	Common causes	Potential effects
Keyhole pores	• Excessive input energy density	• Reduction in mechanical properties • Reduction in fatigue properties
Lack of fusion pores	• Insufficient input energy density	• Reduction in mechanical properties • Reduction in fatigue properties
Gas pores	• Gas entrapped in feedstock • Gas entrained into the melt pool	• Reduction in fatigue properties
Cracking and delamination	• Residual stresses exceeding the local ultimate tensile strength • Insufficient bonding between layers	• Part failure
Deformation	• Residual stresses exceeding the local yield stress	• Conformance failure
Alloy compositional variance	• Improper powder deposition • Differing chemical mobility • Preferential evaporation • Gas incorporation/adsorption	• Inhomogeneous mechanical properties
Balling	• Low/high input energy density • Surface oxidation	• Part/conformance failure • Formation of other defects
Rippling	• Instabilities of layer-to-layer deposition	• Part failure • Production failure
Spatter/particle ejection	• Overheated melt pool • Recoil pressure and melt plume	• Formation of other defects

In situ measurement and monitoring techniques using various sensors and NDT methods have been extensively utilized and studied over the last few years for understanding and predicting the alterations in AM process parameters and, consequently, the quality of the manufactured parts. In situ measurement data obtained over the entire period of manufacturing processes, combined with ex situ material characterization and information from process modeling and simulation, are essential for reducing the time and cost of process development, improving part quality, and minimizing defect formation (Hossain et al. 2022; Koester et al. 2018b).

A large body of existing and rapidly growing literature is devoted to in situ monitoring methods, surveying various in situ monitoring techniques and sensors used for different types of AM processes. High-speed visible imaging (Scipioni Bertoli et al. 2017), thermography (Raplee et al. 2017), and X-ray imaging (Calta et al. 2018) are among the most used methods for in situ process monitoring for AM. Optical-based in situ monitoring methods can monitor process conditions and variations on the surface of the parts but are limited in assessing bulk material behavior. In addition, high-resolution imaging at high scanning velocities requires an external illumination source (Lott et al. 2011). Also, a wide range of magnification may be needed to cover the imaging of the entire melting pool (Lott et al. 2011). Arntz et al. (2018) analyzed the melt flow dynamics of a laser cutting process by in situ high-speed video diagnostics (>100 000 fps). They showed a correlation between fluid dynamics, cutting velocity, and the average roughness of the cut flank (Arntz et al. 2018). In contrast, X-ray-based measurement methods can penetrate the materials and provide valuable information regarding the structure of the part. However, the complexity and cost of the X-ray monitoring technique and availability to most industries and manufacturers for widespread implementation of AM is a significant challenge. On the other hand, acoustic-based techniques have been used historically for a variety of process monitoring and part qualification applications, such as in the welding process, where its rapid solidification phenomena are very similar to the AM process (Taheri 2018). Recent work has investigated the potential application of acoustic emission testing (AET) for AM processes (Koester et al. 2016, 2018a, 2019a).

Accordingly, despite the type of sensing and measurement technique used for in situ AM process monitoring, analyzing the recorded dataset to identify, map, and potentially characterize the defects will be the next challenging step. The large dataset size and real-time processing are significant challenges in processing data for in situ measurement (Taherkhani et al. 2022). Artificial intelligence (AI) and machine learning (ML) algorithms can be promising solutions for such problems (Taheri et al. 2022). Researchers have used various supervised (Gobert et al. 2018), unsupervised (Scime and Beuth 2018), and reinforcement learning algorithms (Knaak et al. 2021) for the prediction of defects during AM processes.

AI/ML methods have significant potential to improve the AM processes and the quality of manufactured parts. The necessity of AI/ML integration to AM processes is due to the contemporary need for reduced labor cost and time, digitization in AM, and massive data availability (Kumar et al. 2023). AI/ML can be integrated into different sectors of manufacturing. In design, AI/ML increases acceptance of novel approaches and saves time and resources. In production, application of AI/ML saves time and energy and avoids waste. Finally, smart manufacturing can be interpreted as application of AI/ML in assembly processes to adjust any error in real time. Addin et al. (2007) demonstrated the potential application of ML in material science and design. In their paper, the Naïve Bayes classification is used for deterioration detection in construction. Jin et al. (2020) indicated that an ML model based on real-time camera images and deep learning algorithms can detect different levels of delamination conditions in FDM and determine the tendency of warping before it actually occurs.

This paper aims to survey the application of AI and ML for data processing in acoustic-based in situ monitoring of AM processes. First, an overview of the acoustic emission NDT method for in situ monitoring of AM processes is presented. Then, various AI/ML techniques used by different researchers and the outcome of their analyses are described. The paper concludes with a summary of the discussion, existing challenges, and potential future work.

Acoustic Emission for In Situ Monitoring in AM

Acoustic emission (AE), also known as acoustic emission testing (AET), as a monitoring technology has been explored by several research groups (Koester et al. 2018a; Wasmer et al. 2019; Wu et al. 2016). AE refers to the generation of elastic (mechanical) waves released by materials when subjected to an external impetus, such as raising the gas pressure inside a cylinder, stimulating a given structure will cause deformation inside of it, such as crack growth. Consequently, this will trigger the rapid release of stored strain energy as transient elastic waves, typically from a localized source. Formally, AE refers to both the generation mechanism and the waves themselves (ASTM 2020). Rapid melting and solidification occurring during the AM processes is a significant potential source of elastic waves that AE can hypothetically detect (Morales et al. 2022). Rapid generation of defects, such as cracks or porosity, can also produce elastic waves in the form of AE. A standard AE setup includes a set of piezoelectric transducers coupled to a structure, connected via cables to a monitoring system that performs data acquisition and processing. The data is stored on a computer and can be visualized in real time for further analysis after testing is complete. For the sake of brevity, this paper will not go into further technical details of AE fundamentals (Hossain et al. 2020).

Most AE systems use a hit-based mode, which identifies transient waves in the signal and extracts features from them. A small set of parameters can describe discrete AE, which is digital (Taheri et al. 2013). The most commonly used parameters are rise time, peak amplitude, duration, MARSE (measured area under the rectified signal envelope) energy, and (ring-down) counts, as highlighted in Figure 1. The rise time is the time it takes for the signal to reach its peak amplitude after the first threshold crossing (defined by the operator), measured in microseconds. The duration of the hit is the time measured (usually in microseconds) from the first to the last crossing of the threshold, after which the AE hit will remain below the signal detection threshold, which the user identifies. The duration is often measured in microseconds. Given reflection and other mechanisms in a specimen, AE systems use different timing parameters to compute rise time and duration.

The burst signal energy, or MARSE, is computed by taking the integral over time of the squared electrical signal over its duration. Finally, ring-down counts are the number of threshold crossings of an AE signal. It is another valuable parameter to help distinguish between AE signals and background noise. Combined with other signal features, some or all of these parameters can be correlated with the AM process condition through statistical signal processing and ML techniques and used to identify potential discontinuities in the manufactured parts (Bond et al. 2019; Taheri et al. 2019).

For instance, Li et al. (2021) observed that the AE signals collected over a laser-cladding AM process where cracks exist in the parts have larger amplitude and energy than AE signals collected over a normal cladding process. Hossain and Taheri (2021a) discussed the potentials, limitations, and opportunities of acoustic techniques for process monitoring of AM. In this paper, the authors highlighted the capability of acoustic techniques for volumetric quality identification and adaptability to various manufacturing techniques as the major promising features of acoustic techniques for in situ process monitoring for AM. These abilities have been investigated in various manufacturing processes, including but not limited to AM, by other researchers. Ramalho et al. (2022) showed that the influence of contamination in WAAM can be identified through the analysis of the acoustic spectrum of the process. Ramalho et al. aimed to establish a microphone-based acoustic sensing method for WAAM quality monitoring. WAAM parts were fabricated with

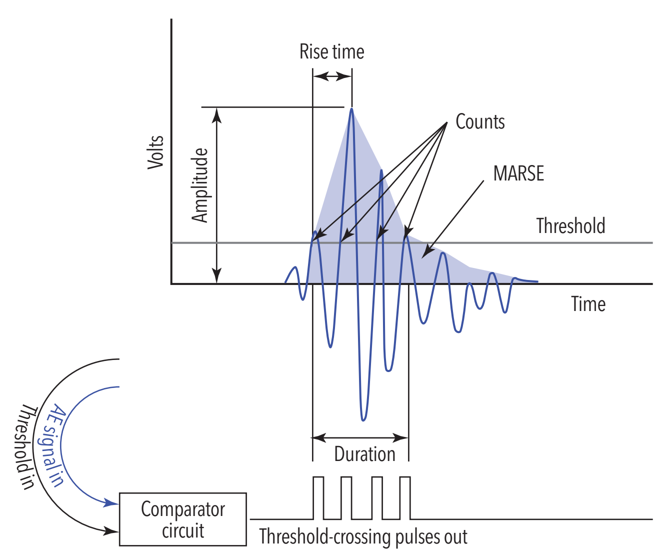


Figure 1. A burst-type AE signal and associated features (from nde-ed.org).

introduced material contaminations in Ramalho et al.'s work, and acoustic signals were recorded during the manufacturing process. Power spectral density (PSD) and short time Fourier transform (STFT) were used to pinpoint the location of discontinuity formation (Ramalho et al. 2022). Active acoustic methods, or ultrasonic, have also been studied for in situ monitoring of the WAAM process. Hossain et al. (2020) designed a fixture to connect an ultrasonic transducer to the build plate of the WAAM system and keep it in constant contact during the manufacturing process. The features extracted from ultrasonic signals showed that there is a detectable difference between the values of root mean square (RMS), root-sum-of-square (RSSQ), and peak magnitude-to-RMS ratio (P2R), which was interpreted as the indication in process deviation from the typical window of WAAM (Hossain et al. 2020). The features extracted from AE signals can be correlated with the AM process condition through statistical signal processing and ML techniques or be used to identify the potential discontinuities in the manufactured parts. Despite the large amount of information that can be extracted from AE signals, challenges exist in interpreting the signals due to the potentially low signal-to-noise ratio (SNR) and significant variation in the magnitude or frequency of the AE signal over the monitoring period of the AM process. The literature discussed previously reveals that AE shows a promising ability to distinguish variations in the operating conditions of AM systems, known as process conditions. The contrast between AM process conditions is the main cause of quality variation and changes in AM parts. Studies have also shown that AE not only distinguishes between contrary AM processing conditions, which potentially cause different types of defects, but also differentiates various levels of defects. As an example, Shevchik et al. (2019) showed that three levels of quality categories of AM parts manufactured by LPBF can be identified by detecting AE signals analyzed by ML techniques. In their study, quality categories are defined as high, medium, and poor corresponding to various levels of porosity of 0.07%, 0.30%, and 1.42%, respectively (Shevchik et al. 2019).

Machine Learning Techniques for Acoustic Data Processing

Massive datasets are ubiquitous across scientific and engineering disciplines in the current era, and this trend can be attributed to the meteoric rise in computing power over the past few decades. Consequently, applying ML algorithms to infer patterns and gain insight from these datasets has become a new mode of scientific inquiry (Brunton et al. 2020). The NDT industry is no exception to this trend, especially for AET.

ML is a subset of AI and is usually divided into three main categories: supervised, unsupervised, and reinforcement learning. Several learning algorithms fall under each of these categories, and in the context of NDT, the fundamental task is to discover or find discontinuities in the specimen of interest.

This section aims to avoid discussing ML jargon for brevity. Instead, this paper will elucidate the workings of selected ML algorithms relevant to AE testing as applied to AM. This paper will explain mathematical concepts with analogies, where necessary, to reach a wider audience.

One of the challenges in AE signal processing is the high level of dependency on human expert participation. However, this could be a major limiting factor when AE is used for in situ monitoring and control of the manufacturing processes. Specifically, this can be an issue when instant and accurate feedback is desired. AE is a data-intensive technology and using ML algorithms to analyze large datasets is of considerable interest to researchers and practitioners. Additionally, utilizing ML algorithms makes the technique more quantitative and less vulnerable to subjective judgments made by technicians and engineers when analyzing AE test data. However, despite the large amount of information that can be extracted from AE signals, challenges exist in interpreting the signals due to the potentially low SNR and a considerable variation in the magnitude or frequency of an AE signal over the monitoring period of the AM process. The forthcoming sections briefly discuss how classifiers using various ML techniques are built to help sort AE data obtained from AE systems in the context of AM. ML methods can handle these situations with reasonable efficiency. However, there are still some challenges associated with various ML techniques that must be resolved.

Supervised Classification of AM Process States

Supervised learning refers to a learning paradigm that requires prior knowledge of the answers to the problem at hand, which implies providing both the input data and the corresponding output labels when training the ML model. The model then learns a pattern to better predict or classify future data based on the knowledge from the examples during training. Supervised learning is analogous to a pupil learning a subject by studying a set of questions and their corresponding answers. Classes of problems that require supervised learning include regression and classification problems.

Neural Networks

This section provides an overview of neural networks, including the differences between artificial neural networks (ANNs), convolutional neural networks (CNNs), spectral convolutional neural networks (SCNNs), reinforcement learning (RL), and support vector machines (SVMs).

ARTIFICIAL NEURAL NETWORKS

ANNs are a commonly utilized ML architecture, modeled loosely on the human brain, mimicking how biological neurons communicate with one another. The perceptron, demonstrated by Frank Rosenblatt of Cornell in 1958, was the first trainable neural network (NN) (Rosenblatt 1958). However, it consisted of only a single layer, as opposed to the modern iteration of neural nets (also known as feedforward NNs), which have multiple layers of neurons (multilayer perceptron, or MLP). Figure 2 shows a sample ANN with one input layer (with five neurons), two hidden layers (each with four neurons), and one output layer with two neurons.

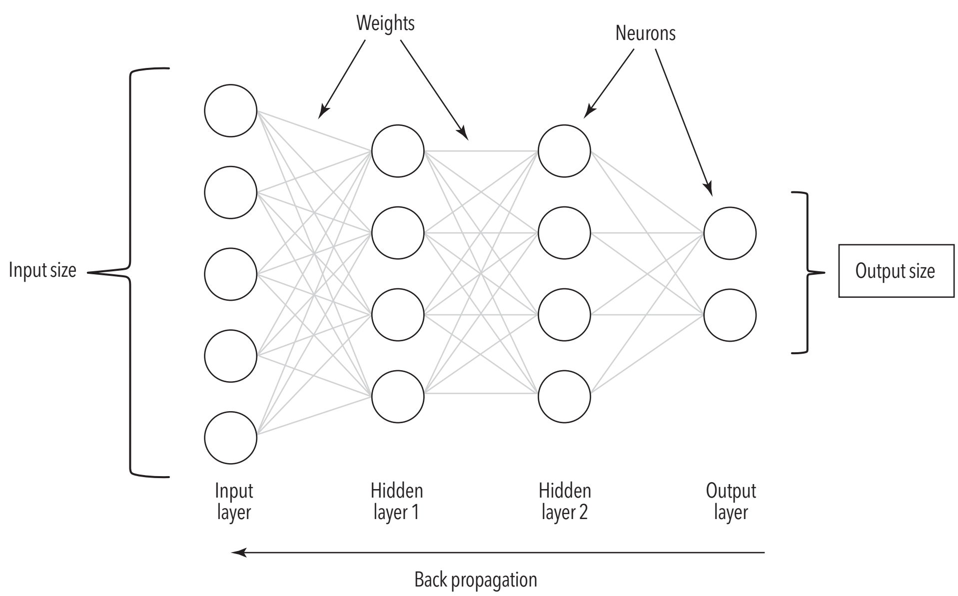


Figure 2. An artificial neural network with various components labeled. The arrow shows the direction of back propagation.

In NNs, weights are coefficients that act as scaling factors for the output of any given layer in an NN. They are the fundamental parameters of an NN, and the aim is to optimize the values of these scalars to minimize the objective (or loss) function during the training phase. Back propagation (also known as backprop for short) is the primary algorithm for performing gradient descent on NNs. It involves performing a forward pass through the network by computing the output value of each node. Then, a backward pass through the network is performed, adjusting the values of the weights in the network.

A weighted linear combination of all its inputs is calculated at each neuron. The inputs to the neurons are multiplied by their corresponding weights and then summed up. The result is then passed through an activation function. The activation function decides if the neuron should be activated or not and, if activated, decides its value. The sigmoid function is one example of an activation function. Training an NN requires defining the objective or loss function, typically the mean squared error (MSE) for regression problems or the cross-entropy loss for binary classification problems (relevant to NDT).

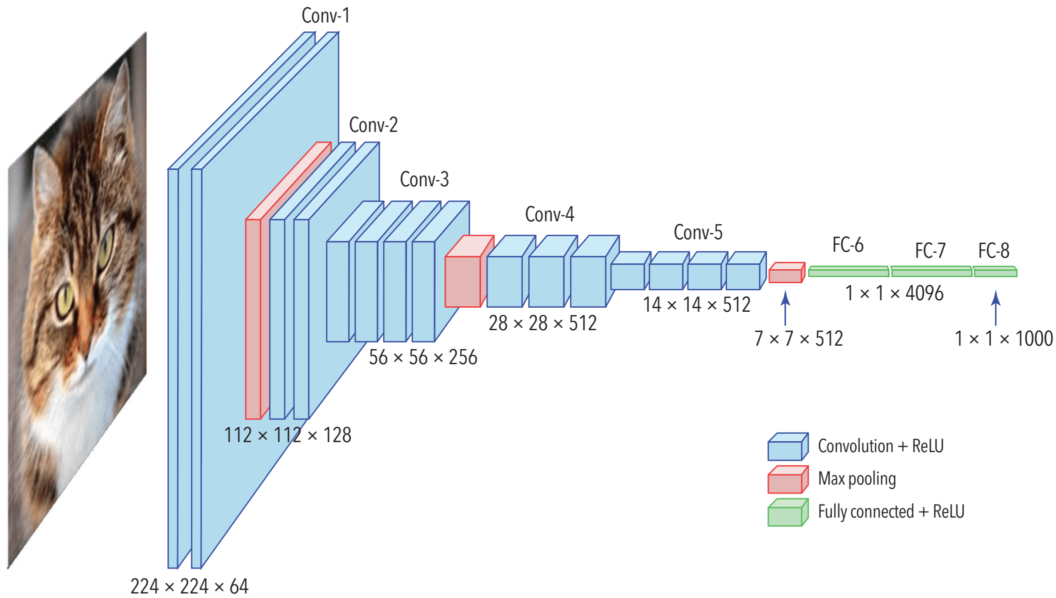
With the rise of more powerful hardware, especially graphics processing units (GPUs), NNs can now be trained faster, requiring less computational hours while simultaneously being "deeper." The "deep" in deep learning simply refers to the depth of layers in an NN, typically in the hundreds and thousands of hidden layers. The use of deep NNs has revolutionized the field of AI and ML, and frameworks such as PyTorch allow engineers in various fields to apply these powerful algorithms to problems in their respective domains of expertise.

CONVOLUTIONAL NEURAL NETWORK

CNNs, also known as ConvNets, are a class of NNs that are exceptionally well-suited for applications involving images and videos, such as image and video recognition, driverless cars, and image classification. Like ANNs, CNNs have an input layer, hidden layers, and an output layer. However, the hidden layers will have one or more convolution layers (hence the name). In conjunction with the convolution layers, CNNs also have pooling layers, and together form a single layer of a CNN. The architecture of a CNN is shown in Figure 3.

The function of the convolution layer is to detect specific features in an image using the convolution operation that utilizes the concept of the inner (or dot) product between two vectors. In a CNN, the convolution operation is executed using a kernel that is the same size as the window of data it operates on. It is important to note that the kernel elements are weights the network learns when trained. The pooling layer is utilized to reduce the spatial dimension of the data, which helps reduce computational costs and makes the network resistant to overfitting. Each convolution layer has a rectified linear unit (ReLU) activation function that converts all negative values to zeros. The fully connected layer is not a characteristic of the CNN and contains an activation function just like an ANN, converting features into class probabilities (in classification problems).

CNNs can process data with a similar grid structure. Local connections, weight sharing, and down-sampling are the main characteristics of CNNs that make them suitable for several types of AE signal analysis. CNN methods are based on the translation invariance of feature extraction and ignore the time correlation of signals. In the case of cyclic NNs, the complex structure and numerous parameters involved in the process make them difficult to optimize and train. Considering these limitations and challenges, research needs to be done to enhance the application of deep learning techniques for AE in situ monitoring for manufacturing processes, specifically in the case of AM. Li et al. (2022) presented a new AE signal recognition method based on a temporal convolution network called acoustic emission temporal convolution network (AETCN) for real-time polymer flow state monitoring in an FDM process.



SOURCE: LEARNOPENCV (2023)

Figure 3. A convolutional neural network (CNN) model.

AETCN uses the dilated causal convolution and dilation convolution as the cornerstone of building a network such that it has both the convenience of convolution and the advantage of using correlation information of time series, so it reduces the intervention of expert knowledge in feature extraction. To obtain information over time in an AETCN, causal convolution is used. In causal convolution, the output prediction Y_t of a time sequence at time t only depends on the timesteps from the sequence X_t and before X_t. The fact that causal convolution cannot see the future data is the main difference with traditional CNN. Figure 4 shows the basic idea of the AETCN and its construction. In the proposed AETCN by Li et al. (2022), to prevent performance degradation and gradient disappearance or explosion in the deep network, a residual network structure was introduced as can be seen by "Resblock" in Figure 4b. Network degradation, gradient explosion, and gradient subtraction can influence the performance of a deep NN, and this effect increases as the network becomes deeper.

The source of elastic waves generated over the AM processes is commonly intermittent, nonstationary, or a time-varying phenomena. This characteristic means that the generated acoustic waves are subject to rapid change in time and frequency. In such a situation, the wavelet transform (WT) can be an efficient method of capturing both time and frequency information of the signals. To address this issue, several researchers used WT for the preliminary signal processing and feature extraction from AE signals recorded from in situ AM process monitoring. Hossain and Taheri (2021a) used WT to decompose the AE signals recorded during the different process conditions in a DED process into various discrete series of sequences over different frequency bands. These segments were then analyzed to identify different process conditions using a CNN. The results show a classification accuracy of 96% and validation accuracy of 95% for different process conditions (Hossain and Taheri 2021a, 2021b).

