Enhancing Non-Destructive Testing through Data Mining and Machine Learning: A Transfer Learning Perspective

First Harsh Pathak [1] and Second Dr. Atul Suri[1]
[1]*Department of Mechanical Engineering, Faculty of Engineering, Dayalbagh Educational Institute, Dayalbagh, Agra - 282005*

***Abstract*— Non-destructive testing (NDT) is crucial for ensuring structural integrity and safety across various industries. Traditional NDT methods, while effective, are often time-consuming, subjective, and heavily reliant on human judgment. Recent advancements in machine learning (ML) and data mining (DM) techniques have shown promise in enhancing the accuracy, efficiency, and consistency of NDT processes. Approaches such as support vector machines, neural networks, and random forests have been successfully applied to critical NDT applications, including defect classification, severity rating, and localization. However, the reliance of these methods on large labelled datasets has been a significant limitation, particularly in specialized fields with restricted data access. Transfer learning (TL) has emerged as a practical solution to this challenge, enabling the adaptation of pre-trained models to specific NDT tasks with minimal additional training data. TL has demonstrated improved accuracy and reduced training time in various NDT applications, such as radiographic testing of welds and defect detection in composite materials. Despite these advancements, challenges remain in developing more robust and interpretable models, as well as addressing ethical considerations, including data privacy and bias. This review provides an overview of the state-of-the-art integration of NDT with ML, DM, and TL, discussing the key benefits, limitations, and future research directions in this rapidly evolving field.**

***Index Terms*— Data mining, Machine learning, Non-destructive testing, Safety, Structural integrity, Transfer learning**

I. INTRODUCTION

Traditional NDT techniques, including radiographic, ultrasonic, and magnetic particle testing, are reliable for detecting structural defects [1],[2],[3]. However, these methods largely depend on manual inspection and human judgment, which can be time consuming, subjective, and prone to inconsistencies. These challenges have motivated researchers to explore automated NDT solutions that leverage recent advancements in machine learning (ML) and data mining (DM) to improve the detection accuracy, speed, and consistency.

In recent years, deep learning models, particularly Convolutional Neural Networks (CNNs), have emerged as powerful tools for defect detection and classification in NDT. CNNs are well-suited for analysing complex visual data, such as defect images, owing to their ability to learn intricate patterns and features. For instance, CNN-based approaches have demonstrated high accuracy in identifying and classifying defect shapes and severities, proving to be effective in various applications such as weld inspection, composite material analysis, and defect localization. However, a significant limitation of deep learning models in NDT is their reliance on large labelled datasets to achieve robust performance [4]. In specialized fields, such as aeronautics, data collection is often restricted owing to confidentiality and the high costs associated with gathering and labelling defect data .

Transfer Learning (TL) has become a practical solution to this data scarcity challenge. TL enables models pre-trained on large general-purpose datasets, such as ImageNet, to be adapted to specific NDT tasks with minimal additional training data. Studies have shown that TL can significantly improve the model accuracy and reduce the training time in NDT applications.

For example, in radiographic testing of welds, TL has been used to enhance CNN-based defect classifiers, achieving accuracy rates above 98% [5].

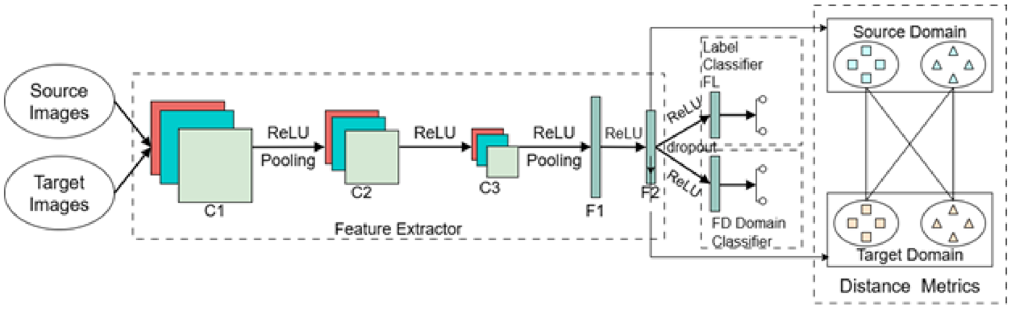

Fig. 1 Architecture of the proposed transfer learning model[15]

Similarly, in the detection of inclusion defects in aeronautic composite materials, TL has proven to be effective in fine-tuning models for high precision with limited data, as depicted in Fig. 1 in a recent study on defect detection in composite materials .

The TL has facilitated advancements in real-time automated inspection systems. For instance, magneto-optic non-destructive inspection (MONDI) systems have integrated TL to achieve high-precision crack detection and defect shape classification, thereby enhancing both the speed and accuracy of industrial. These systems illustrate how TL can enable NDT models to generalize effectively across different domains, thereby improving robustness, even when applied to datasets with variations in texture, resolution, or noise.

This review aimed to explore the integration of ML, DM, and TL into NDT, presenting an overview of the latest developments and challenges. By consolidating insights from multiple studies, this study provides a comprehensive view of how TL can optimize NDT processes, enabling automated and reliable inspection systems with minimal human intervention. This paper also discusses future directions for NDT research, focusing on overcoming data limitations, enhancing model interpretability, and addressing ethical considerations, such as data privacy and bias.