SPECTRAL CONVOLUTIONAL NEURAL NETWORK

Researchers at Empa, the Swiss Federal Laboratories for Materials Science and Technology, have done extensive work on the application of ML techniques for AE signal processing in AM in situ monitoring and published their approaches in several articles (Masinelli et al. 2021; Shevchik et al. 2018, 2019; Wasmer et al. 2018, 2019). They used a fiber Bragg grating sensor to record the acoustic signals during the powder bed AM process at different intentionally altered processing regimes. The acoustic signals' relative energies were considered the features and extracted from the frequency bands of the wavelet packet transform (Shevchik et al. 2018). Wavelet packet transform can be described as applying a set of filters on a signal, as shown by Equations 1 and 2:

$$(1) \quad \varphi_j(n) = \sum_n h_0(k)\sqrt{M}\,\varphi(Mn-k),\ k \subset Z$$

$$(2) \quad \psi_{ji}(n) = \sum_n h_{m-1}(k)\sqrt{M}\,\psi(Mn-k),\ k \subset Z$$

where

h_0 is a low pass and h_m is a high pass filter,
φ and ψ are the scale and wavelet functions, respectively,
j is a scale,
n is the current sampling point of the digitized signal, and
the parameter m is the total number of filter channels.

A spectral convolutional neural network (SCNN) classifier was developed by Mathieu et al. (2014). It could differentiate the acoustic features of the different quality of AM parts with the different level of porosities. The confidence in classifications varies between 83% and 89%.

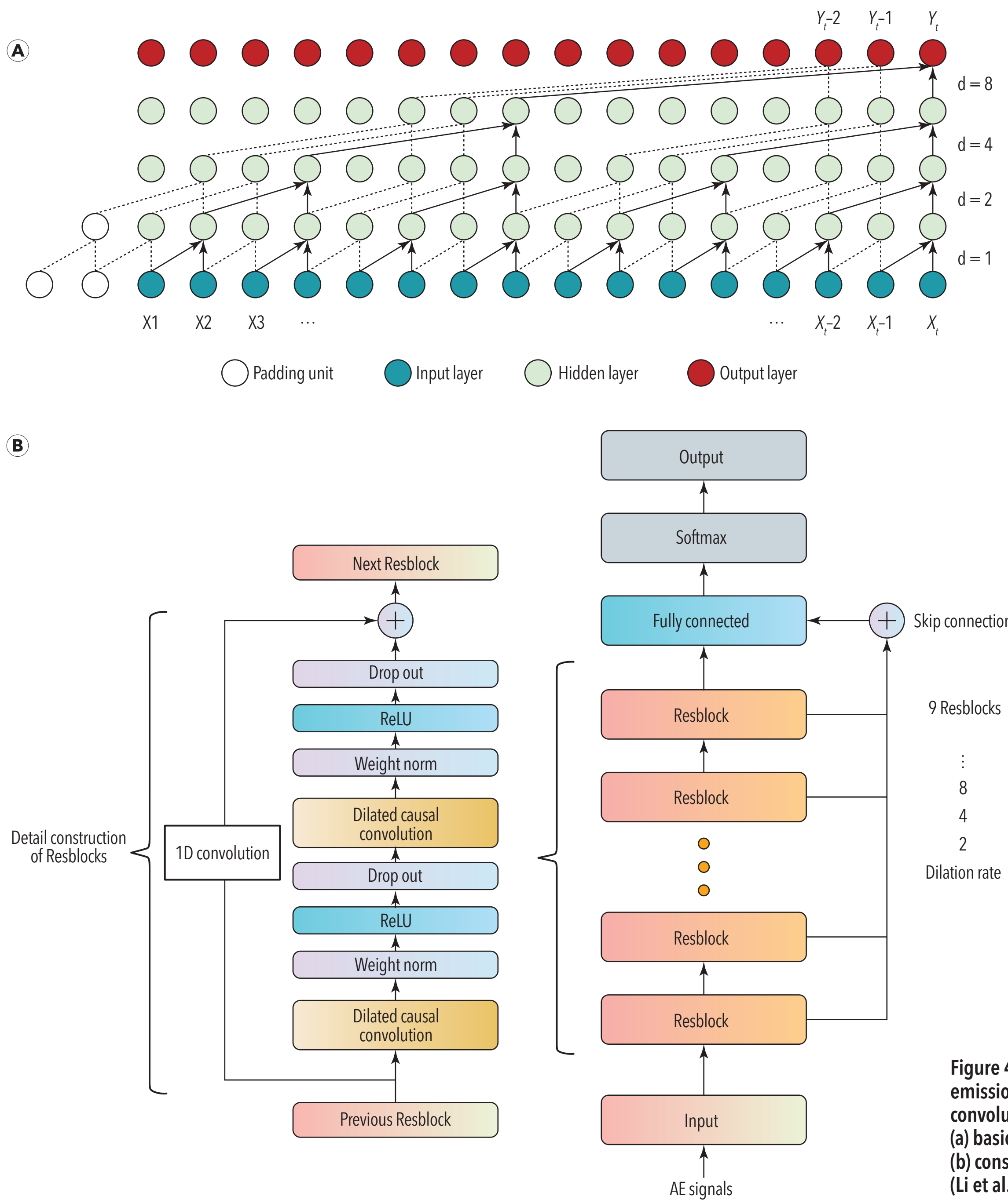


Figure 4. Acoustic emission temporal convolution network: (a) basic concept; (b) construction (Li et al. 2022).

REINFORCEMENT LEARNING

Using the same dataset, the Empa group studied the application of a reinforcement learning (RL) approach to classify different levels of quality for parts manufactured using AM (Wasmer et al. 2019). The RL technique is inspired by the human cognitive capabilities of learning in its surrounding world. In RL, knowledge is acquired through trial and error (or reward and penalty) in an environment by performing the actions and seeing the results of actions (Sutton and Barto 2018). In their approach, a Markovian process is the way of interaction between the RL agent and the environment. The initial state was set to s_0 in the classification process and the algorithm reached the goal s_g by the actions that win the maximum reward. The governing equation for the optimal reward is given by Equation 3:

$$(3) \quad T_\pi(s) = E\left\{ \sum_t \lambda R(s_t, \pi[s_t]) | s_0 = s \right\}$$

where

E is the expectation,

the discount factor $\lambda \subset [0,1)$, and $\pi(s_t)$ is a policy that maps the states to the actions, and

R is the space of the rewards.

The confidence level of the RL-based classification in this case (Wasmer et al. 2018) was between 74% and 82%, which shows a slightly lower performance compared to their SCNN approach.

Despite the encouraging results from the SCNN and RL, researchers at Empa empowered their acoustic-based ML approach by verifying the results using high-speed X-ray imaging techniques. Four categories of conduction welding, stable keyhole, unstable keyhole, and spatter were defined in a laser welding experiment and gradient boost with both independent component analysis and with CART were used to classify the different process conditions. 74% to 95% of accuracy was achieved in their assessments (Wasmer et al. 2018).

SUPPORT VECTOR MACHINE

Support vector machines (SVMs) can be used for both classification and regression problems, although typically used for classification. The idea behind the SVM is to find the optimal hyperplane (the hyperplane with the highest margin) that separates the two classes. SVM is fundamentally a binary classifier, and a hyperplane is a decision boundary that separates the two classes. If the dimension of the input data or the number of features is two, then the hyperplane is a line. For a three-dimensional feature space, the hyperplane is a two-dimensional plane.

AE, in combination with accelerometers and thermocouples data, was used by Nam et al. (2020) to train an SVM algorithm for diagnosing health states of the FDM process. The researchers first obtained the RMS values from the AE, accelerometers, and thermocouples data. They applied both linear and nonlinear SVM algorithms to identify the state of the FDM process as healthy or faulty. This research is a good case study of how to use SVMs for studying an AM process with the help of AE. However, it is to be noted that the SVM algorithm is ineffective when the dataset has more noise, which is a downside of using AET.

Unsupervised Classification of AM Process States

Unsupervised learning is a learning paradigm that does not require prior knowledge of the solution to the problem at hand, which implies that specifying the output is not required, or in some cases where such data may not be available. The implications of this approach are that we can learn inherent patterns in the data that we were not privy to; there may be several solutions to the problem; and different results can be obtained each time we run the model. In the following sections, we discuss the application of specific unsupervised learning algorithms to the study of AM using AET.

CLUSTERING BY FAST SEARCH AND FIND OF DENSITY PEAKS

The clustering by fast search and find of density peaks (CFSFDP) approach was used by Liu et al. (2018) to identify the FDM process state. Liu et al. used reduced feature space dimension by combining both time and frequency domain features and then reducing them with the linear discriminant analysis for their work. Consequently, CFSFDP, as an unsupervised density-based clustering method, is applied to classify and recognize different machine states of the extruder (Liu et al. 2018). Density-based clustering methods such as CFSFDP used by Liu et al. update the clusters iteratively without grouping the data. This approach is contrary to distance-based clustering methods such as hierarchical and partitioning algorithms like k-means. As a result of using CFSFDP, the FDM machine states were identified within a much smaller feature space, which helps to reduce the computational cost of classification and state identification. Liu et al.'s work declared that reducing dimension in feature space remarkably improves the efficiency of state identification. For dimensionality reduction, the operator part of the algorithm can be customized by linear discriminant analysis.

K-MEANS CLUSTERING

The k-means clustering algorithm is one of the most widely used algorithms due to its flexibility and ease of implementation. It is an unsupervised learning algorithm, a class of ML algorithms that can find patterns within a dataset without being explicitly told what the underlying mechanism is or might be. The only user-defined parameter required to train a k-means clustering algorithm is the number of clusters, *k*. Figure 5 shows an example of two clusters, with optimal locations of centroids represented by triangles.

The algorithm works as follows:

1. The user defines the number of clusters, *k*, and a corresponding number of cluster centroids (or means) are randomly chosen.
2. Each observation (or point) in the dataset is assigned to one of the clusters, based on its distance from a given centroid. There are several metrics used in ML to compute distances, but a commonly utilized measure is known as the Euclidean distance.

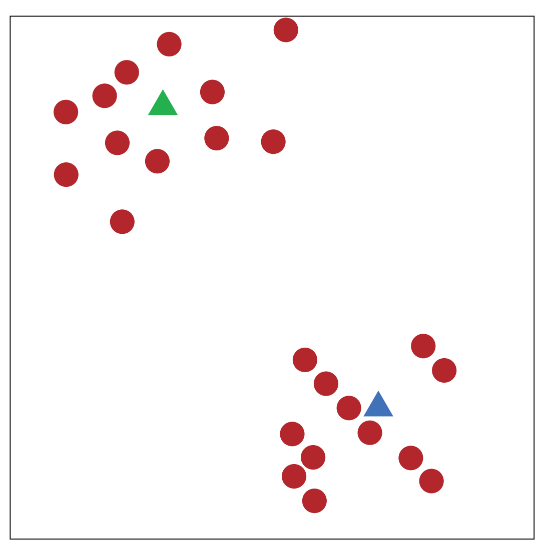


Figure 5. Setup for a k-means clustering algorithm.

3. The centroid locations are recomputed based on the assignment of data points in the previous step.
4. The process repeats, until one of the following conditions is met: (a) the centroid locations are stable; (b) the data points do not change clusters; or (c) the maximum number of iterations has been reached.

An application of the k-means clustering algorithm to the in situ monitoring of an AM process using AET is found in Taheri et al. (2019). In this study, acoustic signatures were used for in situ monitoring of the DED AM process where the deposition was performed with the machine operating in five different states. These states included "control," under which there was just powder spray, and "baseline," under which there were no active deposition activities, as well as optimum (normal) process, low laser power, and low powder feed.

Dominant features of acoustic signatures in both the time and frequency domains were identified and extracted from the acoustic signatures for all process conditions. The k-means clustering algorithm was applied to classify different process conditions, as shown in Figure 6. Correlations were demonstrated between metrics and various process conditions, which showcase the capability of AE for in situ monitoring of the AM process. Clear isolation of the baseline condition, at which no active deposition or laser-powder interaction occurs, shows that basic acoustic response of the AM system is distinct from when active manufacturing is happening. The next observation is related to the optimum settings (C1) versus powder feed only (CO) conditions. However, a separation of C1 and CO clusters was observed for C1 and CO, but the smaller isolation of clusters and larger overlap of cluster data could be an indication of significant influence of laser-material interaction compared to system and material characteristics. Last but not least, comparison of the conditions where manufacturing processes are happening (C1, C2, and C3) is interpreted as the indication of AET for separation of manufacturing processes and significant influence of laser-material interaction in AM processes.

Summary and Conclusions

Acoustic techniques are proven methods for many traditional inspection and quality monitoring applications. Due to the promising capabilities of acoustic methods for nondestructive inspection and monitoring of many kinds of processes, they have been identified as an auspicious candidate for in situ measurement and monitoring for AM processes. Two major reasons impede the application of acoustic techniques for in situ monitoring in AM processes. First is the quite low SNR due to the high sensitivity of acoustic sensors to environmental noise, which is the case in AM processes. The second is interpreting the signals to identify a correlation between the acoustic signals and the actual events. Various sensors and sensing approaches have been used to enhance the low SNR, such as using noncontact acoustic measurement via microphone or laser. Researchers have also utilized fiber-optic sensors to improve acoustic signal detection, which provides a new way of improving signal recording for in situ monitoring. Advanced signal processing techniques were used to perform data preparation, such as noise reduction and band filtering, to address the data processing and interpretation challenge. Consequently, ML algorithms have been adapted in different formats to extract and analyze the features of acoustic signals effectively. These algorithms showed an effective way and significant improvement in analyzing acoustic signals under different conditions for in situ process monitoring of AM and provide a promising pathway for the manufacturers to implement acoustic techniques for monitoring and maintaining the quality of products. Sensor integration into the AM system, detection scheme, and SNR are the existing major gaps and barriers in acoustic-based in situ monitoring of AM processes

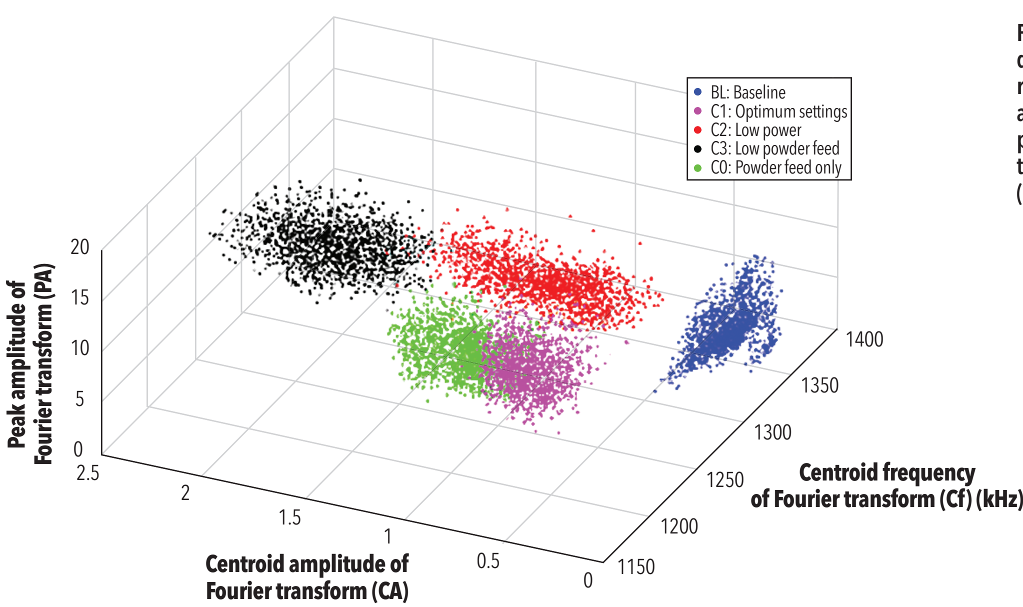


Figure 6. A three-dimensional graphical representation of the additive manufacturing process condition using three spectral features (Taheri et al. 2019).

and parts. Future direction and recommendations of research in this field include improving SNR by reducing undesired influence of environmental and systems factors, integration of complementary monitoring techniques such as X-ray to facilitate subsurface defect monitoring, and surface-sensitive optical detection approaches. Integrating other measurement techniques with AET in a combined approach reduces signal deviations caused by other variations in the process and improves the reliability in detecting process abnormalities that lessen the quality of the AM components. Lastly, a comprehensive study on an inclusive model of effect, optimization, and sensitivity of multiple process parameters on the final AM part quality is required for successful implementation of this technique in the AM industry.

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REAL-TIME AI-DRIVEN INTERPRETATION OF ULTRASONIC DATA FROM RESISTANCE SPOT WELD PROCESS MONITORING FOR ADAPTIVE WELDING

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ABSTRACT

Adaptive resistance spot welding systems typically rely on real-time analysis of dynamic resistance curves and other indirect measurements to estimate weld progress and guide adaptive weld control algorithms. Though efficient, these approaches are not always reliable, and consequently there is a need for improved feedback systems to drive adaptive welding algorithms. As an alternative, an advanced in-line integrated ultrasonic monitoring system is proposed, with real-time weld process characterization driven by artificial intelligence (AI) to create actionable feedback for the weld controller. Such a system would require real-time ultrasonic data interpretation, and for this a solution using deep learning was investigated. The proposed solution monitors the ultrasonic data for key process events and estimates the vertical size of the weld nugget proportional to the stack size throughout the welding process. This study shows that adaptive welding using ultrasonic process monitoring backed by AI-based data interpretation has immense potential. This research highlights the importance of nondestructive evaluation (NDE) in the zero-defect manufacturing paradigm.

KEYWORDS: resistance spot welding, ultrasound, artificial intelligence, deep learning, NDE 4.0

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Introduction

Zero-defect manufacturing (ZDM) has been a dream for decades (Psarommatis et al. 2022, 2023). With respect to many manufacturing processes, this dream is considered within reach given the novel technologies that should be ubiquitous in an idealized Industry 4.0. Unfortunately, however, Industry 4.0 is not yet fully realized and thus the realization of ZDM suffers as well (Psarommatis et al. 2022). Though some requirements of Industry 4.0 are increasingly fulfilled (e.g., big data production, storage, and analytics; increased connectivity and Internet of Things; industrial automation), its full realization requires NDE 4.0 (Meyendorf et al. 2017). For example, NDE 4.0 is a prerequisite for Industry 4.0's widely unfulfilled key requirement of decentralized and autonomous decision-making (Escobar et al. 2021). Fulfillment of these requirements with respect to manufactured products and joining processes is promised by NDE 4.0 through (a) the automation of nondestructive inspections; (b) the automated, consistent, generalized, and accurate interpretation of inspection data; and (c) the resultant characterization of manufactured products, which would be used to inform downstream decision-making without human intervention.

Resistance spot welding (RSW) is a manufacturing process for which the ZDM dream is potentially within reach. Many industries heavily rely on RSW joints including automotive, aerospace, rail, and military. RSW is a favorable joining method in many cases because it is inexpensive to perform, has a fast cycle time, maintains integrity of the joined sheets, has minimal added weight and volume, is highly adaptable, is robust, and is generally amenable to nondestructive evaluation (NDE) (El-Banna 2006). However, across all industries, novel materials are increasingly being developed and incorporated into manufactured products (Perez-Regalado et al. 2013). For example, in the automotive industry—which uses RSW approximately 5000 to 7000 times per vehicle—increasing vehicle electrification imposes new engineering challenges with respect to safety, lightweighting, and weight distribution (Dugmore 2021). Consequently, there is an increasing use of novel lightweight and high-strength materials (e.g., advanced high-strength steels and aluminum alloys), as well as dissimilar-material joints, which pose new challenges for RSW (Dugmore 2021). Thus, there is an increasing demand for solutions that enable ZDM of RSW.

There have been several attempts to support the realization of ZDM in RSW through the use of adaptive welding systems. Conceptually, modern adaptive welding systems monitor one or more indirect proxies of weld progress (e.g., dynamic resistance curves, current, voltage, force, tip displacement [El-Banna 2006; Neugebauer et al. 2013; Reis et al. 2016]), process these monitored features in real time to create feedback, and serve the feedback to an algorithm that adapts weld process parameters (e.g., weld time, force, and current) accordingly. In practice, these proxies do not produce sufficiently reliable and consistent feedback for adaptive weld controllers, so these systems generally fail to meet expectations and consequently many users revert to fixed schedules with adaptive capabilities disabled.

RSW is well-positioned to simultaneously meet the requirements of NDE 4.0 and achieve a breakthrough in ZDM, largely due to recent advancements in RSW NDE research. RSW NDE can be conducted either in-process (during the weld) or post-process (after the weld) using a variety of NDE modalities (Runnemalm and Appelgren 2012; Summerville et al. 2019). One of the most prevalent modalities is ultrasound (Chertov and Maev 2004; Denisov et al. 2004; Ouellette et al. 2013; Maev et al. 2014, 2016; Sung Hoon et al. 2020). Ultrasonic inspection has important advantages in inspection speed, insensitivity to sample thickness, adaptability, and the ability to directly inspect the internal geometric properties of the joint. The current state of the art in ultrasonic NDE for RSW consists of post-process offline inspection via portable ultrasonic systems with 2D matrix probes (e.g., Denisov et al. 2004; Maev et al. 2005), post-process robotized in-line systems with a similar ultrasonic configuration, and in-line real-time process monitoring systems using single-element probes (e.g., Chertov and Maev 2004; Ouellette et al. 2013; Maev et al. 2013, 2014; Sung Hoon et al. 2020). In any case, many NDE 4.0 requirements are already being met for such inspection systems, but only the in-line approach can provide real-time process monitoring and NDE data with 100% joint coverage, which is actionable in the context of an adaptive welding system that facilitates ZDM.

In its current form, the in-line inspection approach involves embedding a single-element ultrasonic transducer into a welding electrode (Chertov and Maev 2004; Ouellette et al. 2013; Maev et al. 2014, 2016; Sung Hoon et al. 2020). The transducer is immersed in flowing water, which both cools the transducer and provides coupling. The copper electrode caps focus the ultrasonic waves into the heat-affected zone of the workpiece and provide coupling against the stackup due to the application of intense force during welding (Maev and Chertov 2010). Throughout the welding process, A-scans are sampled every millisecond in pulse-echo mode, aiming through the center of the weld region between the electrodes. An M-scan—a 2D ultrasonic signature of the weld process—is then formed by horizontally stacking A-scans, and currently only post-process interpretation of the ultrasonic signature is conducted for quality control (Maev et al. 2021). Therefore, toward adaptive welding, a major missing piece in existing in-line ultrasonic systems is real-time interpretation of the sequence of A-scan signals as they are collected.

Classically, ultrasonic NDE data interpretation may involve signal/image processing, statistical analyses, search algorithms, model fitting, and hand-coded rules for decision-making. In some cases, these classical approaches are sufficient. However, in many application domains, such as RSW inspection—due to the many potential geometries, material combinations, and weld parameterizations, which can be encountered in a production environment—these approaches fail to meet the required performance, inference speed, and generality. Recently, deep learning approaches have been increasingly applied, to great effect, to a variety of problems in ultrasonic NDE data interpretation spanning essentially all use cases and specific tasks (e.g., defect detection and characterization, measurement automation, and so on [Cantero-Chinchilla et al. 2022; Taheri et al. 2022]). For example, Virkkunen et al. (2021) used a convolutional neural network (CNN) for crack detection in ultrasonic inspection data from butt-fused stainless steel pipes. Similarly, Shafiei Alavijeh et al. (2020) developed an ultrasonic inspection approach using a chord transducer for butt-fused plastic pipe joints. In this case, they used an autoencoder to conduct outlier detection on A-scans. Subsequently, the group developed an approach that classified A-scans in terms of defect presence/absence and according to defect type when a defect is detected (Shafiei Alavijeh et al. 2021). They compared several classical machine learning algorithms to four deep neural network architectures and determined that a CNN generally achieved the best performance on this task. Guo et al. (2019) combined CNN with recurrent neural networks (gated recurrent unit [GRU] and long short-term memory [LSTM]) to achieve high-performance debonding defect detection in ultrasonic C-scans of braided composite materials. They subsequently refined the approach in later works by instead framing the problem as semantic segmentation (Guo et al. 2023). Huang et al. (2022) also combined CNN and LSTM to detect defects in copper pipes in data from laser ultrasonic scanning. Maev et al. (2021) used an object detection approach with YOLOv3 (the "you-only-look-once" v3 object detector) to conduct post-process characterization of ultrasonic weld process signatures by identifying expulsions (discharge of molten material from the stackup due to intense pressure and rapid heating), while also identifying discrete weld-process events and measuring the position of the nugget at its maximum vertical size within the welded stackup. A more recent study by Zamiela et al. (2023) combined infrared with ultrasonic imaging data and developed a two-branch U-Net, which conducts semantic segmentation on the aligned images simultaneously to identify and characterize pores in metal structures in a single, unified output map. Deep learning has been proven to outperform classical computational NDE data interpretation approaches in terms of performance, inference speed, and generality; thus, it is a promising potential solution for time-sensitive contexts such as real-time inspection and adaptive welding.

The purpose of this study was first to investigate the feasibility of a deep learning approach for real-time interpretation of ultrasonic NDE data from RSW process monitoring. Subsequently, a novel approach was developed and evaluated for real-time characterization of ultrasonic data from the RSW process, which adheres to the needs of an adaptive weld controller that requires either continuous or discrete feedback.

Methodology

A summary of the experimental work is provided here, and a detailed description of the methodology follows. First, a large dataset of weld samples was developed with ultrasonic process monitoring enabled. Subsequently, a machine learning task was devised, the outputs of which could be used as actionable feedback for welding. The ultrasonic M-scan data were labeled to produce a machine learning dataset accordingly. A feasibility study was conducted to identify neural network architectures to perform the task within time constraints, and finally a feasible neural network was trained and evaluated.

Ultrasonic Configuration

Ultrasonic data were collected using an in-line real-time ultrasonic process monitoring system for spot welding (Figure 1). In this system, a 12 MHz single-element transducer is embedded into a welding electrode and immersed in water to keep the transducer cool; the water also acts as an ultrasound couplant. The transducer aims through the center of the weld region, between the electrodes. Ultrasonic A-scans are obtained every 1 ms in pulse-echo mode with a sampling frequency of 125 MHz. The number of samples in a given A-scan was set such that the entire stackup was visible in the A-scan throughout welding. Resultant M-scans were composed by horizontally stacking the A-scans.

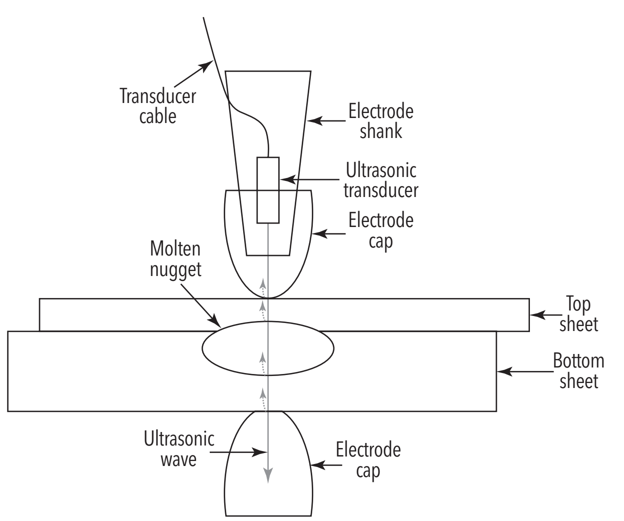

Figure 1. Ultrasonic configuration schematic for in-line real-time ultrasonic process monitoring system for spot welding. Ultrasonic waves (gray) are transmitted into the welded stack every 1 ms throughout welding process, and the transducer receives reflected waves as A-scan signals. The graphic shows an instant of an asymmetrical two-sheet weld already in progress (i.e., the molten nugget has been formed).

Dataset Development

A weld dataset of 18 223 RSWs, with the ultrasonic process monitoring system enabled, was developed. The welds were designed to cover a wide variety of weld geometries, materials, and parameters that are observed in automotive assembly. The dataset covered more than 80 sheet thickness combinations including 2- and 3-sheet similar- and dissimilar-material welds of 0.65–2.0 mm sheets made of mild and high-strength steels. Weld times varied from 75 to 400 ms, force ranged from 300 to 1000 kN, and current from 6 to 13 kA. Resultant welds were fabricated with diameters ranging from 0 to ~10 mm, with vertical maximum nugget size proportional to stack of ~0.0–0.8, and in some cases expulsions were purposely induced. Resultant M-scans were generally 75–400 pixels wide (based on weld time) and 100–400 pixels high (based on A-scan length, which varies by stack size).

For each weld, alongside its M-scan (Figure 2a), various metadata were captured, such as current-on timing, current-off timing, sheet thicknesses, and so forth. Metadata were used in the data preprocessing and augmentation stages to compute

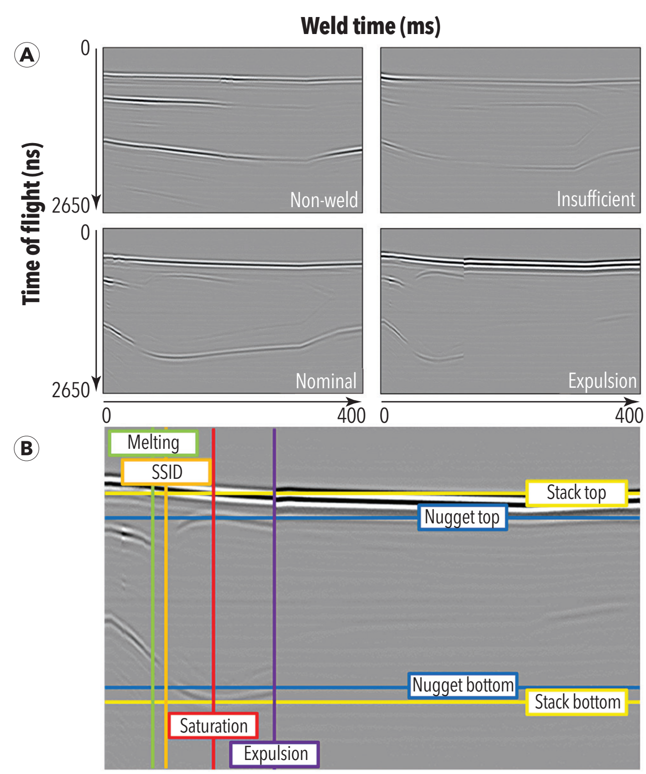

Figure 2. Ultrasonic M-scan samples from welds of same stackup but varying quality: (a) ultrasonic time of flight (Y axis) given the weld time (X axis). The top-left weld fails to breach the steel-steel interface, top-right weld insufficiently penetrates top sheet, bottom-left weld is ideal, and bottom-right weld features an expulsion (abrupt discontinuity in weld process). (b) Ultrasonic M-scan sample labeled for deep learning model development.

the regions of interest in ultrasonic scans and facilitate image cropping (see the Model Training and Performance Evaluation Section). The M-scans were labeled (Figure 2b) for the timing of four types of key events (see the cumulative distribution function plots in Figure 3): melting (the moment at which the molten nugget was first visible; 17 102 events); steel-steel interface disappearance (SSID; the moment at which all steel-steel interfaces appeared to have been breached by the molten nugget; 16 907 events), saturation (the moment at which the molten nugget appeared to stop growing vertically; 14 500 events); and expulsions (all first moments of discontinuity in the M-scan, which were suspected to be due to expulsion; 6375 events). In addition, the top and bottom of the nugget as well as the top and bottom of the stack were labeled, relative to the ultrasonic M-scan, at the moment of saturation. As observed in the M-scan, historical vertical maximum nugget size (MNS) proportional to the stack throughout the weld was then derived from these labels. To derive MNS, a linear interpolation l between melting-event timestamp to saturation-event timestamp (horizontally) and zero to maximum overall nugget size proportional to the stack (vertically) was first computed. Given melting timestamp m, saturation timestamp s, maximum overall nugget size proportional to the stack n, and weld timestep t:

$$l = 0, \text{ if } t < m$$

$$l = \frac{t-m}{s-m} \times n, \text{ if } m \leq t \leq s$$

$$l = n, \text{ otherwise}$$

Then, a sigmoidal function of the following form was fitted to l using the SciPy software package (Virtanen et al. 2020):

$$y = \frac{n}{1 + e^{-a \times (t-b)}}$$

where

a is a free parameter that controls the nugget growth rate, and

b is a bias that shifts the nugget growth in time.

Finally, a blend between l and y was computed such that the curve began fully linear at the melting point (i.e., the weight of l = 1, weight of y = 0) and ends fully sigmoidal at the saturation point (i.e., the weight of l = 0, weight of y = 1). MNS was the resultant blended curve.

Consequently, at each time step of the welding process, the model was tasked with binary classification for the first occurrence of each of the key events: melting, SSID, saturation, and expulsion. That is, for each event, the model was tasked to output zero for every time step prior to the first occurrence of the event and one for every time step thereafter. The model was also tasked with regression of MNS.

Model Design, Training, and Performance Evaluation

The machine learning task defined previously is essentially many-to-many sequence processing. Many-to-many sequence processing produces any number of sequential outputs given any number of sequential inputs; here, for every A-scan input the model is tasked with producing a corresponding output that describes the occurrence of events and MNS. All outputs are real numbers in the range of zero to one. A 1 ms per A-scan processing time constraint was imposed due to the required temporal resolution and response time such that feedback to a weld controller is actionable, as well as the rate of data acquisition such that the AI system does not accumulate latency throughout the course of a weld. Due to the severe computational time constraint of <1 ms per A-scan, the aim to maximize performance, and the sequential nature of the ultrasonic data, a recurrent neural network approach was investigated. In particular, to exploit the spatial information in each A-scan and

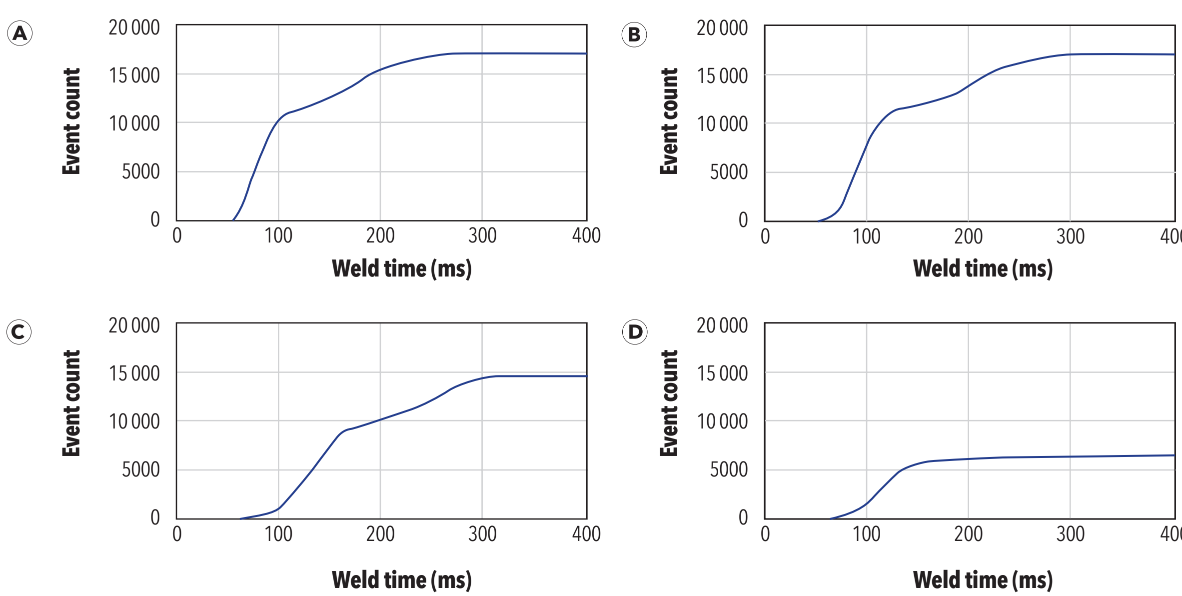

Figure 3. Cumulative distribution functions for the four events over the entire dataset: (a) melting; (b) SSID; (c) saturation; (d) expulsion.

long-term dependencies in weld sequences, convolutional long short-term memory (ConvLSTM) architectures (Shi et al. 2015) were explored. All investigations were conducted with Tensorflow (Abadi et al. 2015) and Keras (Chollet et al. 2015) for Python. Due to the sequential processing of ConvLSTMs and relatively small sequence items (resized A-scans; see the Model Training and Performance Evaluation Section), the amenability of processing to parallelization is heavily reduced for this task, and it was consequently found in preliminary work that CPUs were faster for both training and inference. Sequence processing using ConvLSTM differs from, for example, a pure CNN or transformer architecture, which is highly parallelizable and benefits greatly from computing on GPU. Thus, all computations were performed using an Intel® Core™ i7 CPU.

FEASIBILITY STUDY

The feasibility of a ConvLSTM-based architecture was investigated with input M-scans (i.e., arbitrary-length sequences of A-scans) resized vertically to 128 pixels. This investigation was designed to estimate the upper limit on the number of filters per layer and the number of layers based on the processing time requirement of <1 ms per A-scan in a production environment, which includes input preprocessing and potential communications overhead. Preliminary tests determined that the production environment ran inference approximately 35–45% faster than the development environment due to, for example, the removal of training overhead in the exported network graph, differences in Tensorflow compilation, differences in programming language, and so on. Accounting for the speedup in the production environment, along with overhead from preprocessing and so forth, a cutoff of 1.1 ms per A-scan was imposed. An overarching architecture (Figure 4) was designed with one ConvLSTM module and one max pooling operation per layer; variants were tested having 1–5 layers and an initial layer with 8–32 filters, with number of filters doubling per layer. Following a flattening, the last layer was a time-distributed (i.e., shared across all time steps) fully connected layer with five outputs. To guard against extra computational overhead from initial resource allocation, one M-scan was fully processed prior to recording inference times. Subsequently, 10 randomly selected, arbitrary-length M-scans, comprising of a total of 2589 A-scans, were processed, during which inference times were recorded. As M-scan length has no impact on mean inference time per A-scan, though it may subtly impact variance of inference times, the selected M-scans were held constant through all trials so that the same exact A-scans were processed in each trial. The largest feasible model was used for further training and evaluation.

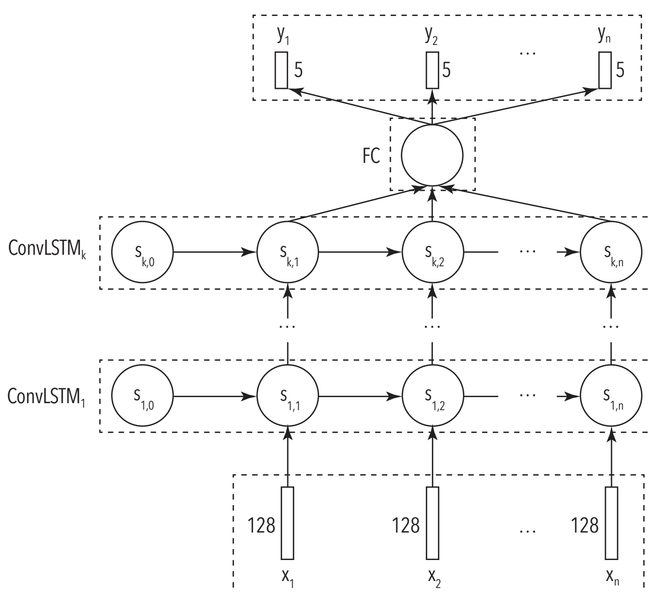

Figure 4. An unrolled schematic diagram of the ConvLSTM architecture used in this study. Data flow over depth of network is from bottom to top. Data flow over weld time is from left to right. Input A-scans (x_t = 1…n) are fed to the network. ConvLSTM layer (1…k) states (denoted s; composed of C and H states observed in standard LSTMs) are initially zeros and modified over time given previous states and new inputs from previous layer. A max pooling operation follows each ConvLSTM. Outputs of the last ConvLSTM layer are fed into the time-distributed (i.e., shared across all time steps) fully connected decision-making layer (denoted FC in the figure). Input and output dimensionalities are depicted.

MODEL TRAINING AND PERFORMANCE EVALUATION

At both training and testing time, M-scan images were cropped vertically to tightly focus on the welded stackup, resized to a height of 128 pixels, and cropped horizontally starting at the current-on timing until the end of the weld process. Data augmentation was conducted only at training time and was designed to desensitize the model to various potential situations that could occur in a production system (e.g., electromagnetic interference, slight misreporting of current-on timing, gain and contrast variance, shift in A-scan gating, etc.). Thus, augmentation involved some typical image augmentation steps such as random vertical shifts of both top and bottom image cropping positions prior to resizing vertically to 128 pixels, random horizontal shift of current-on (image left edge) position, addition of artificial noise, and random contrast adjustments. In addition, random horizontal resizing of M-scans to uniformly distributed randomly-selected widths from 75–400 pixels was conducted to desensitize the model to the weld timing distribution of the training data, with the aim of producing a more robust model such that it can correctly interpret data from welds having weld times vastly different from those typically observed in the training data. Key event timings and MNS curves were adjusted according to any augmentations performed. Due to the random horizontal resizing, inputs and targets were zero-padded after the end of the sequence.

Three models were trained using Monte-Carlo validation and evaluated on a held-out testing dataset. Of the 18 223 labeled M-scan samples, 16 400 were used for training, 1640 for validation, and 1823 for testing. Each model was trained using the Adam optimizer (Kingma and Ba 2015) for 400 epochs with

TABLE 1
Summary of feasibility study results

Architecture (filters per ConvLSTM layer)	Parameters	Inference time (ms)
8	3461	0.866 (0.193)
8-16	8133	1.024 (0.155)
8-16-32	26 693	1.060 (0.129)
8-16-32-64	100 677	1.221 (0.142)
8-16-32-64-128	396 101	1.428 (0.155)
16	8453	0.952 (0.304)
16-32	27 013	0.954 (0.160)
16-32-64	100 997	1.085 (0.151)
16-32-64-128	396 421	1.344 (0.132)
16-32-64-128-256	1 577 093	1.992 (0.154)
32	23 045	0.999 (0.268)
32-64	97 029	0.970 (0.108)
32-64-128	392 453	1.264 (0.126)
32-64-128-256	1 573 125	1.942 (0.144)
32-64-128-256-512	6 293 765	4.271 (0.189)

Note: Mean inference time per A-scan over 2589 A-scans, standard deviation in parentheses

a batch size of 32, with early stopping and learning rate reduction based on validation loss. Binary cross-entropy loss was used for the event outputs, while mean-squared error was used on the MNS regression output. Inputs and loss were masked such that models would skip the zero-vector A-scans during training and not backpropagate loss on those inputs; thus, the model did not learn from the zero-padded regions.

To evaluate performance, a number of different performance indicators were used for each task. With respect to event detection, performance was evaluated using sensitivity with respect to the absolute error of ground truth versus model predictions of event timings from 0–30 ms, overall specificity, and histograms of timing error for true positives. MNS regression performance was assessed using the percentage of A-scans that are correct within an absolute difference of 0.1.

Results

The results of the feasibility study and performance evaluation are discussed next.

Feasibility Study

The feasibility study results (Table 1) demonstrated that architectures starting with eight filters in the first layer were feasible up to three layers (Figure 5a). The three-layer architecture with eight filters in the first layer had an inference time of 1.06 ms (SD = 0.13 ms), whereas a four-layer architecture had an inference time of 1.22 ms (SD = 0.14 ms). With 16 filters (Figure 5b),

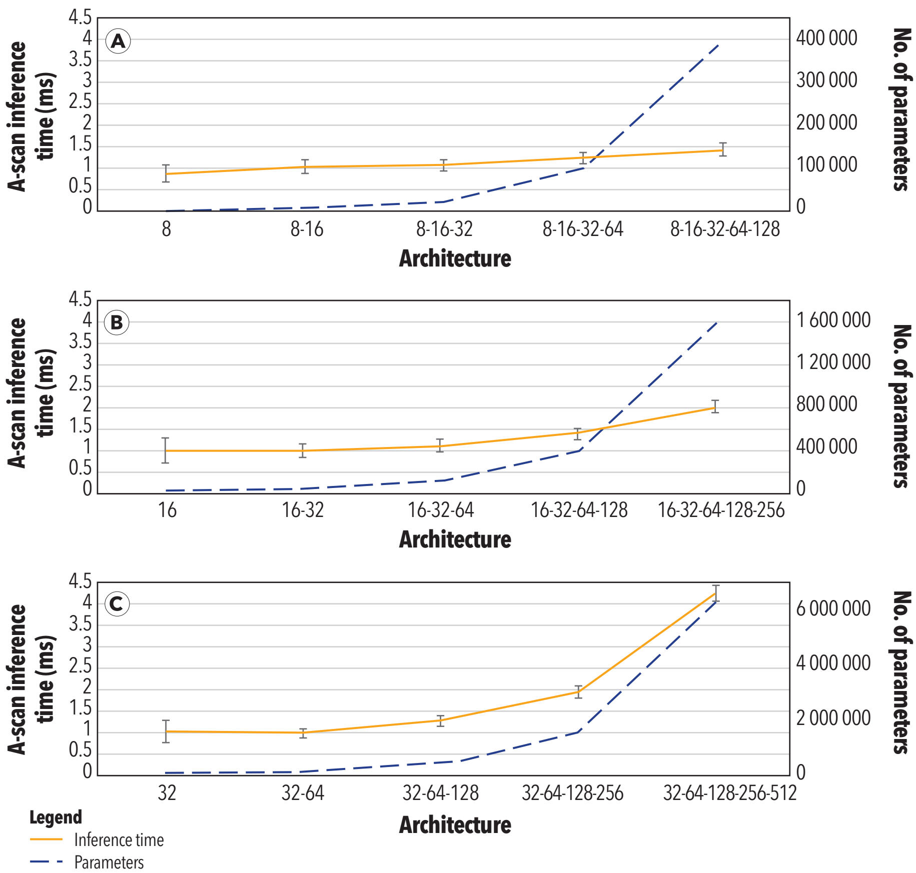

Figure 5. Inference time per A-scan in milliseconds (orange line) and parameter count (blue dashed line) per architecture (X axis; 1–5 layers), with first layer number of filters: (a) 8; (b) 16; and (c) 32. Inference time generally grows superlinearly with respect to both number of layers and parameters. Means across all 2589 A-scans are plotted with 1 standard deviation of mean shown with error bars.

TABLE 2
Summary of performance results

	Melting	SSID	Saturation	Expulsion
Sensitivity (within 10 ms)	0.870 (0.010)	0.886 (0.009)	0.742 (0.023)	0.935 (0.005)
Sensitivity (within 20 ms)	0.963 (0.006)	0.962 (0.007)	0.860 (0.014)	0.954 (0.006)
Sensitivity (within 30 ms)	0.984 (0.003)	0.979 (0.002)	0.898 (0.009)	0.977 (0.001)
Specificity	0.807 (0.025)	0.821 (0.031)	0.933 (0.018)	0.986 (0.002)
% A-scans correct (within 0.1)	90.5 (0.4)			

Note: Mean sensitivity for each event within 10, 20, and 30 ms of event ground truth, mean specificity for each event, and mean accuracy of MNS within 0.1. Standard deviation in parentheses.

a three-layer architecture was feasible with an inference time of 1.08 ms (SD = 0.15 ms), while a four-layer architecture was infeasible at 1.34 ms per A-scan (SD = 0.13 ms). Finally, with 32 filters (Figure 5c), architectures with up to two layers were feasible with 0.97 ms per A-scan (SD = 0.27 ms), while a three-layer architecture had an inference time of 1.26 ms (SD = 0.13 ms). In terms of parameter count, the largest feasible architecture was three layers with 16 filters in the first layer, yielding 100 997 parameters. Thus, this architecture was used for all subsequent experimentation.

Performance Evaluation

The architecture selected in the feasibility study demonstrated a very strong performance overall (Table 2). Within 10 ms of the event, the sensitivity of the four events ranged from 0.742 (SD = 0.023) to 0.935 (SD = 0.005). Within 30 ms, sensitivity reached 0.977 for all events but saturation, which peaked at 0.898 (SD = 0.009). Overall, specificity for expulsion events was highest at 0.986 (SD = 0.002), while the melting and SSID events had proportionally more false positives with specificity of 0.807 (SD = 0.025) and 0.821 (SD = 0.031), respectively. Event detectability curves were similar for melting and SSID, while curves for expulsion and saturation differed greatly and models were consistent with respect to each event across all timing error windows (Figure 6). Expulsion detection reached an asymptote at approximately the 5 ms error window and melting and SSID reached an asymptote at approximately 15 ms, while saturation reached an asymptote at approximately 30 ms of absolute error.

Example distributions of timing error for melting (Figure 7a) and SSID (Figure 7b) events showed very symmetrical distributions, centered at approximately zero with relatively mild variance. Saturation (Figure 7c), on the other hand, yielded a timing error distribution with slight negative skew and greater variance, and was centered slightly above zero. Expulsion timing error (Figure 7d) yielded an extremely tight distribution centered just above zero. All models yielded similar error distributions.

Model outputs plotted over time and compared against ground truth data (Figure 8) showed stability and smoothness on relatively clear M-scans, while output noise increased with decreasing M-scan quality. Overall, the models were insensitive to reasonable amounts of electromagnetic noise, weld time, stackup, and weld quality. Output curves for MNS were smooth and consistent with ground truth curves in terms of shape and position. In addition, welds without nugget formation (e.g., Figure 8a) were often correctly characterized. In general, welds with extremely late nugget formation (e.g., Figure 8b) were more difficult to characterize than those with earlier nugget formation (Figure 8c).

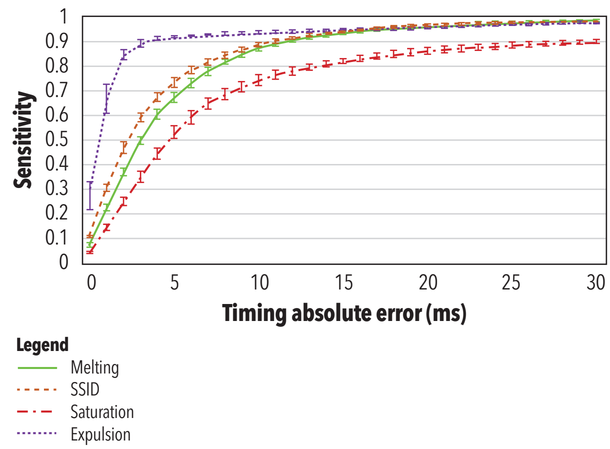

Figure 6. Event detection sensitivity per event given absolute error of model prediction of event timing versus ground truth event timestamp. Means across three models are plotted with 1 standard deviation of mean shown with error bars. Expulsion (purple line) was most easily detectable, SSID (orange line) and melting (green line) were similarly moderately detectable, and saturation (red line) was most difficult to detect.

Discussion

A fast and performant approach was developed for real-time interpretation of data from ultrasonic RSW process monitoring, with the aim of creating actionable feedback to a weld controller using deep learning.

All events were reliably detected; over 95% of events were detected within 18 ms of ground truth for all events except for saturation, which was detected at a rate of 90% within 30 ms. It was expected that expulsions would be most reliably detected as they appear very clearly on M-scans as a discontinuity in which the stack bottom boundary abruptly moves upward

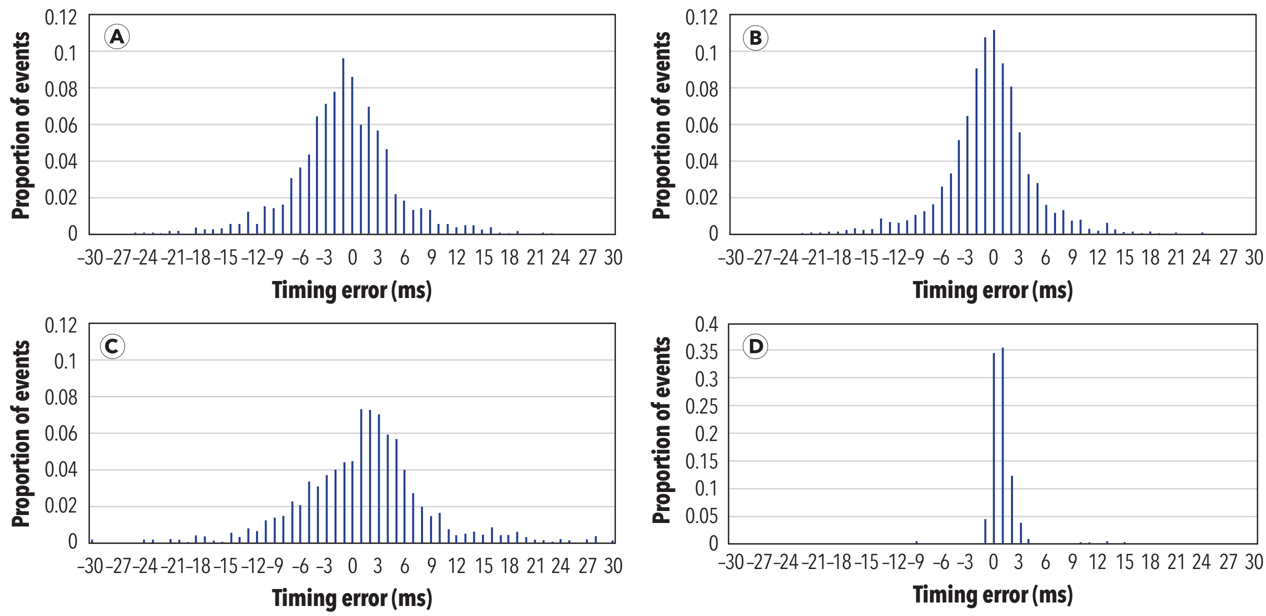

Figure 7. Timing error distributions for detected (a) melting; (b) SSID; (c) saturation; and (d) expulsion for the model with the best overall performance.

in the M-scan (Figure 8d). It was not expected, however, that they would be so rapidly detected with >90% of detections occurring within 4 ms of ground truth. Because they appear so clearly in M-scans, they are also the easiest event to label during dataset preparation. On the other hand, saturation is by far the most difficult event to label as the saturation point was defined as "the moment at which the molten nugget appeared to stop growing vertically," which is highly subjective without perfect nugget and stack boundary annotations. Similarly, but less so, melting and SSID are not always as apparent as expulsions. Thus, from our experience in reading these images, and considering the relative difficulty for a human to interpret ultrasonic M-scans and identify these events and the relative consistency of event annotations, we found that the relative detection rates of the four events completely align with expectations.

Relatedly, as the ground truth labels for event timing as well as the top and bottom labels for the nugget and stack were used to develop the curves for MNS, the subjectivity and consistency of labels affects the performance of the models on the regression task as well. In particular, stack boundaries are almost always reasonably visible aside from after expulsions, while nugget boundaries vary in visibility based on nugget pool size, stage of weld, and stack geometry. With the investigated

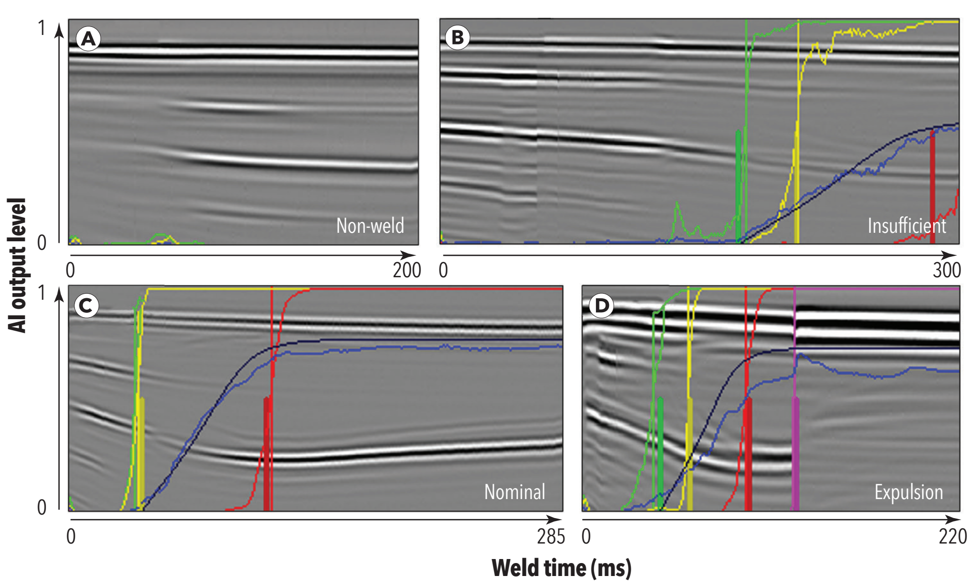

Figure 8. M-scan samples with ground truth markup and model outputs superimposed. Ground truth event timestamps are shown as dark thick vertical lines reaching the halfway mark vertically in images; ground truth MNS is darker blue curve. Model outputs (thin curves – unprocessed model outputs; thin vertical lines – event probability outputs thresholded at 0.5) are from most performant model. For event colors, green – melting; yellow – SSID; red – saturation; purple – expulsion. Blue indicates model output for MNS. All model outputs and MNS targets are superimposed on images with 0 = bottom of image, 1 = top of image. Images cover various stackups and weld outcomes.

approach, continuous feedback could be provided to an adaptive weld controller using the regression output of MNS, or other discrete events could be derived from it. In either case, optimal use of MNS output in a production implementation would likely require calibration welds for novel weld type (given, for example, sheet thicknesses, sheet materials, etc.) to determine an appropriate threshold or target value for MNS output. In future work, this ultrasound-based approach with AI-driven feedback will be rigorously compared against alternative feedback approaches (e.g., resistance-based feedback, etc.).

With respect to this AI-based approach, a more rigorous optimization of hyperparameters within the feasible space of architectures may yield better performance. In this study, the largest model possible (in terms of parameter count) was used based on feasibility study results; however, it is possible that better performance may be achieved by using various popular modules in the network (if feasible), for example, skip connections (He et al. 2016; Ronneberger et al. 2015), atrous spatial pyramid pooling (Chen et al. 2018), batch normalization (Ioffe and Szegedy 2015), attention mechanisms such as convolution block attention module (Woo et al. 2018), and so forth. Alternatively, other novel architectures, such as vision transformer (Liu et al. 2021), could be explored in future work. In addition, providing known welding parameters to the model as inputs (such as sheet thicknesses, sheet material encodings, force, welding cap face diameter, etc.) is another potential opportunity for improvement, which can be investigated in the future.

Precise and continuous annotations, for both the nugget and stack, at all times throughout the weld would be ideal in order to derive event timestamps and MNS curves. From the standpoint of dataset development, this would essentially be the same as labeling the M-scans for semantic segmentation of the nugget and stack boundaries, which is significantly more tedious and laborious than the proposed approach, and still subjective (though, perhaps less subjective as it is less abstract). One advantage of the proposed approach is that it required, at most, eight clicks per annotated M-scan (each of the four event timings, two nugget labels, two stack labels) during data annotation, whereas semantic segmentation would conservatively require 20 clicks per segmented region to delineate each polygon—40 clicks in total between nugget and stack regions—so the proposed approach yielded a fivefold reduction in data preparation time. That said, semantic segmentation of the ultrasonic data is still a natural next step for this work like in the case of Guo et al. (2023). Other works have demonstrated the potential for semantic segmentation in real-time ultrasonic inspection in both NDE and medical contexts (Fiorito et al. 2018; Hu et al. 2022; Shandiz and Tóth 2022). If it were found to be performant, generalizable, and still sufficiently fast for adaptive RSW (i.e., <1 ms per A-scan inference time in a production environment), semantic segmentation could yield more precise and continuous measurements, and consequently better feedback. This would be especially valuable if continuous feedback to an adaptive weld controller was preferred over discrete feedback, or perhaps necessitated for a particular adaptive welding algorithm.

Conclusion

The investigated approach is not limited to ultrasonic NDE nor resistance spot welding; such an approach could be applied to the interpretation of NDE data from a variety of other modalities for a variety of other joining methodologies. In all, the investigated approach is an exciting first step toward real-time interpretation of ultrasonic NDE data from RSW. It demonstrates the enormous potential of ultrasound-based process monitoring backed by real-time interpretation using deep learning, for real-time adaptive feedback systems in modern manufacturing. Such NDE 4.0 systems are integral to Industry 4.0 and the ZDM paradigm, and this work brings zero-defect RSW closer to reality.

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ACOUSTIC EMISSION SOURCE LOCALIZATION USING DEEP TRANSFER LEARNING AND FINITE ELEMENT MODELING–BASED KNOWLEDGE TRANSFER

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ABSTRACT

This paper presents a novel data-driven approach to localize two types of acoustic emission sources in an aluminum plate, namely a Hsu-Nielsen source, which simulates a crack-like source, and steel ball impacts of varying diameters acting as the impact source. While deep neural networks have shown promise in previous studies, achieving high accuracy requires a large amount of training data, which may not always be feasible. To address this challenge, we investigated the applicability of transfer learning to address the issue of limited training data. Our approach involves transferring knowledge learned from numerical modeling to the experimental domain to localize nine different source locations. In the process, we evaluated six deep learning architectures using tenfold cross-validation and demonstrated the potential of transfer learning for efficient acoustic emission source localization, even with limited experimental data. This study contributes to the growing demand for running deep learning models with limited capacity and training time and highlights the promise of transfer learning methods such as fine-tuning pretrained models on large semi-related datasets.

KEYWORDS: acoustic emission, deep neural network, finite element modeling, transfer learning, fiber optics, source localization

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Introduction

Acoustic emission source localization is crucial in structural health monitoring (SHM) and proactive maintenance of metallic structures. The constraints in deploying acoustic emission testing (AE) sensor arrays in real-world structures necessitate a shift toward intelligent, automated single-sensor approaches. Holford et al. (2001) pioneered the application of AE for damage location in steel bridges, establishing its importance in SHM. Ebrahimkhanlou and Salamone (2017) further examined acoustic source localization and its significance in determining the origin of acoustic emission waves and assessing damage severity. Cheng et al. (2021) developed an acoustic emission source localization method using Lamb wave propagation simulation and artificial neural networks, proving effective in I-shaped steel girder inspections. Ai et al. (2021) studied source localization on large-scale canisters used for nuclear fuel storage, addressing the need for optimal AE sensor deployment. Ciampa and Meo (2010) proposed an approach using wavelet analysis and a Newton-based optimization technique for acoustic emission source localization and velocity determination, contributing to the broader understanding of acoustic emission wave propagation and source detection.

Significant progress has been achieved in acoustic emission source localization through the application of deep learning, demonstrating its promise in localizing acoustic emission signals (LeCun et al. 2015). Ebrahimkhanlou and Salamone (2018) proposed a deep learning approach for localizing acoustic emission sources using a single sensor in plate-like structures. This was further advanced by Ebrahimkhanlou et al. (2019), who introduced a deep learning–based framework for localizing and characterizing acoustic emission sources in metallic panels using only one sensor. Garrett et al. (2022) utilized artificial intelligence for estimating fatigue crack length from acoustic emission waves, a significant step forward in damage localization and quantification. Despite the challenge of false positives, the fusion of artificial intelligence and AE holds promising opportunities for enhancing SHM (Verstrynge et al. 2021; Hassan et al. 2021).

A key challenge in using supervised learning algorithms for acoustic emission source localization is the difficulty in accessing labeled acoustic emission signals for existing structures. Transfer learning is a strategy that assists the supervised learning task when available training data is limited

(Agarwal et al. 2021). Various studies have demonstrated the value of transfer learning in enhancing neural networks for acoustic emission source localization and SHM, such as Chen et al. (2021), who proposed an acoustic-homologous transfer learning approach for rail condition evaluation, and Hasan et al. (2019), who utilized transfer learning for reliable bearing fault diagnosis under variable speed conditions.

Deep learning and transfer learning methods have shown great potential in improving acoustic emission source localization efficiency (Sun 2020; Bengio 2012). Ismail-Fawaz et al. (2022) presented a deep learning approach for time series classification using hand-crafted convolution filters, further enhancing AE capabilities. Ismail Fawaz et al. (2018) explored transfer learning for time series classification, while Zhang et al. (2017) studied the learnability of fully connected neural networks. Weiss et al. (2016) provided a survey of transfer learning, and Bengio (2012) emphasized the importance of deep learning representations for unsupervised and transfer learning. Though significant advancements have been made in applying deep learning and transfer learning to acoustic emission source localization, continued development and optimization of these methodologies are essential for addressing inherent challenges and maximizing their potential in SHM (Bengio 2012; Sun 2020).

In this study, our principal innovation lies in the successful implementation of transfer learning through the pretraining of six deep learning models on a large simulated acoustic emission dataset. This enabled the localization of acoustic emission sources using a single sensor. We pretrained convolutional neural network (CNN), fully convolutional neural network (FCNN), Encoder, ResNet, Inception, and Multi-layer Perceptron (MLP) models using data from finite element method (FEM) simulations of acoustic emission impulses. Through transfer learning, we fine-tuned the pretrained models on the experimental dataset, improving their performance while reducing the number of experiments needed. Our results show that the pretrained models generalized well to variations in acoustic emission signals and could be applied to different model architectures and datasets. Overall, our research highlights the potential of deep learning techniques, particularly transfer learning, for improving the accuracy and efficiency of acoustic emission source localization. These findings can significantly benefit the development of reliable and cost-effective SHM strategies and are readily applicable to other nondestructive evaluation problems.

This paper is organized into four main sections. The first section provides an overview of the laboratory experiments conducted utilizing pencil lead break (PLB) and impact tests at nine distinct positions. In the next section, to aid understanding, data visualization is furnished through raw waveform plots of both simulated and real-life experimental data derived from impact and PLB testing. Additionally, a 2D t-SNE plot is provided to better illustrate the clustering structure of signals originating from nine distinct locations or classes. The third section introduces six distinct deep learning models, including our own, which were designed through the iterative fine-tuning of layers with unique training parameters. The architectural details of both the classifier and the transfer elements of our model are thoroughly analyzed in this section. The final section presents the results obtained by training these fine-tuned models using tenfold cross-validation. To give a comprehensive view of the models' performance, the mean loss and range of loss for each classifier, as well as for the impact and PLB tests, are plotted. The efficacy of each fine-tuned model is further evaluated by computing and representing key metrics such as precision, recall, and accuracy in a box plot format.

Methods and Experiments

The primary objective of the conducted experiments was to scrutinize the effectiveness of the suggested source localization techniques, utilizing a singular AE sensor, on an aluminum plate. As represented in Figure 1, the experimental setup comprised a sensor, constituted by two frail fiber Bragg gratings (FBGs), forming a low-finesse Fabry-Perot interferometer (FPI) on a coiled single-mode fiber. This arrangement facilitated the detection of ultrasound on a solid surface. The setup employed a narrow-linewidth diode laser with wavelength tunability, designed to direct light toward the FBG-FPI sensor via a circulator developed in Karim et al. (2021).

Before reaching the sensor, the light was passed through a three-paddle polarization controller, which facilitated manual adjustments to the laser polarization. The light reflected from the sensor was then directed to a photodetector (PD) through the same circulator. To obtain acoustic emission signals of higher quality, the output from the PD was amplified and filtered using a 50–500 kHz band-pass filter. Additionally, noise removal techniques, such as adaptive filtering, were employed to reduce any extraneous signals present during data collection. It is selected based on its ability to effectively remove noise while preserving the signal of interest. The filtered and noise-free AE signals were subsequently utilized to train and test the deep learning models for source localization.

Acoustic emission is a physical occurrence linked to stress waves, initiated by the abrupt liberation of elastic energy during the formation of cracks or damages within materials. AE signals can be captured and logged by attaching AE sensors to the sample surface. The AE monitoring process involves the collection and analysis of these signals to assess the condition of the object under study. The Hsu-Nielsen PLB test, a widely accepted artificial method for acoustic emission signal generation (Sause 2011), was used in this study. It involves breaking pencil leads on a surface with an affixed AE sensor. For this study, PLB tests were conducted on a 2.54 mm thick aluminum plate measuring 0.30×0.30 m. The plate was partitioned into nine distinct locations as delineated in Figure 2. Each of the nine representative points, denoted by a red dot, underwent the PLB test 10 times, using a 2H mechanical pencil with a 0.5 mm diameter lead.

Furthermore, impact-like signals were gathered by dropping steel balls (4.7 mm diameter) from a height of 25 mm at the same AE sensor location illustrated in Figure 2. The

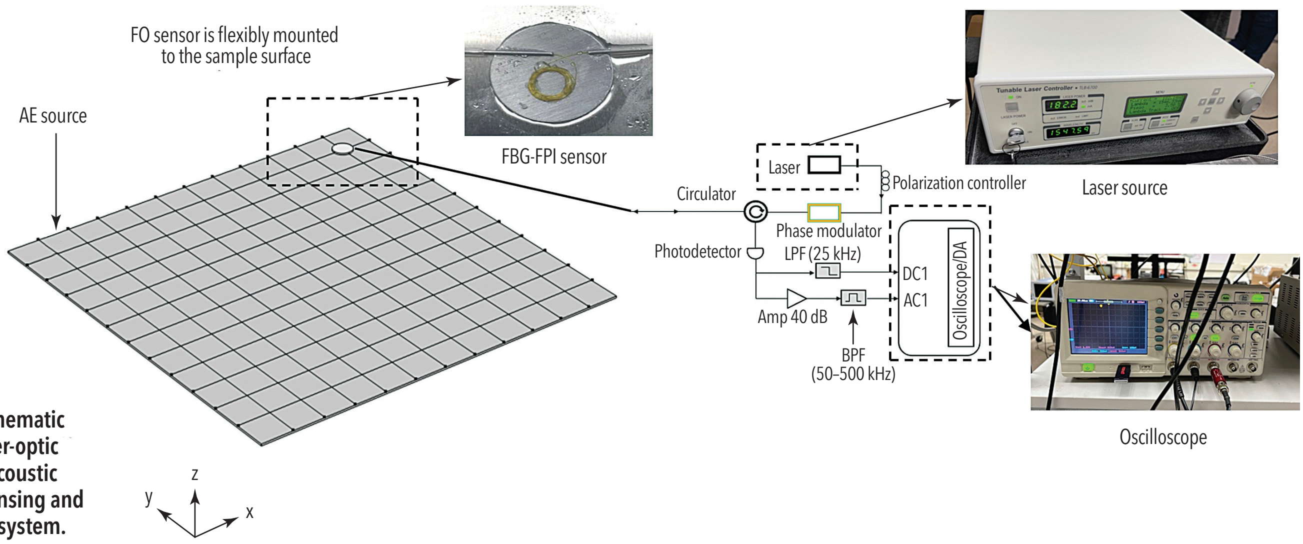

Figure 1. Schematic of novel fiber-optic coil-based acoustic emission sensing and monitoring system.

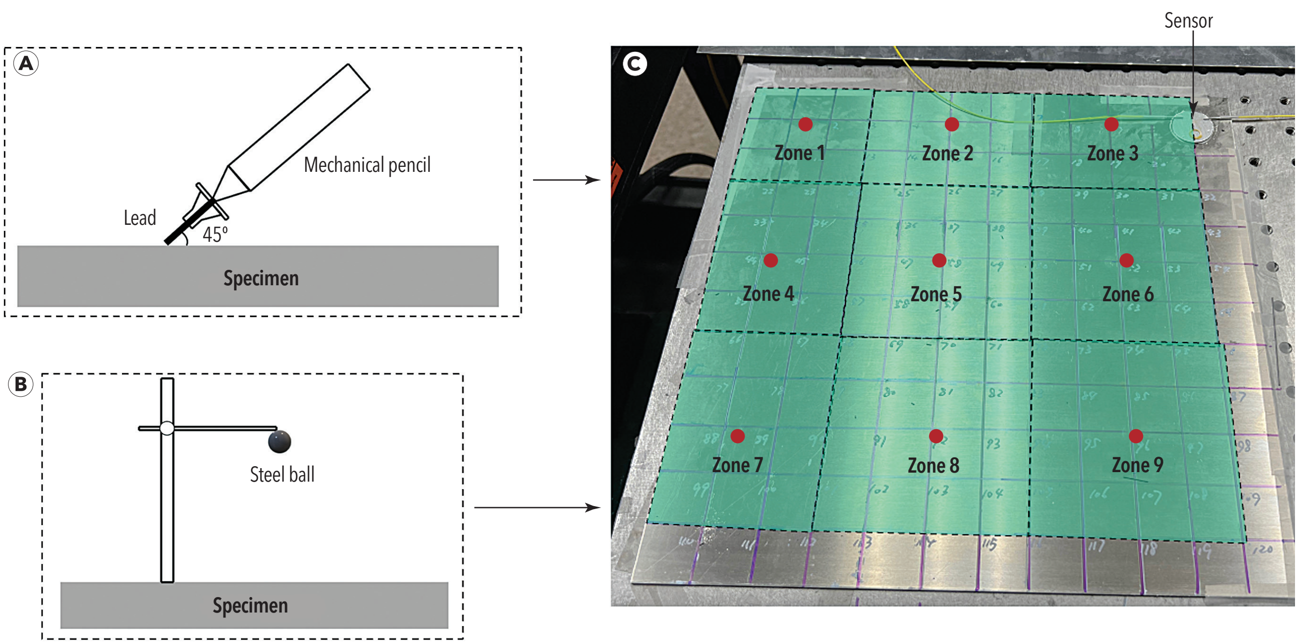

Figure 2. Experimental setup for acoustic emission monitoring: (a) pencil lead break (PLB) and (b) impact tests conducted on an aluminum plate (c) that is segregated into nine identified zones. This setup assists the localization of acoustic emission sources.

equipment and settings for this experiment mirrored those utilized for the PLB tests. The recorded signals were distinguished and examined for acoustic emission source identification and localization, using these procedures. The experimental setup facilitated the collection of precise and accurate data, thereby enabling the evaluation of the proposed method's efficacy in acoustic emission source localization.

Numerical Modeling Assisted Data Augmentation

This study utilizes a 3D computational model for the test specimen to enable an enhanced characterization of acoustic emission impulses, as inspired by Cuadra et al. (2015). The approach hinges on the implementation of pretrained deep learning models, which harness data from FEM-simulated acoustic emission impulses derived from impact-type and PLB tests (Hamstad 2007). The creation of pretraining data via these simulated AE signals propels advancements in acoustic emission source localization within the specimen. This model offers several benefits, such as reducing computational demands and enhancing the performance of AE monitoring systems in real-world scenarios. The accurate characterization of acoustic emission impulses is a vital prerequisite for developing effective signal-processing algorithms. Our proposal presents a robust methodology to pretrain deep learning models using data procured from acoustic emission impulse simulations. The PLB source was strategically positioned in the out-of-plane direction at a predefined location on the plate, with the sensor situated an inch from the right and upper

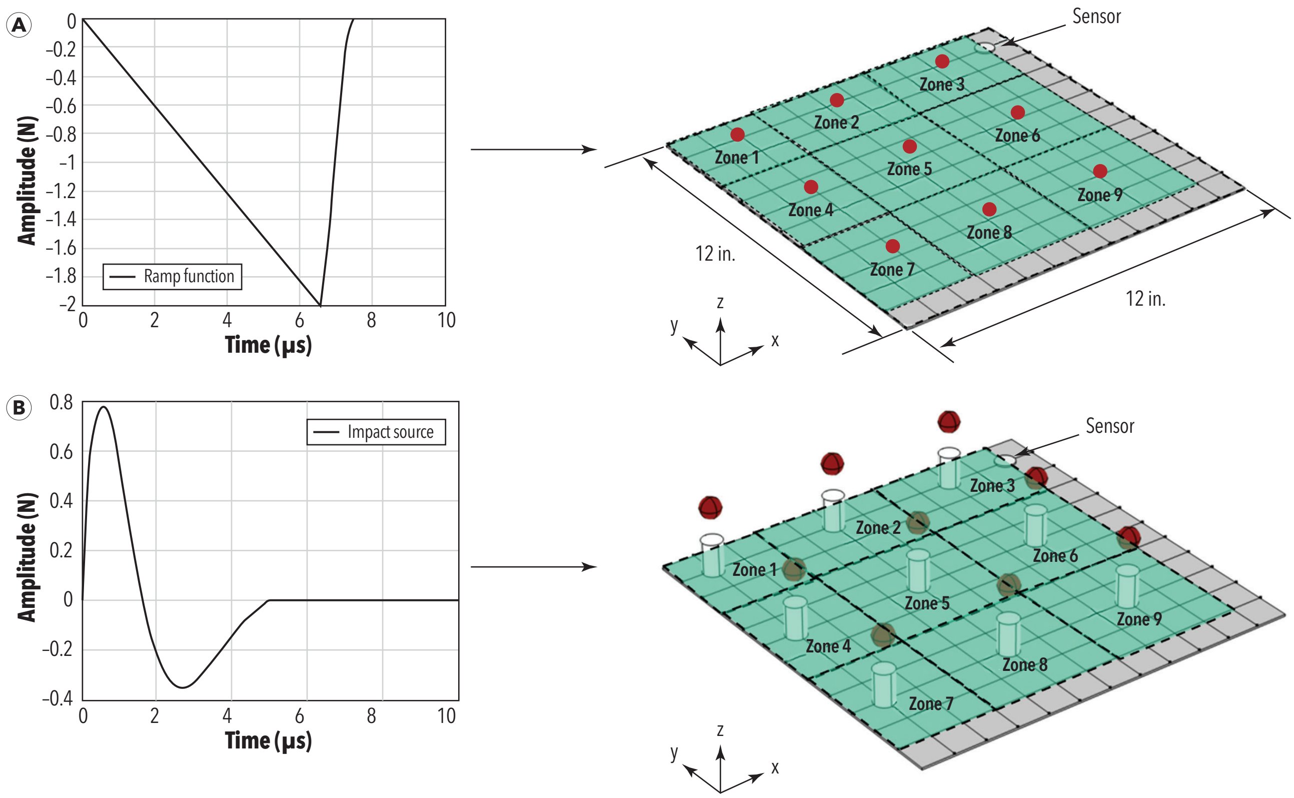

Figure 3. Simulation setup with analytical functions: (a) excitation signal to simulate PLB test; (b) excitation signal to simulate impact test.

edges of the plate, respectively. Utilizing FEM simulations, we generated waveforms from nine distinct locations similar to the experimental setup shown in Figure 2. Simulating AE signals via FEM allows us to generate pretraining data for deep learning models, thereby enabling a more accurate and efficient localization of acoustic emission sources within the specimen. These simulated signals furnish an effective means to pretrain deep learning models for AE signal processing algorithms, consequently bolstering the accuracy and effectiveness of these algorithms in real-world contexts. For the PLB test, the excitation signal, $F_1(t)$, simulates the response of an aluminum plate to mechanical loading and is defined as follows:

$$F_1(t) = \begin{cases} -2t/t_1, \ 0 < x < t_1 \\ -cos(\pi[t - t_1]) - 1, \ t_1 < x < t_2 \\ 0, t_2 < x \end{cases}$$

The function was selected due to its ability to elicit a gradual increase in the excitation signal. Here, t_1 and t_2 are time intervals that define specific stages of the excitation signal. t_1 signifies the duration over which the excitation signal increases gradually, while t_2 denotes the time after which the signal ceases. This particular function was chosen as it prompts a gradual increase in the excitation signal, thus adequately representing the mechanical loading process. For the impact test, $F_2(t)$ is represented as:

$$F_2(t) = Ce^{-\gamma t/t_0} \sin\left(\frac{4\pi}{1 + \frac{t_0}{t}}\right)$$

where
C is the initial amplitude of the excitation signal,
γ is the damping factor,
t_0 is the characteristic time of the excitation signal, and
t is time.

This function, representing a damped sinusoidal wave, is a common signal observed in impact tests and serves to simulate the material response to mechanical loading. The shape of the

TABLE 1
Parameters for simulation

Parameters	Values
Young's modulus	206 GPa
Poisson's ratio	0.3
Density	2710 kg/m^3
t_0	5 μs
t_1	6.5 μs
t_2	7.5 μs
Decay rate γ	1.85

$F_1(t)$ and $F_2(t)$ is shown in Figure 3 and specifications of these parameters are shown in Table 1.

Figure 4 showcases the signals derived from the impact and PLB tests and their corresponding simulation signals. We present these waveforms to emphasize the clear correlations and dissimilarities between test and simulation data; such contrasts highlight the feasibility of employing deep learning models in acoustic emission source localization. The duration of these signals is distinct for the tests and simulations; the test signals span a duration of 250 µs, while the simulation signals extend over a period of 100 µs. This discrepancy is a consequence of the methods employed to gather sufficient

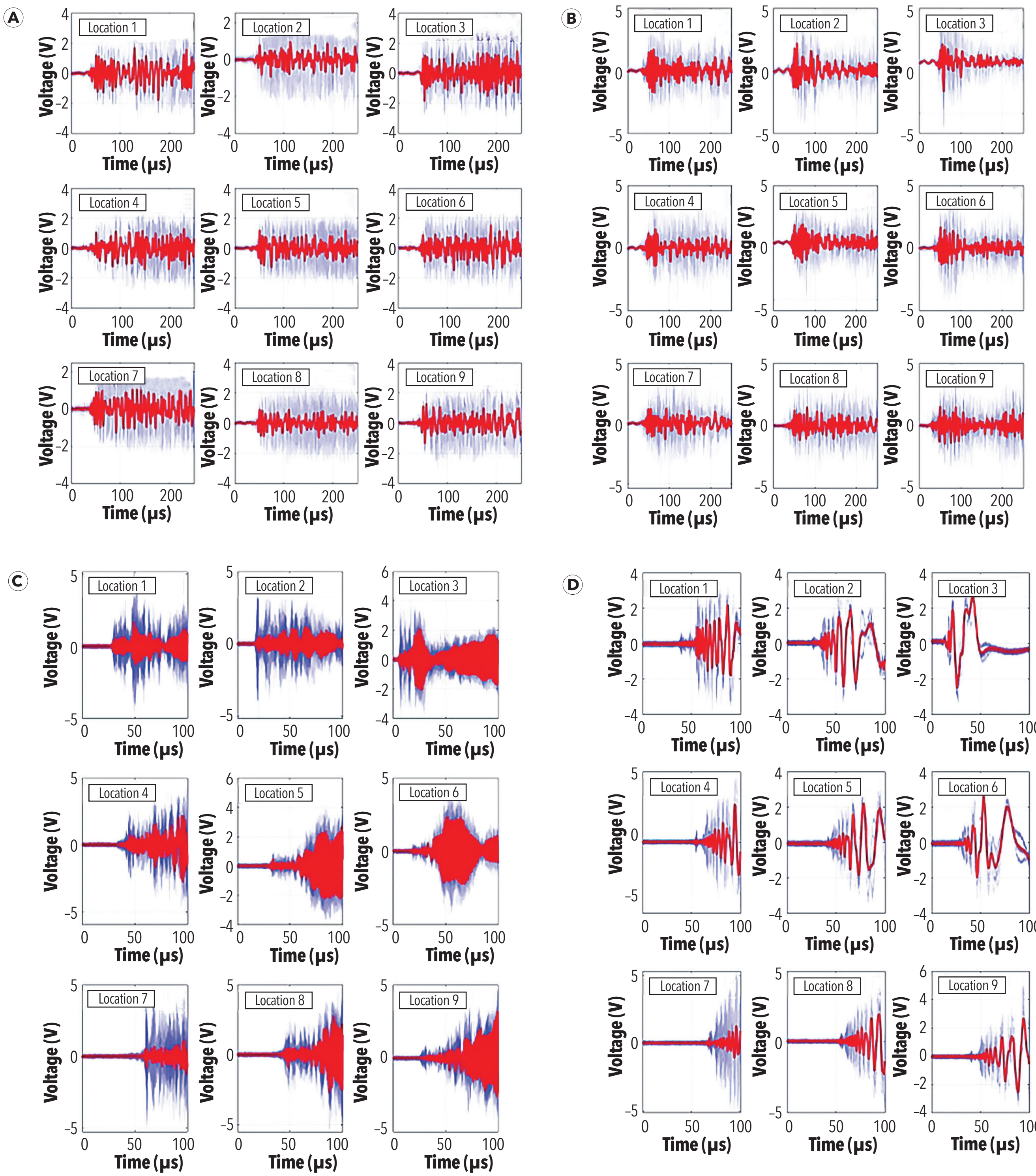

Figure 4. Signals obtained from: (a) impact test; (b) PLB test; (c) impact simulation; and (d) PLB simulation. The raw signal is denoted in blue, while the red line signifies the average waveform.

data from finite element modeling. We deployed a point domain network consisting of a 5 × 5 grid of sensing locations to gather the simulation data, which increases the complexity of the surrounding mesh, substantially slowing the collection of the reverberation pattern (reflected signals after 100 μs). As such, for practicality and computational efficiency, we limited the simulation data collection to the initial 100 μs. The simulation was conducted using a workstation equipped with a 3.1 GHz multi-core processor and a 4 GB dedicated graphics card. On average, each round consumed approximately 40 min. To gather an adequate volume of source domain data (simulation dataset), a data augmentation process was executed, resulting in the accumulation of 900 waveforms. It is noteworthy that differences in the reflection and trigger mechanisms between simulations and experiments, as observable in the figures, stem from variations in the interaction with adjacent substrates and boundary conditions, resulting in distinct reverberation patterns. Furthermore, while the simulation model logs the accurate time of arrival, the experimental process depends on manual trigger thresholding.

t-SNE is a powerful technique for visualizing high-dimensional data by mapping each data point to a two- or three-dimensional space. While t-SNE was originally designed for static data, it has been adapted for use with time series data in some cases. Visualizing AE data can be challenging due to its complexity and high dimensionality. However, t-SNE can be used to map time series data onto a low-dimensional space while preserving its underlying structure. To apply t-SNE to time series data, we first need to transform the sequential nature of the data into a set of fixed-length feature vectors that can be used as input to t-SNE. This can be done using various techniques such as sliding windows or feature extraction methods like Fourier transforms or wavelet transforms. Once we have transformed the time series data into feature vectors, we can compute pairwise similarities between them using a Gaussian kernel:

$$p_{I,j} = \frac{\exp\left(\frac{-\|x_i - x_j\|^2}{2\sigma^2}\right)}{\sum_k \sum_l \exp\left(\frac{-\|x_k - x_l\|^2}{2\sigma^2}\right)}$$

where
x_i and x_j are two feature vectors,
sigma is a parameter that controls the width of the Gaussian kernel, and
$p_{I,j}$ is the probability that x_i would pick x_j as its neighbor if neighbors were picked in proportion to their probability density under a Gaussian centered at x_i.

Next, we compute pairwise similarities between points in the low-dimensional map using a Student-t distribution:

$$q_{i,j} = \frac{\left(1 + \|y_i - y_j\|^2\right)^{-1}}{\sum_k \sum_l \left(1 + \|y_k - y_l\|^2\right)^{-1}}$$

where
y_i and y_j are two points in the low-dimensional map, and
$q_{i,j}$ is the probability that y_i would pick y_j as its neighbor if neighbors were picked uniformly at random from all other points.

Finally, t-SNE minimizes the difference between these two distributions using gradient descent on a cost function that measures their divergence:

$$KL(P\|Q) = \sum_i \sum_j p_{i,j} \log \frac{p_{i,j}}{q_{i,j}}$$

We've employed this t-SNE technique to enhance our understanding of the relationship between our simulation and experimental datasets. Two-dimensional plots generated by this method, as depicted in Figure 5, showing the similarities between AE signals collected from nine distinct zones. Figures 5a and 5b demonstrate that the experimental data from both the impact and PLB tests exhibit larger variability and less distinct clustering, suggesting more complexities and uncertainties in real-world scenarios. On the other hand, Figures 5c and 5d illustrate that the simulation data from both tests have a clearer clustering effect, indicating the advantages of using controlled and predictable simulation data for improving AE source localization techniques. Nevertheless, it's important to recall that the simulation data might not encapsulate all the complexities and variations inherent in real-world scenarios. Therefore, further optimization of our proposed source localization techniques is necessary to incorporate more uncertainty factors, ensuring effectiveness across diverse real-world applications.

Deep Transfer Learning for Knowledge Transfer

This study investigates the effective application of transfer learning to new data, leveraging the insights obtained from pretrained models. A variety of deep learning models, including convolutional neural network (CNN), fully connected neural network (FCNN), Encoder, Residual Network (ResNet), Inception, and Multi-Layer Perceptron (MLP), were assessed for their ability to analyze simulated datasets and to extract underlying features using a layer-wise fine-tuning strategy. The employed methodology entailed signal acquisition from the simulated datasets, followed by data preprocessing, feature extraction via fine-tuned deep learning models, and finally classification based on acoustic emission source location. To scrutinize impact and PLB test simulations, six deep learning models with distinct architectures and capabilities were investigated. This innovative strategy leads to a broader comprehension of the data, permitting the recognition of overlooked patterns and features when using a singular model. Detailed summaries of the architectures used for the networks mentioned are as follows:

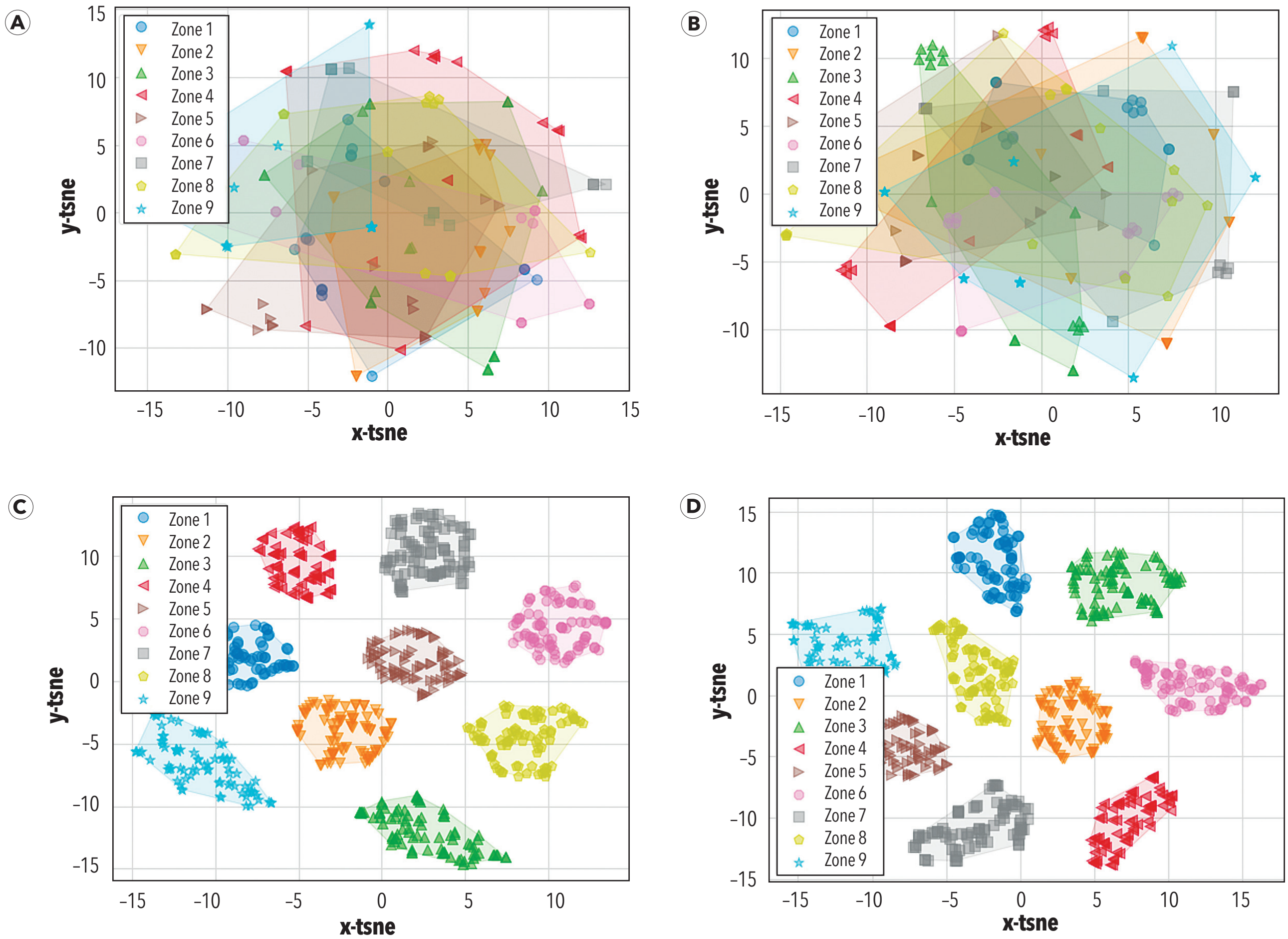

Figure 5. The two-dimensional t-SNE plot for: (a) impact test dataset; (b) PLB test dataset; (c) impact simulation dataset; and (d) PLB simulation dataset.

- CNN implements two convolutional blocks with 1D convolutions, instance normalization, and dropout. Each block comprises a Conv1D layer, succeeded by instance normalization, dropout, and max pooling. Hierarchical features are extracted from the input time series by the convolutional blocks. These features are then flattened and transmitted to a SoftMax classifier. The CNN model employs "categorical_crossentropy" loss and Adam optimizer (Simonyan and Zisserman 2014).
- FCNN resembles the CNN architecture but replaces max pooling with global average pooling to minimize spatial information loss. The global average pooling layer compacts the spatial information into a 1D vector, with these compressed features then passed to the SoftMax classifier (Zhang et al. 2017).
- ResNet uses residual blocks to circumvent the vanishing gradient issue. Residual blocks add the input directly to the stacked convolutional layers, enabling direct gradient flow. It uses batch normalization and weight regularization (L2 regularization). Each residual block comprises two Conv1D layers followed by batch normalization and activation, with the output of the residual blocks average pooled and transmitted to the SoftMax classifier size (He et al. 2015).
- Encoder resembles CNN's convolutional blocks but employs Parametric Rectified Linear Unit (PReLU) activation and instance normalization. After the convolutional blocks, an attention mechanism is applied. This attention layer assigns weights to the feature maps, focusing on pertinent features. The attended features are flattened and passed to the SoftMax classifier extraction (Vincent et al. 2008).
- MLP substitutes the convolutional layers with dense layers for time series classification. The input time series is flattened and sent to the dense layers. It uses two dense layers with dropout for regularization. The output dense layer utilizes SoftMax activation for the classification (Delashmit and Manry 2005).
- Inception utilizes an inception module with parallel branches of 1×1, 3×3, and 5×5 convolutions and max pooling. The outputs of the parallel branches are concatenated, forming the inception module. It employs batch normalization and the dropout post inception module. The features are flattened and transmitted to the SoftMax classifier (Zhang et al. 2022).

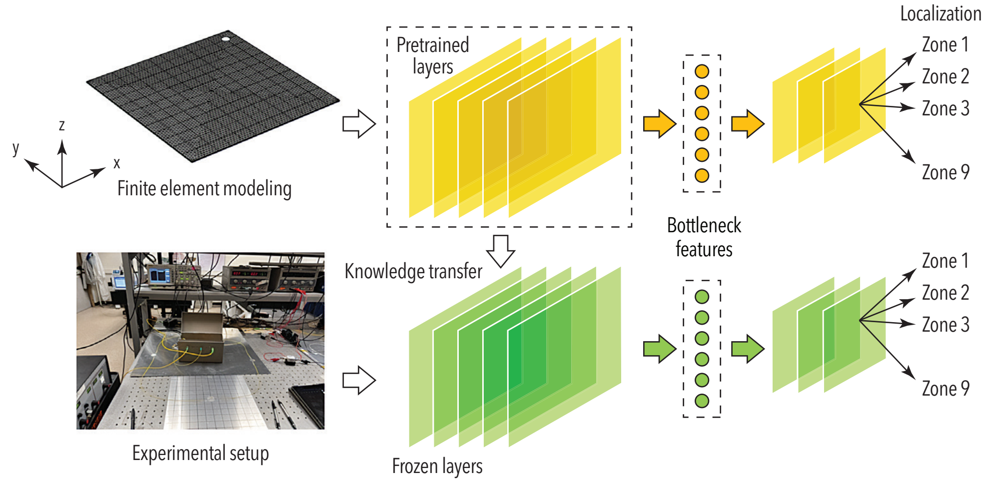

Figure 6. Schematic and structure of knowledge transfer via deep transfer learning.

Our research employs transfer learning, a technique capable of enhancing the performance of deep neural networks across various tasks. We illustrate its efficacy by applying it to improve the performance of deep neural networks in acoustic emission source localization. AE is a nondestructive testing method that leverages sound waves to identify and analyze material defects, and acoustic emission source localization pertains to the determination of the origin of the acoustic emission signals. We initialized our process by pretraining a deep neural network on a large simulation dataset, allowing the network to capture the general features of AE signals. Following this, we fine-tuned the deep neural network on a smaller experimental dataset, a process that facilitated the network's learning of specific features present in the experimental data. Our process involves first transferring layers from a pretrained model, and subsequently freezing their parameters. As new AE data is processed, it passes through these frozen layers before progressing through the trainable layers, allowing us to localize the acoustic emission source. Owing to the intrinsic connection between simulation and experimental data, the feature extractor can be applied to the latter, incorporating it as a nonadjustable layer in our model. We designate the high-level features extracted from these layers as "bottleneck" features due to their high level of condensation and their position at the classifiers' preceding constriction point (as illustrated in Figure 6). The applied deep learning architecture comprises one of six classifiers, each consisting of multiple fully connected layers following global pooling. This design enables nonlinear mapping of bottleneck features to AE source localization. Additionally, a fusion layer is utilized to amalgamate extracted features, and an extra layer is employed to link bottleneck features to location predictions. During fine-tuning, the pretrained model's weights serve as the initial values, and the model undergoes further training with available target domain data. As a consequence, the fine-tuned model can acclimatize to the target domain's unique characteristics, offering superior performance to a model trained from scratch.

Results and Discussion

In this section, we compare the performance of various deep learning models with and without transfer learning applied to acoustic emission source localization tasks. We analyze the mean loss and loss range over 200 epochs for CNN, FCNN, Encoder, ResNet, MLP, and Inception architectures. These models were trained on two different datasets, namely the impact dataset and the PLB dataset, which both contain distinct acoustic emission source localizations. In the first scenario, we trained CNN models without transfer learning directly on the experimental dataset. Both models exhibit a similar pattern over the epochs, initially having high loss values and gradually improving to achieve a significant reduction in loss. However, the validation loss does not decrease as substantially, which may indicate overfitting. In this case, the models have learned the training data too well but struggle to generalize on new, unseen data. In contrast, for the second scenario, we employed transfer learning, where the CNN models were first pretrained on a large, simulated dataset before being fine-tuned on the experimental dataset. Both models begin with lower loss values than those without transfer learning, which could be attributed to the initial learning from the simulated dataset. Over 200 epochs, these models improve significantly. One model achieves a very low validation loss, suggesting excellent generalization capability, while the other model has a slightly higher validation loss. The performance of the other models, such as FCNN, Encoder, MLP, Inception, and ResNet, are also compared with and without transfer learning. Some models, such as the Encoder and MLP, exhibit significant improvements when transfer learning is applied, while others show minor or negligible differences. Interestingly, the ResNet model demonstrates good performance on both the impact and PLB datasets, with and without transfer learning, though it experiences more fluctuations in the loss curve without transfer learning. Figures 7, 8, and 9 illustrate the mean loss and loss range for each model with and without transfer learning on the impact and PLB datasets. These visualizations provide a clear comparison of the models' performances, highlighting the advantages of transfer learning in various cases. In summary, our findings suggest that transfer learning can significantly enhance the performance of deep neural networks on acoustic emission source localization tasks, particularly when high-quality training data is scarce. It highlights the utility of leveraging preexisting knowledge to expedite learning and bolster the model's ability to generalize. However, not all models benefited from transfer learning. The Inception model's performance was affected slightly, possibly due to the complexities inherent in its architecture. Intriguingly, the FCNN model performed better without transfer learning, indicating that its architecture might be more suited to direct learning from the training data. This observation underscores the need to consider the specificities of each model when applying transfer learning.

The presented study evaluates the performance on the test dataset. Our discussion is supplemented with statistical

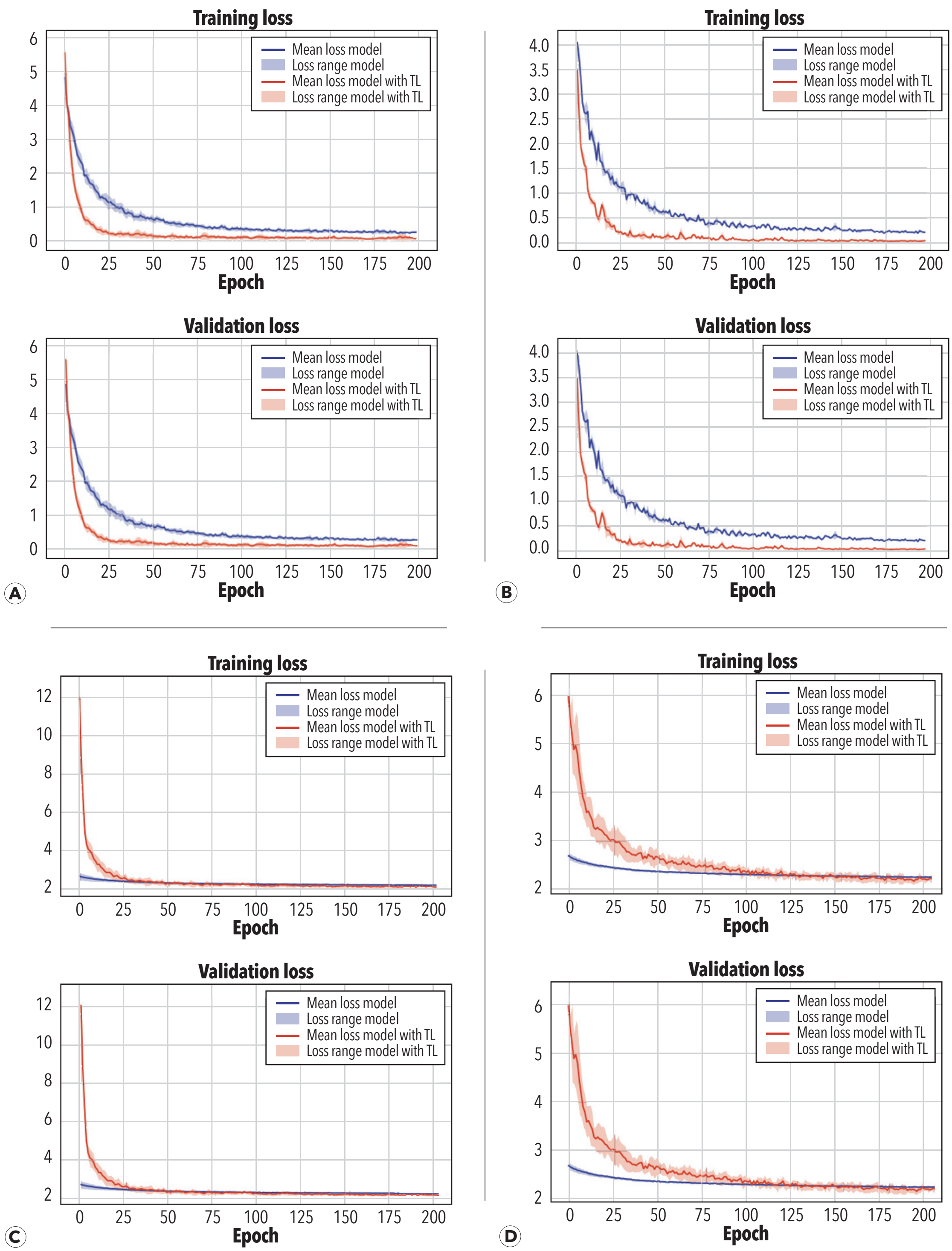

Figure 7. Comparative analysis of mean loss and range with and without the implementation of transfer learning for: (a) CNN model applied to the impact test dataset; (b) CNN model applied to the PLB test dataset; (c) FCNN model applied to the impact test dataset; and (d) FCNN model applied to the PLB test dataset.

metrics such as the minimum (the smallest value in the dataset), maximum (the largest value), median (the middle value when arranged in increasing order), first quartile (Q1: the middle value between the minimum and the median), and third quartile (Q3: the middle value between the median and the maximum). Analyzing the box plot as illustrated in Figures 10 and 11, we have added a few things to reduce overfitting:

- Early stopping: By stopping training if validation loss does not improve for 20 epochs, we prevent the model from overfitting to the training data. If the validation loss is no longer improving, continued training is unlikely to generalize better to new data.
- Restore best weights: By restoring weights from the epoch with the best validation loss, we "roll back" the model to the point before overfitting started to occur. This gives us the model that generalizes best to new data.

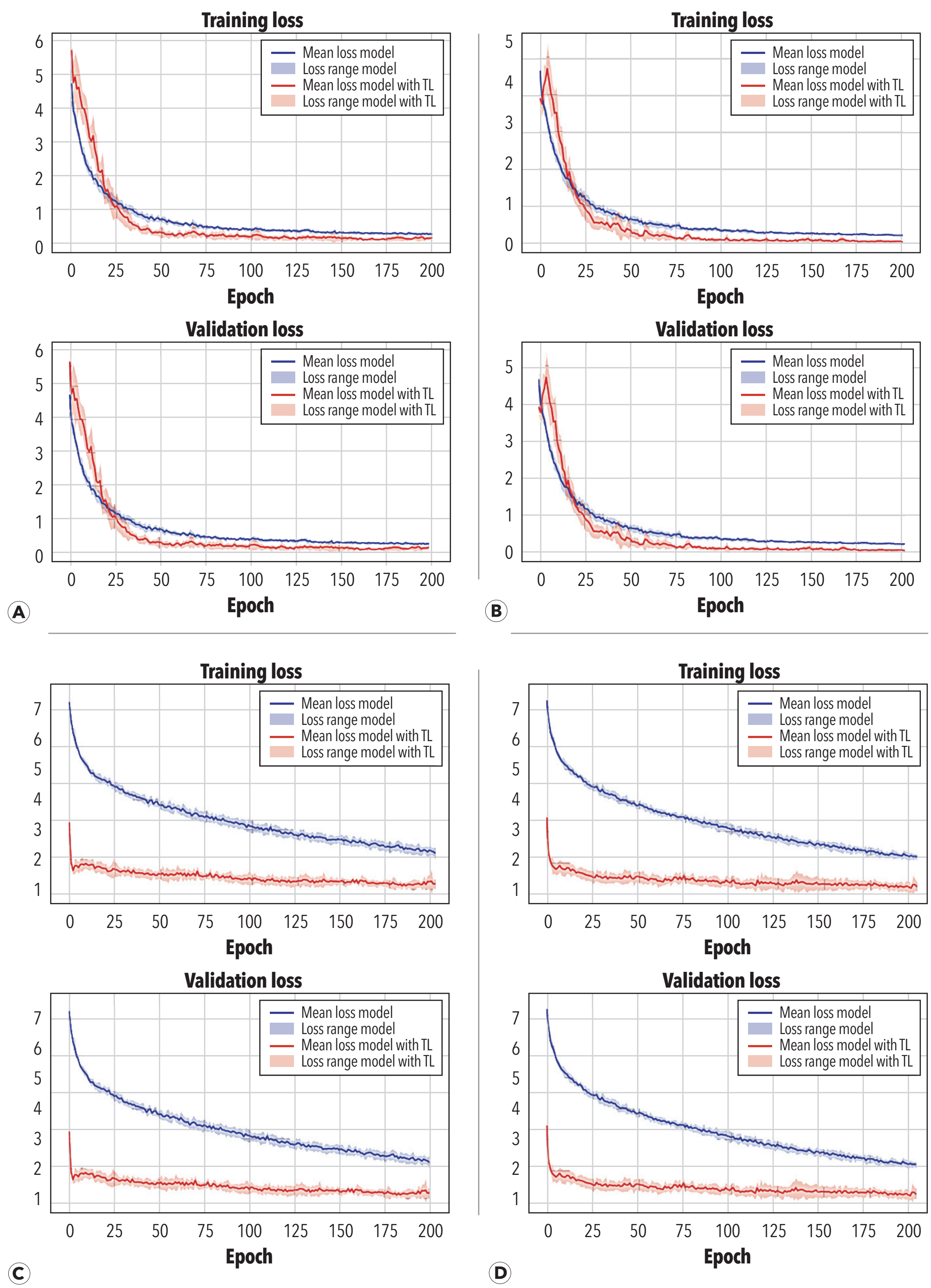

Figure 8. Comparative analysis of mean loss and range with and without the implementation of transfer learning for: (a) Encoder model applied to the impact test dataset; (b) Encoder model applied to the PLB test dataset; (c) MLP model applied to the impact test dataset; and (d) MLP model applied to the PLB test dataset.

- Patience: The patience value of 20 epochs means we are willing to tolerate a fair number of epochs without improvement before stopping training. This avoids stopping too early and allows temporary plateaus in validation loss, but ultimately stops before severe overfitting occurs.

In the Impact dataset, the CNN and MLP models, with and without transfer learning, achieved comparative performance in terms of accuracy, precision, and recall, with slight enhancements observed in models using transfer learning. Conversely, FCNN underperformed, showing negligible improvement from transfer learning; unlike CNN and MLP, which recorded accuracies above 0.8, FCNN yielded a mere 0.2. Transfer learning substantially increased ResNet's performance variance regarding recall, precision, and accuracy. Inception showed a similar trend to CNN and MLP, where transfer learning resulted in minor enhancements. The Encoder model

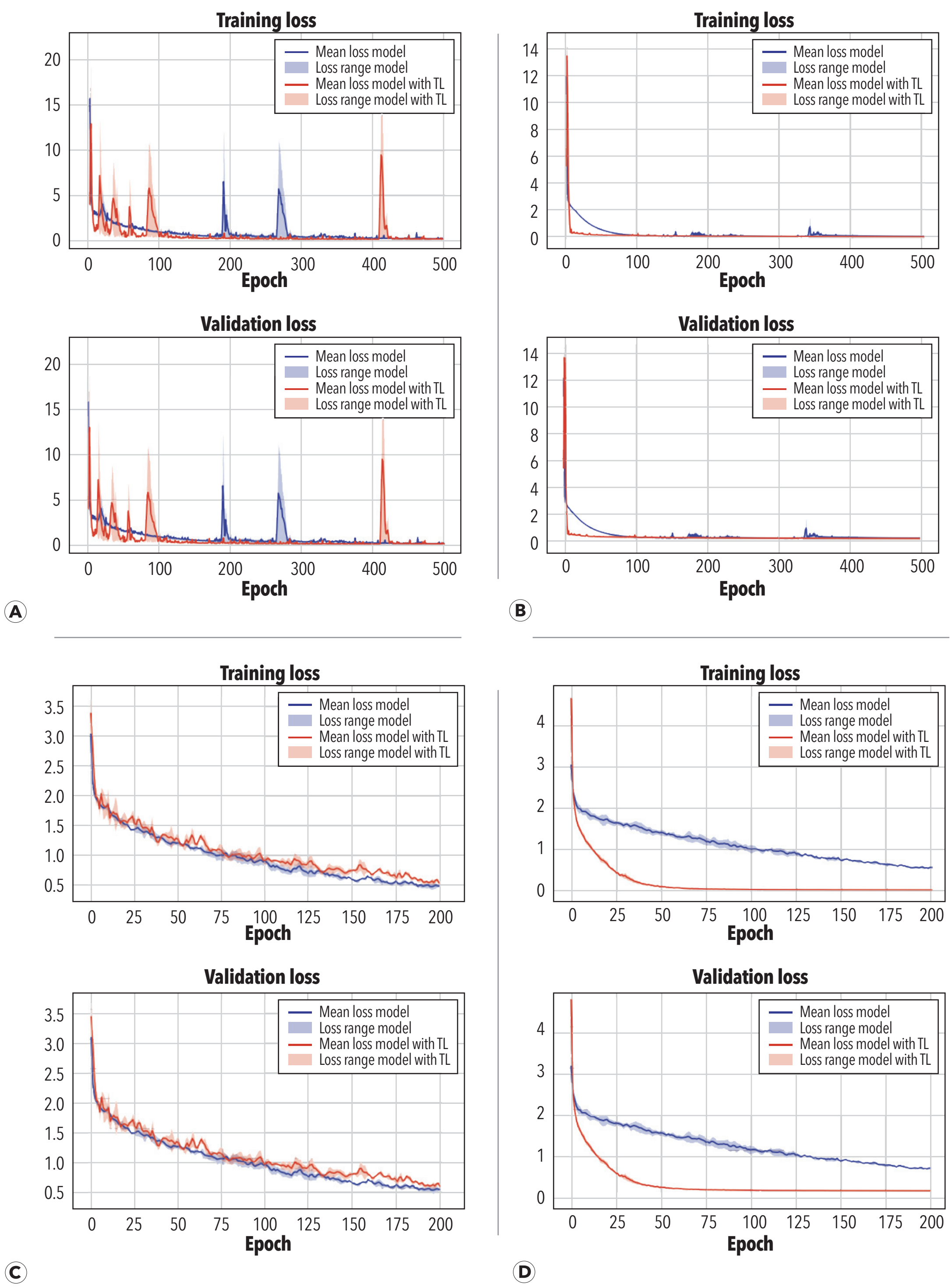

Figure 9. Comparative analysis of mean loss and range with and without the implementation of transfer learning for: (a) Inception model applied to the impact test dataset; (b) Inception model applied to the PLB test dataset; (c) ResNet model applied to the impact test dataset; and (d) ResNet model applied to the PLB test dataset.

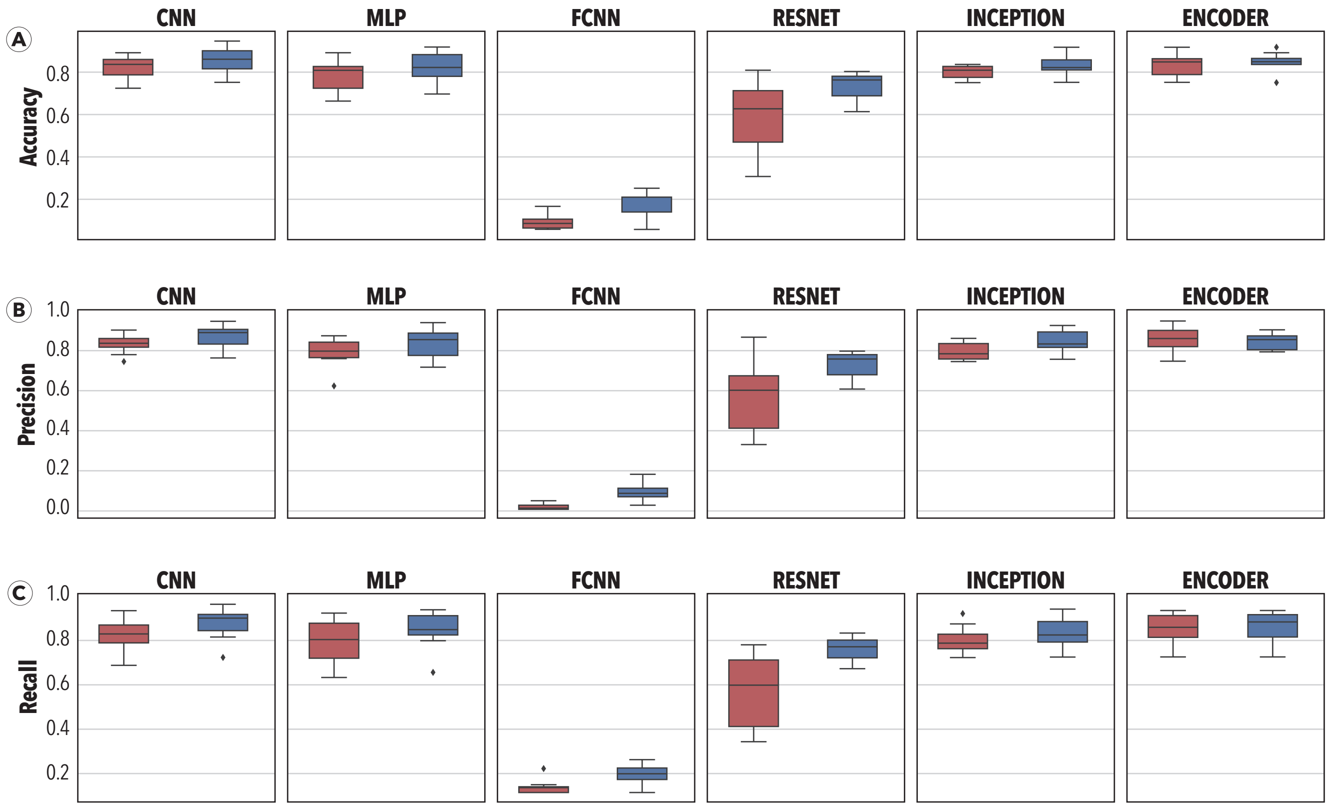

Figure 10. The distribution of: (a) accuracy; (b) precision; and (c) recall from a tenfold cross-validation for six classifiers on the impact test dataset. Models without transfer learning are indicated by red bars, while those with transfer learning are shown in blue.

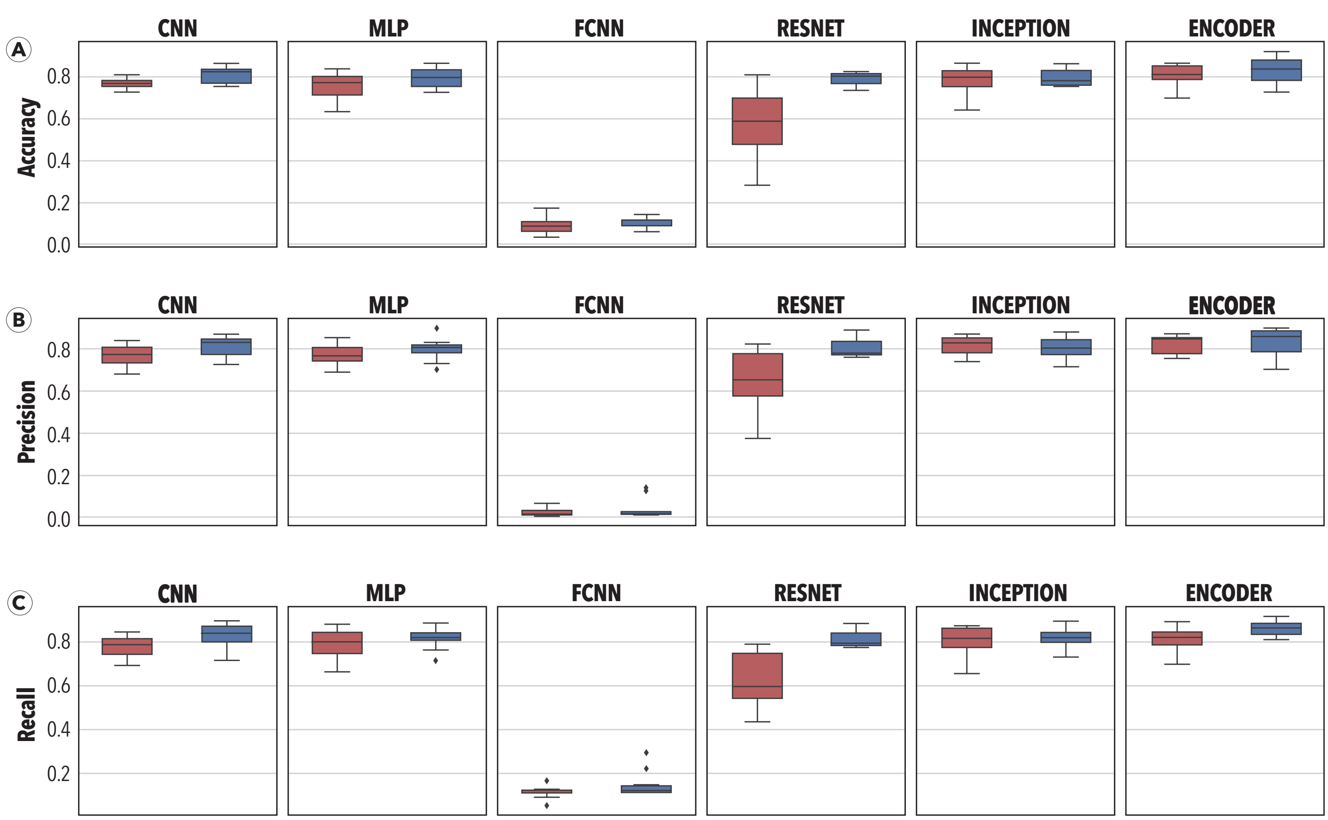

Figure 11. The distribution of: (a) accuracy; (b) precision; and (c) recall from a tenfold cross-validation for six classifiers on the PLB test dataset. Models without transfer learning are indicated by red bars, while those with transfer learning are shown in blue.

showed minimal variation in performance; precision was slightly higher without transfer learning, while recall remained unchanged. Accuracy was slightly improved with transfer learning.

As for the PLB dataset, the CNN and MLP with transfer learning slightly outperformed their counterparts without transfer learning. FCNN underperformed with an accuracy of less than 0.1, while transfer learning further deteriorated its performance. Again, ResNet showed significant improvement through transfer learning. Unlike the Impact dataset, Inception with transfer learning showed slightly worse performance compared to without transfer learning. Encoder, similar to CNN and MLP, had slightly higher precision, recall, and accuracy with transfer learning.

The observations from this study can be explained by the fundamental advantage of transfer learning, which can be explained by the reusability of the learned features. Models without transfer learning, though adept at discriminative patterns from training data, face difficulties in generalizing to unfamiliar data. This process often results in memorizing training data rather than assimilating generalizable patterns, thereby leading to elevated validation losses. On the contrary, models employing transfer learning derive initial benefits from patterns and features harvested from an extensive simulated dataset. These models exhibit reduced initial loss values, indicating that the simulated dataset provides a beneficial starting framework for interpreting the limited experimental data. Furthermore, fine-tuning allowed these models to adapt to the specific characteristics of the experimental data, resulting in significant improvement over epochs and better generalization capabilities. The distinct performance outcomes of different models, as illustrated by statistical metrics and visualizations, underscore the crucial role of model architecture in harnessing the effectiveness of transfer learning.

Conclusions

This paper proposes a novel data-driven approach to accurately localize two types of acoustic emission sources in an aluminum plate using six deep learning models: CNN, MLP, FCNN, Inception, ResNet, and Encoder. The models incorporate deep transfer learning techniques to enhance their effectiveness in identifying the source of acoustic emission signals. The deep learning models were trained and evaluated using simulations of impact and PLB tests with a distributed sensor array designed to maximize information acquisition from the simulations. The results demonstrate the efficacy of deep neural networks with transfer learning in mapping acoustic emission waveforms to their sources and uncovering valuable insights from the simulations. However, this study's limitation is the inability to identify the exact coordinates of the sources of the acoustic emissions. Future research should optimize the deep neural networks using larger training datasets and explore automated solutions like numerical simulations or robotic solutions to address this limitation. Additionally, while in this study Hsu-Nielsen tests were used to simulate fatigue cracks, further research should conduct more formal tests on actual propagating cracks to verify the performance of the proposed deep learning approaches under real states of stress. These efforts could lead to the development of more robust and accurate deep learning models for acoustic emission source localization in real-world applications.

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A MESSAGE FROM YOUR OUTGOING PRESIDENT

DANNY L. KECK
ASNT PRESIDENT, 2022–2023
VICE PRESIDENT, ASNT CERTIFICATION SERVICES LLC
VICE PRESIDENT, ASNT FOUNDATION
DKECK@ASNT.ORG

I would like to take this occasion to say, thank you! It has been an honor and privilege to serve as our Society's 81st President from July 2022 to June 2023. It was a rewarding experience to have the opportunity to work with such a dedicated staff and an extremely professional and effective Board of Directors (BOD) as we together guided our Society through some very trying times. I am so looking forward to taking on the new challenge of serving as Chairperson of the Board beginning in July 2023 as the BOD, including the five new directors just recently elected (see page 88), will continue to strive to make our Society stronger and provide even more opportunities for our members.

Over the past year, we have expanded our portfolio of benefits by acquiring NDT Classroom and we will be further developing those online training courses to fit the needs of our Level I and Level II members (and nonmembers, for that matter). We have successfully administered over 1200+ UT Thickness (UTT) performance verification examinations through our highly successful Industry Sector Qualification (ISQ) performance demonstration program, rolled out the ISQ UT Shear Wave (UT-SW) exams, and are currently rolling out the ISQ UT Phased Array (UT-PA) exams as I write this note in early June. Watch for more on the ISQ program to come in the very near future. Through ASNT Certification Services LLC, a newly formed company that handles all the certification efforts within ASNT, we have finally released the new ASNT 9712 program. This will replace the old ACCP program and will be fully compliant with the latest ISO 9712 standard for the qualification and certification of NDT personnel. Additionally, we have introduced the EBC (employer-based certification) Audit Program wherein service companies can have their in-house SNT-TC-1A and/or CP-189 programs audited by ASNT and receive an accreditation of full compliance for their program once the audit is completed. There is much more to come on this in the very near future that will benefit ASNT members as well.

I was extremely proud to be part of the opening of the new ASNT Houston training and testing facility, as well as the newly formed ASNT India Pvt. Ltd., part of our international expansion efforts. Both of these facilities will provide lower costs to our members while still producing revenue to grow the Society.

During my year-long tenure as President, I was fortunate to have the privilege to represent ASNT at leading NDT conferences around the world. I was asked to attend the British Institute of Non-Destructive Testing (BINDT) annual conference, where I gave a short speech and follow-up toast to their Society. I was honored to host, along with Chairperson of the Board John T. Iman and Vice President Dr. John Z. Chen, the US-Japan NDT Symposium, which is held every four years in Hawaii. I also represented ASNT at the Asia Pacific Conference for NDT in Melbourne, Australia. I was selected and voted in as the President of the next Asia Pacific Conference, which will be hosted by ASNT in Honolulu in 2026. Lastly, I was an invited lecturer at the 70th anniversary ceremonies of the Japanese Society for Non-Destructive Inspection in Tokyo, Japan—an event I will remember for a lifetime. I managed to make a few local section meetings (not as many as I had planned due to unforeseen issues): one being the Charlotte Section's annual shrimp boil, as well as

LEADERSHIP FROM P. 85

one in the Kingdom of Saudi Arabia while I was there on an unrelated business trip. All in all, it has been a very busy and productive year for me.

During my speech at the 2022 Annual Conference in Nashville, I quoted two past US presidents who spoke of the rewards of service to others as well as how to overcome difficult issues and learn from them. I can say that volunteering for ASNT and working with the other great volunteers of our Society over the past 40+ years has been extremely rewarding. Along the way we have experienced many bumps in the road; however, by working together we have overcome so many of the obstacles. I am certain that after the dust of the years to come has passed over our Society, we, too, will be remembered, not only for our accomplishments (victories or defeats), but for our contribution to the human spirit as volunteers.

In closing, thank you for allowing me to be your 81st President. Thank you to all the volunteers who donate their valuable time to assure our Society is the gold standard for the NDT community around the globe. Thank you to the staff at ASNT for their relentless support. Thank you to our executive director and the BOD for their guidance and leadership. I would also like to thank and acknowledge the Directors whose three-year terms on the BOD ended on 30 June: Tsuchin (Phillip) Chu, Gerry Churchwell, Larry Gill, and Anish Poudel. Last but certainly not least, thank you to our outgoing Chairperson of the Board, Mr. John Iman. John has led our Society through uncharted waters over the past two years, kept us on track throughout the journey, and never wavered on his pursuit for enhanced workforce development programs, the formation of the new ASNT Foundation (for which he has been appointed President), and the aggressive but much needed Strategic Plan. It is people like Mr. Iman who make this Society and our industry great. We are truly a society of professionals that work daily to create a safer world. ME

ASNT ANNOUNCES

On Monday, 17 April 2023, ballots were tallied and results were confirmed by ASNT's election partner, Intelliscan Inc. The ASNT Leadership Development Committee is pleased to announce the following individuals will be taking their seat on the Board of Directors of the American Society for Nondestructive Testing, for three-year terms, beginning 1 July 2023. Read on to meet your new Directors!

DAVID ALLEYNE

David Alleyne, PhD, is the CEO of Guided Ultrasonics Ltd. (GUL), a spin-out company from the Mechanical Engineering Department at Imperial College in London, UK. He co-founded the company in 1999 with products that were based on his foundational research. Since 1999, he has driven the adoption of guided wave testing (GW) technology globally to the point where it is now a significant and growing part of the NDT and structural health monitoring (SHM) market. GUL exports most of its products and services. Under Alleyne's leadership, GUL has been pivotal in the creation of the GW methodology and industry codes and standards, as well as all levels of associated engineering professional certifications.

Alleyne completed his PhD at Imperial College in 1991. His research was to gain understanding of how guided waves (Lamb wave) in plates could be used for NDT. After starting GUL with a colleague (Brian Pavlakovic, PhD), the two continued the development of innovative GW technologies using the torsional modes. Over the next 23 years, Alleyne led and directed development and commercialization of transformational technologies for the global NDT industry. From 1999 till 2015, he was the operations director with responsibility for developing training schemes and material for the NDT industry based around a practitioner-based syllabus for Levels I, II, and III. Since 2015, Alleyne has led the company as CEO, devising strategies and business plans with the core objective to diversify the company's technology base to include SHM and invent new application-directed tools for quantitative measurements (QSR). The new developments have also incorporated artificial intelligence via machine learning tools to aid inspectors' training and technical expertise uptake.

Alleyne is an acknowledged world leader in the industrial application of GW technology and has gained a wealth of invaluable experience from wide-ranging collaborations with universities and industrial partners. This has resulted in an outward-facing approach that values talent with an emphasis placed on innovation via teamwork, respect, and customer service.

Alleyne also serves on the advisory committee of a major UK charity (IntoUniversity) that works to assist and support young people through learning centers where they are inspired to achieve. Alleyne has also done committee work at ASNT and has been involved in many national and international code bodies, including ASTM, NACE, BSI, and ISO.

NEWLY ELECTED DIRECTORS

KATHY FERGUSON

Kathy Ferguson is a materials engineer who has spent her career working in the field of NDT. Ferguson joined Boeing in 2008 where her broad background in NDT, failure analysis, and materials selection allowed her to support multiple airplane programs including the F-22, 787, 737, 777X, P-8, and the 767 Tanker programs. She has been a role model and mentor to students and colleagues in the field of NDT for her entire career. Ferguson has received numerous technical achievement awards, including a Boeing Meritorious Invention Award, and she currently holds five US patents in a variety of different technologies.

Ferguson has served continuously for 13 years on the Board of Directors for the Pacific Northwest Section of ASNT. She served as chair for three years, ensuring that the Section continued winning Gold recognition in the ASNT President's Award program. During that time, she was honored for her years of mentoring women and students pursuing careers in NDT with the 2018 ASNT Advancement of Women in NDT Recognition and the 2019 ASNT Mentoring Award. She has encouraged countless students with her message that NDT is the "Ultimate Superhero Career" because NDT saves lives before catastrophes strike and makes the world a safer place. She encourages every member to recognize the contributions that they have made in making the world a safer place. To that end, she has nominated numerous Pacific Northwest Section members resulting in them winning the following ASNT awards: Lou DiValerio Technician of the Year Award, Robert C. McMaster Gold Medal Award, three ASNT Fellow Awards, two Mentoring Awards, and the Advancement of Active Military and Veterans in NDT Recognition Award.

Ferguson launched a "Building Connections" initiative, which helps students to network with other ASNT section members and to advance their NDT careers. Ferguson mentors high school and college students by making STEM presentations about NDT and organizes student tours of aerospace companies in the Seattle area. She served on the 2013, 2015, 2017, and 2019 Program Committee for the Pacific Northwest Section NDT of Composites Conference.

Ferguson has been a role model to NDT students at Clover Park Technical College, many of whom she encouraged to join ASNT and later hold leadership positions on the Pacific Northwest Section board. She was part of the leadership team that created the Pacific Northwest Section David Hall Student College Scholarship Fund, which encourages students to pursue careers in NDT. She also consistently serves on the Scholarship Committee, Radiation Safety Committee, NDT of Composites Planning Committee, and the annual Pacific Northwest Section Golf Tournament Committee, which provides funding for the scholarship fund.

Ferguson began her NDT career working for the Naval Aviation Depot in Jacksonville, Florida, after graduating with a degree in materials engineering from the University of Florida. While there, she mentored fleet and depot technicians in the appropriate techniques to use for inspecting airplanes for cracks and corrosion. She later joined a large chemical manufacturing plant in Pensacola, Florida, as the lead metallurgist, where she established an SNT-TC-1A certification program for plant NDT inspectors. She also began Ferguson Consulting Services, which provided failure analysis support in litigation matters involving industrial and aircraft accidents.

Ferguson has spent her entire career mentoring students, technicians, and engineers in NDT and supporting the vision of ASNT. Her primary goal has been to help others build greater connections and form a more meaningful bond with ASNT.

ANITA GREGORIAN

Anita Gregorian graduated with a master's degree in materials engineering from the California State University in Northridge. The focus of her studies was on corrosion and vapor phase inhibitors in pipelines and other industrial structures. Immediately after graduation she became a member of the NDT team at The Aerospace Corp. based in the Los Angeles area, providing technical oversight of space missions to military, civil, and commercial customers. Her position at The Aerospace Corp. necessitates knowledge and experience in materials, physics, and NDT to provide mission-critical solutions. Gregorian has extensive experience in reviews and audits. Her expertise is also called upon in emergency on-site inspections of space hardware and failure investigations. In her role, she regularly interacts with NDT practitioners on the manufacturing floor, assisting with inspections, new technique development, and transfer of knowledge toward practical applications.

Working with aerospace and governmental contractors across the United States has given Gregorian insight on the needs of NDT technicians, training, and certifications. This experience is the drive behind her ASNT NDT Level III and IRRSP certifications, Society volunteer work, and urge to serve on the ASNT Board of Directors. In addition to her ASNT certifications, she is also certified in Cathodic Protection for the Association for Materials Protection and Performance.

Furthermore, Gregorian strongly believes that the circumstances of the past few years have demonstrated the importance of supply chains to meet national security demands. Manufacturers competing for contracts are increasingly integrating new materials, composites, additively manufactured parts, and NDE 4.0 into their processes. In this rapid progression in industry, new NDT applications often lag due to time required for validation and reliability. Both Gregorian's responsibilities at work as well as the topic of her PhD research focus on these issues–closing the gap between the NDT world and industry.

BRIAN J. MCKENNA

Brian J. McKenna graduated from Spartan College of Aeronautics and Technology in 1998 and worked his way up to Level II status in MT, PT, UT, and RT. He spent several years of his career in the construction industry, working in California, Alaska, and even for some time in the Middle East. In December 1998, McKenna started the company Engineering & Inspections in Hawaii, which began with three employees and grew to 18 full-time employees. In January 2007, the company opened its Pennsylvania office with three employees, and it grew to 75 employees before the COVID-19 pandemic. In March 2022, the company opened its Tulsa operations with six employees. Engineering & Inspections International offers all the basic NDE services along with computed radiography, digital radiography, phased array ultrasonic testing, and automated ultrasonic testing.

McKenna was also instrumental in helping start the Hawaii Section of ASNT and served as its president for many years before leaving Hawaii.

SATISH S. UDPA

Satish S. Udpa, PhD, serves as a University Distinguished Professor at Michigan State University (MSU) as well as Campus Mobility Director. Prior to reverting to his current position in October 2019, he served in many administrative capacities at MSU including Acting President, Executive Vice President for Administration, Dean of the College of Engineering, and Chair of the Department of Electrical and Computer Engineering. MSU is one of the premier land grant universities with an enrollment of more than 50 000 students and more than 12 000 faculty and staff. He also served as the President of the Michigan State University Foundation. Udpa was the Whitney Professor of Electrical and Computer Engineering at Iowa State University and a faculty member at Colorado State University before joining MSU in 2001.

Udpa has worked in the area of NDT since the early 1980s. He has focused his energies on developing a variety of sensors for NDT applications together with tools for modeling and developing them. The NDT systems and the algorithms he has developed for analyzing data generated by sensors are used extensively in industry. He has published extensively, holds 10 patents in the field of NDT, and was the technical editor of the *Nondestructive Testing Handbook, Vol. 5: Electromagnetic Testing*, third edition, published by the American Society for Nondestructive Testing. He served as the editor of the *IEEE Transactions on Magnetics* and the regional editor of the *International Journal of Applied Electromagnetics and Mechanics* until recently. His students have gone on to pursue highly productive careers in industry and academia. As Mobility Director, he has championed major initiatives to catalyze several mobility-related activities on campus, including the first autonomous (self-driving) bus on campus.

Udpa is a Fellow of ASNT, Institute of Electrical and Electronics Engineers (IEEE), and the Indian Society of Nondestructive Testing. He is also a Fellow of the National Academy of Inventors. He currently serves as a member of the Michigan Governor's Council on Future Mobility and Electrification. ME

CHARLOTTE

CHARLOTTE, NC
14 MARCH 2023
14 ATTENDING

▶ Sonaspection hosted a technical meeting of the Charlotte Section at its Concord, North Carolina facility. Jeremy Ring of Applied Inspection Systems gave a presentation on microwave testing of composite structures.

CLEVELAND

CLEVELAND, OH
20 MARCH 2023
22 ATTENDING

▶ The Cleveland Section met at Mavis Winkles Restaurant in Twinsburg, Ohio. Colleen Snyder from the Cleveland Museum of Art (CMA) gave a presentation on nondestructive testing techniques used in her work.

COLORADO

DENVER, CO
13 APRIL 2023
10 ATTENDING

▶ The Colorado Section held a virtual meeting. Greg Floor presented "NDE in the Ski Industry," discussing his career inspecting ski lifts across North America.

CONNECTICUT YANKEE

GROTON, CT
11 APRIL 2023
11 ATTENDING

▶ The Connecticut Yankee Section held a joint meeting with the American Welding Society's (AWS's) Connecticut section at Fischer Technology Inc. in Windsor, Connecticut. Rob Weber, Fischer Technology's Technical Director, gave a presentation on measuring the ferrite content of steel, the coating thickness on steel or aluminum, the thickness of electroplated coatings, and the durability or adhesion of coatings.

GREATER HOUSTON

HOUSTON, TX
8 MARCH 2023
75 ATTENDING

▶ The Greater Houston Section met at Republic Grill at Battleground Golf Course in Deer Park, Texas. Randy Moreland, Quality-Inspection Advisor at EM Golden Pass LNG Terminal, gave a presentation on "Remote Quality Surveillance."

GREATER LOS ANGELES

LOS ANGELES, CA
17 JANUARY 2023
13 ATTENDING

▶ The Greater Los Angeles Section met at Bruce's Prime Rib in Santa Fe Springs, California. Jim Bemis presented on "Radiation and Safety Compliance."

SPOTLIGHTCONNECTICUTYANKEE

The Connecticut Yankee Section and AWS Connecticut section presented a certificate of appreciation to Steven Pomerantz, Chief Operating Officer of Fischer Technology Inc., for presenting, hosting the joint meeting, and providing a tour of their facility. From left: Al Moore, Kari Slattberg Thibodeau, and Pomerantz.

LEWIS & CLARK

PORTLAND, OR
14 MARCH 2023
12 ATTENDING

▶ The Lewis & Clark Section met and covered old business. Guest Jason Boyer of Lisin Metallurgical Services presented on failure analysis.

METRO NY/ NORTHERN NJ

ROCKVILLE CENTRE, NY
22 MARCH 2023
15 ATTENDING

▶ John Nucatola gave a presentation titled "Ground Penetrating Radar (GPR) for NDE of Concrete & Masonry" at the Metro New York/Northern New Jersey Section meeting.

OLD DOMINION

RICHMOND, VA
23 MARCH 2023
78 ATTENDING

▶ The Old Dominion Section joined with members of the Richmond Joint Engineers' Council at their annual awards banquet held at the Jefferson Hotel in Richmond, Virginia. The keynote speaker, Mark Walker of Dominion Energy, delivered a presentation on the challenges of building and delivering electric power derived from solar power to the Virginia grid.

PIEDMONT

GREENVILLE, SC
14 APRIL 2023
3 ATTENDING

▶ The Piedmont Section held a virtual officer meeting and discussed and reviewed events, presentations, and more.

SOUTHWESTERN ONTARIO

MISSISSAUGA, ON, CANADA
30 MARCH 2023
7 ATTENDING

▶ The Southwestern Ontario Section held a virtual executive meeting. The Section's business plan, membership, financial report, and more were discussed. ME

MOLLY BROWN

2023 Engineering Undergraduate Scholarship winner Molly Brown is a sophomore at the State University of New York College of Environmental Science and Forestry (SUNY ESF) majoring in environmental resources engineering and earning a minor in mathematics. Throughout the semester, she works as a tutor at SUNY ESF's Math Learning Center, where she assists students with whatever math-related questions they may have. After this semester, she will be assisting one of her professors with research on carbon cycling and sequestration ecosystem services in natural and managed surface water systems.

By the nature of studying engineering at an environmental school, it becomes apparent how prevalent nondestructive testing (NDT) methods are in terms of creating sustainable solutions. Brown was also able to see sustainable solutions firsthand through her internship at Vector Magnetics LLC, where she assisted with tasks such as parts assemblies, projects in the machine shop, and electronics testing to assist the company as they worked toward various goals.

ABOUT THE ENGINEERING UNDERGRADUATE SCHOLARSHIP

The Engineering Undergraduate Scholarship is a cash award, currently US$3000 per award, that provides an incentive to undergraduate students enrolled in US universities and colleges with recognized engineering programs to choose NDT/E as their field of specialization.

LAUREL LOGAN

2023 Engineering Undergraduate Scholarship winner Laurel Logan has always been fascinated by the physical sciences and understanding how the world around her works. Choosing a major in college was a challenge because she wanted to learn and understand everything, but she ultimately decided on mechanical engineering due to its broadness and focus on underlying mechanics.

During Logan's time in college, she had the opportunity to work on several research projects, including acousto-optic nondestructive inspection, which sparked her interest in optics and NDT. She also worked at Virginia Tech in a mechanical engineering lab with a focus on cell mechanics and biomedical engineering, which exposed her to a different side of mechanical engineering research. Logan found herself fascinated by the technology they used to conduct their studies and began to think more about researching and developing engineering sensors and testing technology.

This summer, Logan is excited to be interning at Boeing's Advanced Development Center to work on developing and improving nondestructive evaluation technology. Logan is eager to explore a wide range of sciences and gain exposure to different testing, sensor, and ultrasonic technology. Her goal is to continue this work in research and development after completing her graduate education in mechanical engineering.

MICHAEL WILSON

2023 Engineering Undergraduate Scholarship winner Michael Wilson was born and raised in Arizona, where his family established an inspection and NDT business. Growing up, Wilson experienced many aspects of the business firsthand and learned the importance of uncompromising standards in inspection and testing, integrity, and safety. Today, Wilson is a motivated engineering student currently double majoring in mechanical engineering and engineering design at Rose-Hulman Institute of Technology (RHIT). Wilson recently put together a team to develop an invention of his, which was awarded the Bill Kline Innovation award at RHIT. A current Dean's List student, Wilson says that the knowledge and work ethic he has gained through his experience with NDT and the industry has given him a solid foundation that will serve him well in his future career as an engineer. ME

ASNT Lifetime Member **Sreenivas Alampalli** has been honored with inclusion by ASCE in its 2023 class of distinguished members for eminence and professional contributions to research, practice, and technology transfer in inspection, evaluation, testing, and monitoring of bridge infrastructure. Alampalli's unique engineering contributions include advancing NDT methods for quantitative evaluation of bridges to assure safety, developing a robust bridge inspection program, and pioneering applications of fiber-reinforced polymers for bridge applications.

Alampalli's research portfolio and leadership record are the products of a visionary government engineer and researcher who has spent much of his career promoting the development of numerous programs on bridge safety and management, not only for the New York State Department of Transportation (NYS DOT) but for other state DOTs and federal agencies as well. From 2003 to 2006 he served on the international stage as a Director at Large on the ASNT Board of Directors.

After the Minnesota Bridge collapse in 2007, Alampalli was asked to lead the ASCE-AASHTO-FHWA Task Force to develop a white paper on critical research needs in the areas of bridge inspection and evaluation. More recently, while at NYS DOT he was tasked with the massive undertaking of migrating the US$100 million annual inspection/evaluation program he managed from a state-specific system to an AASHTO element-based national system. In all, Alampalli has assembled 30 years' worth of asset management and policy development, building successful strategic public-private-academic partnerships, implementing data-driven decision-making processes and web-based software tools, advising senior management, effectively managing a diversified and decentralized workforce, and more. He has authored more than 250 technical publications in civil infrastructure and made more than 150 presentations on infrastructure research. He has been very active with professional societies throughout his career including serving on several ASCE committees and journal editorial boards. He also chaired the Transportation Research Board (TRB) Committee AFF40 on Testing and Evaluation of Transportation Structures. He is the founding president of the International Association for Bridge Maintenance and Safety (IABMAS) USA National Group.

Alampalli started out in the Department of Irrigation in A.P. State, India, as an assistant executive engineer. He was an adjunct at Rensselaer Polytechnic Institute and eventually made his way to NYS DOT, Prospect Solutions, and then Stantec, where he has been since 2021. His doctoral degree is from Rensselaer in Troy, New York.

Selected honors include the Aftab Mufti Lifetime Achievement Award (2021) from the International Society for Structural Health Monitoring of Intelligent Infrastructure, the Hall of Fame Award (2016) from the Make the Right Move Chess Foundation, the ASNT Bridge NDT Lifetime Service Award (2014), the ASCE Outstanding Projects and Leaders award (2021), and the ASCE Henry L. Michel Award for Industry Advancement of Research (2013).

Simpson Gumpertz & Heger (SGH) has welcomed **Keith Kesner** as a Project Director, bolstering the firm's repair and rehabilitation expertise and knowledge of concrete performance for new and existing structures. He will join SGH's Structural Engineering division in New York City, partnering closely with professionals across the East Coast while operating out of Philadelphia, Pennsylvania. Kesner brings more than 30 years of industry and academic experience, specializing in evaluating and repairing concrete, masonry, and steel structures; assessing concrete material performance and deterioration through NDT and corrosion analysis; and conducting facade inspections and repairs.

The Society for the Advancement of Materials and Process Engineering (SAMPE) North America search committee is pleased to announce **Rebekah Stacha** as its CEO, effective 1 June 2023. Stacha is the first woman CEO for SAMPE in its 79-year history.

Stacha is a seasoned association professional with over 20 years of experience in leadership, publishing solutions, operations management, and people development. As Director of Multimedia and Publishing at the Society of Petroleum Engineers, she was instrumental in the organization's digital transformation, which streamlined workflows that increased efficiency and customer satisfaction. A graduate of the Mays School of Business at Texas A&M University with a degree in management, she is a Certified Association Executive and is an active member of several professional organizations including the Council of Engineering and Scientific Society Executives, Society of Scholarly Publishing, and American Society of Association Executives.

APPOINTMENTS

ASNT's **Dalton Vidosh** has been promoted to Accounting Manager. Vidosh will be overseeing the daily accounting cycle for ASNT and all its subsidiaries.

ASNT member **Raj Venkatachalam** has been promoted to Senior Systems

Engineering Manager at Varex Imaging Corp.

ASNT Lifetime Member **Don Locke** has started a new position as NDT Nadcap Auditor at Performance Review Institute.

HUVRdata, a next-generation Inspection Data Management Software Platform, has announced that ASNT Lifetime Member **Dave Bajula** is joining the HUVR Advisor Network (HAN). Bajula is the latest of nine industry veterans with backgrounds in a range of disciplines and asset integrity management technologies to join HAN. He brings more than 40 years of insight and perspective formed, in part, from his time as general manager of advanced NDT services at Acuren, as well as from his time as President and Chairperson of ASNT's Board of Directors.

ASNT Lifetime Member **Marybeth Miceli** has accepted an appointment to the Transportation Research Board: National Academies of Sciences, Engineering, and Medicine AKT60 Committee on Bridge Preservation. This is a three-year appointment, and Miceli will work with the committee to make strides on preservation, inspection, and monitoring methods.

North German high-tech company Automation Technology, located in Bad Oldesloe near Lübeck, is starting a new chapter in its 25-year company history by expanding to North America. The management of the office in the Boston metropolitan area will be taken over by US-American **Gretchen Alper**, who has already many years of experience in the field of machine vision.

MILESTONES

ASNT member **Anish Poudel** has been awarded the People's Choice Award for Best Presentation at the 2023 International Wheelset Congress conference.

CGM CIGIEMME S.p.A.'s **Eugenio Feneri**, Head of CGM Electrical Department, and **Matteo Borini**, Head of CGM Mechanical Department, have obtained the CMSE® – Certified Machinery Safety Expert certification. ME

***Do you have news** you'd like to share with the NDT community? **People Watch** publishes notices of ASNT members' promotions, retirements, honors, and other milestones. Please send notices to the ASNT press release inbox at press@asnt.org.*

NEWCERTIFICATIONS

ACCP Level II CWI
James Berg
Tracy D. Blankenship
William Braun
Michael Curry
Greggory Damis
Bryan Doheny
Eddie Estrada
Veronica Garcia
Chad Geary
Dustin Haba
Jacob Martinez
Juan Mendez
Kyle Morgan
Randy Ramos
Kyle Stevenson
Robert Weatherholt
Kyle Whitfield
James Woods
Roy J. Ybarra, Jr.

ACCP Professional Level III
Leighton McMillan, Jr.

ASNT NDT Level III
Niousha Amani
Htet Lwin Aung
Joshua D. Bell
Stephanie Melissa Berry
Young Tak Chun
Paramaguru Dhayalan
Hitesh Grover
Allan E. James
Matthew A. Johnson
Harold Jones
Abdul Bari K P
Raghupathy Kanniyappan
Narasinga Rao Kolipaka
Surekha Krishnan
Suraj Manjal
Paul G. Mattison
Efrain Munoz, Jr.
Jamie M. Nehrkorn
Donald A Niles, Jr.
Sun Cheol Noh
Joseph Perrone
Tyler Pettit
Slamet Riyadi
Daniel Rodriguez
Jishnu S. Ajay
Derek J. Schneider
Syedriaz Shamsudeen
Bandaru Srinivasarao
Antony Symonds
Stephen Andrew Thompson
Ikuo Torisu
Prabhu Velusamy
Satish Vishwakarma
Mas Prasetyo Wibowo
Brian A. Wright

ISQ – Oil & Gas (UTT)
Landon Ansley
Steven Brooks
Andrew Dugo
Justin Edwards
Pablo Garcia
Brendan Higginbotham
Richard Meade
Ramon Mendoza
Cecil Reiss
Matheus Romano
Matthew Sawyer
Yong Ton
Nathan Tullos
Golden Ugbodu

SOCIETYNOTES

EARN CEUS WITH ON-DEMAND WEBINARS

Looking for a quick way to earn recertification points? ASNT Education is here for you! Recordings of selected past webinars may be accessed and viewed for credit. Webinars are divided into sections by topic. To view the lineup, go to pathlms.com/asnt/courses and scroll down to "Webinar Recordings for Credit." Price: ASNT member US$29, nonmember US$49. Credit value per webinar: 1.0 contact hour (0.1 CEU); 0.35 recertification point.

EXCLUSIVE HEALTH COVERAGE

ASNT's exclusive health coverage partner, LIG Solutions, wants you and your family to stay healthy for 2023. To learn more about all ASNT-endorsed business solutions and how to access this exclusive member benefit program, go to asnt.org > Membership > Benefits. To request more information, go to ligmembers.com/asnt.

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JOHN CHEN

ONE KBR Tech Fellow, KBR
ASNT President (2023–2024)
HOUSTON, TX

HOW DID YOU FIRST BECOME INVOLVED IN NDT?
I started my graduate research project in 1995. It had to do with ultrasonic testing. Since then, I have been more or less working in NDT, mostly within the materials engineering field.

CAN YOU TELL US ABOUT YOUR CERTIFICATION AND TRAINING?
I have six ASNT NDT Level III certificates, a CWI from AWS, and a Professional Engineer license from six states. Every job I've had has provided training opportunities for me, on average a full week (maybe more) of away-from-your-job-type training each year for the past 20 years. A lot of this training has been directly in NDT techniques; others are attending seminars to learn new things.

WHAT'S YOUR EDUCATIONAL BACKGROUND?
I received a BE in 1995, a PhD in 1999, and another PhD in 2005. They are all in materials engineering and welding engineering. I grew up in an atmosphere where my mother and father had always emphasized the necessity of college and graduate studies. So, I always thought a college degree is a must-have for all.

IS YOUR WORK FOCUSED ON A PARTICULAR FIELD?
My day-to-day work focuses on routine NDT methods and procedures that have already matured and need be codified into industry standards. I review a lot of NDT procedures. The part of KBR I'm involved in encompasses engineering, procurement, and construction work. The company bids on large projects and after winning the projects—usually whole industry plants—the plants get designed and built. When the equipment, pressure vessels, piping, and so on, are being built in the shop and erected in the field, I make sure that the NDT procedures used meet construction code requirements.

DESCRIBE YOUR WORKING ENVIRONMENT.
I work in an office most of time but there are occasions I need to visit shops or construction sites. Sometimes I work alone; other times I am a member of a larger team.

ARE YOU INVOLVED IN YOUR SECTION?
I've served in officer, director, committee chair, and committee member positions for the Greater Houston Section. I've been serving at the national level for ASNT for awhile. I have served in officer, director, committee member, and committee chair positions (including Technical Editor of *Materials Evaluation*), and I start my term as President this July. I have come to know many, many individuals in the industry, who I would have never come to know if I had not been volunteering for ASNT.

HOW HAS NDT CHANGED DURING YOUR CAREER? WHAT TRENDS DO YOU SEE?
Digitalization. This will continue and is an enabling technology for artificial intelligence.

WHAT'S BEEN YOUR GREATEST CHALLENGE ON THIS JOURNEY?
There are so many things to learn, at the same time new technologies are constantly coming out. It is overwhelming at times to keep pace with the new developments and frustrating at times to realize that I have never really understood anything. One of the challenges is to get used to that, yet not give up learning.

WOULD YOU SHARE WITH US A PERSONAL OR PROFESSIONAL BUCKET LIST ITEM?
Once I had a wish to get a Level III in all the methods that ASNT offers a Level III certificate. Now I know how hard it really is to be truly qualified and certified in all methods.

DO YOU HAVE A FAVORITE QUOTE THAT INSPIRES YOUR WORK OR PERSONAL LIFE?
Treat everyone the same way you want them to treat you.

ME

NAVY SHIPBUILDERS NDT LEVEL III SPECIFIC EXAM

This month's Q&A focuses on the Navy Shipbuilders NDT Level III Specific Exam, now administered by ASNT. This article is adapted from a recent episode of *Chat NDT with ASNT* featuring Gary Zimak, Director of Quality Supply at Newport News Shipbuilding, and Brian Frye, ISQ Program Manager at ASNT. For more details on these and more topics, listen to the full episode at asnt.org > Publications > Podcast.

Q: What is NAVSEA?

A: NAVSEA stands for the Naval Sea Systems Command, an organization that is an arm of the United States Navy. NAVSEA engineers, builds, buys, and maintains ships, submarines, and combat systems. It provides the requirements for shipbuilders to follow, which includes an NDT program.

Q: What is the Navy Shipbuilders NDT Level III Specific Exam?

A: This is a Newport News Shipbuilding and General Dynamics Electric Boat project, working together with NAVSEA and the US Navy. These organizations have been looking for ways to improve how the shipbuilder suppliers administer the examiner-specific examination to NDT Level IIIs. Currently, all examiner personnel are required to pass an examiner-specific examination in accordance with NAVSEA Technical Publication T9074-AS-GIB-010/271, also referred to as NAVSEA 271. This is a technical publication generated by the Navy that shipbuilders follow to manage their NDT programs.

After evaluating the benefits of using a third party, such as ASNT, the group implemented a detailed strategy working with ASNT to develop and administer the Specific Exams. These exams will be administered through ASNT using Pearson VUE.

Q: What are the benefits of the new Navy Shipbuilders NDT Level III Specific Exam to the industry?

A: Previously, NAVSEA 271 required that the Specific Exams be administered by the employer. Just like any other program or any other process, there's always some inherent variability in the quality of the exams when they're administered by every organization throughout the supply base. Working with ASNT ensures that the exams achieve the highest standards in accordance with the Navy as well as ASNT. This adds consistency and rigor to the examination process and provides a centralized database that can be searched to find certified Level IIIs. It will also eliminate the need for suppliers to administer their own Specific Exam.

Q: What are the benefits of the new Navy Shipbuilders NDT Level III Specific Exam to individuals working in this industry?

A: With this new exam, inspectors will no longer have to continually take multiple Specific Exams for each company they work for. If they have ASNT certification along with this new Specific Exam, one Specific Exam will cover all the work.

Q: Who can take the Navy Shipbuilders NDT Level III Specific Exam?

A: Anyone who performs work in accordance with Newport News Shipbuilding or General Dynamics Electric Boat where a contract invokes NAVSEA 271 can take this exam. That is, if you are a supplier of either Newport News Shipbuilding or Electric Boat and you are performing work in accordance with those requirements, you will be able to take that exam. However, if you're an individual who does not currently have a contract either through one of Newport News Shipbuilding's or General Dynamics Electric Boat's primes or sub tiers, we will not allow you to take the exam at this time.

The individuals who will be taking this exam have either been previously certified through the company they work for—so that company would have previously administered their Specific Exam—or they could be a brand-new Level III just starting for a company, and this might be the first time they're taking this exam.

Q: Will there be training material available to prepare for this NDT Level III Specific Exam?

A: Electric Boat and Newport News Shipbuilding are working together to develop training material that will be available to the NDT Level III Examiner candidates prior to taking the exam.

For more information, visit ASNT Certification Services LLC's website at asntcertification.org or email certification@asnt.org.