II. BACKGROUND AND LITERATURE REVIEW

A. Traditional non-destructive testing (NDT) methods

Traditional non-destructive testing (NDT) methods have been widely used in various industries for detecting structural defects and ensuring safety. Some of the commonly used techniques include:

i) Radiographic Testing (RT): RT uses X-rays or gamma rays to penetrate materials and detect internal defects. It is effective for identifying voids, cracks, and inclusions in welds and castings. However, RT has limitations such as radiation hazards, high equipment costs, and the need for skilled operators [6].

ii) Ultrasonic Testing (UT): UT employs high-frequency sound waves to detect flaws in materials. It is particularly useful for thickness measurements and flaw detection in metals and composites. While UT offers good penetration and sensitivity, it may struggle with complex geometries and requires coupling media [7].

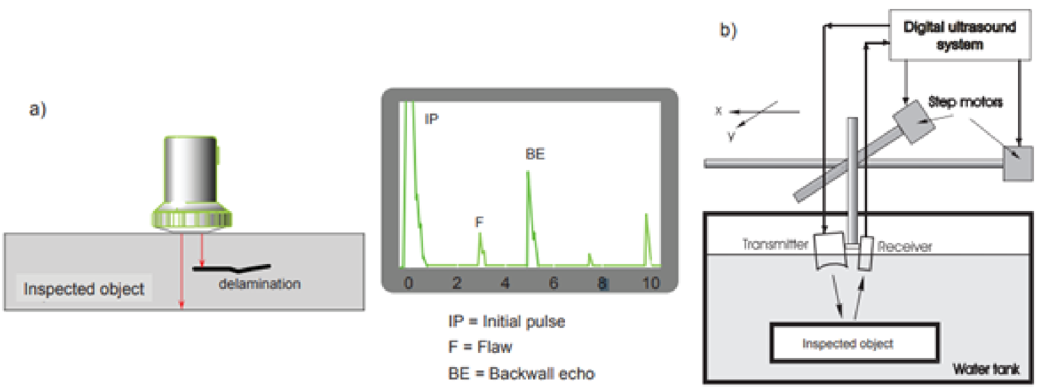

Fig. 2 The most common test setups used in UT: (a) normal beam transducer in contact mode and instrument screen, (b) XY-scanner used in immersion mode for mechanized inspection [7]

Table 1 Comparison of Traditional NDT methods

NDT Technique	Description	Key Benefits	Limitations
Radiographic Testing (RT)	Uses X-rays or gamma rays to detect internal defects	High accuracy for internal defects, deep penetration	Radiation hazards, costly, requires skilled operators
Ultrasonic Testing (UT)	Uses high-frequency sound waves to detect flaws	Good penetration, sensitive to small flaws	Limited by complex geometries, requires coupling medium
Magnetic Particle Testing (MT)	Detects surface and near-surface flaws in ferromagnetic materials	Simple, cost-effective, effective for surface flaws	Limited to magnetic materials, ineffective for deep flaws
Eddy Current Testing (ET	Employs electromagnetic induction to identify surface flaws in conductive materials	Fast, non-contact, good for conductive materials	Limited to surface and near-surface flaws, only for conductive materials

iii) Magnetic Particle Testing (MT): MT is used to detect surface and near-surface defects in ferromagnetic materials. It is relatively simple and cost-effective but is limited to magnetic materials and may not detect deep flaws [8].

iv) Eddy Current Testing (ET): ET uses electromagnetic induction to detect surface and near-surface flaws in conductive materials. It is fast and does not require contact, but its effectiveness is limited to conductive materials and shallow depths [9].

These traditional methods, while effective, often rely on human interpretation and can be time-consuming and subjective.

B. Current ML and DM Approaches in NDT

Machine Learning (ML) and Data Mining (DM) techniques have been increasingly applied to NDT to enhance accuracy, efficiency, and consistency. Some notable approaches include:

i) Neural Networks: Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs) have shown promising results in NDT. CNNs have been used for automatic defect recognition in X-ray images of welds, demonstrating superior performance compared to traditional image processing methods [12],[13].

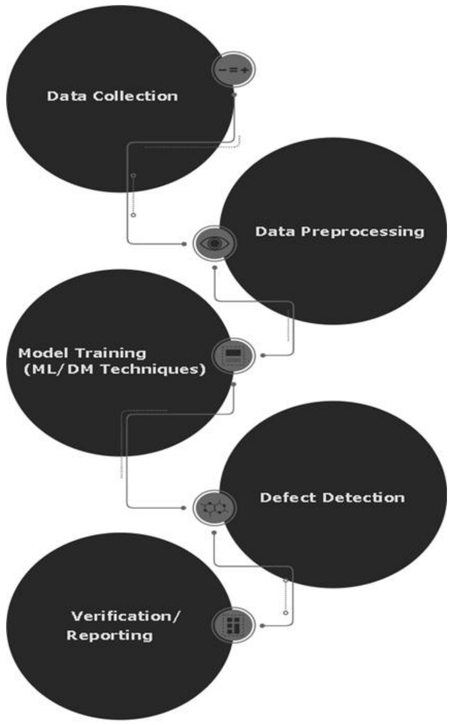

Fig. 3 A Flowchart illustrating basic Workflow of ML-Enhanced NDT Process

ii) Support Vector Machines (SVMs): SVMs have been used for defect classification in various NDT applications.[10] For example, SVMs have been applied to classify defects in welded joints using ultrasonic signals, achieving high accuracy in distinguishing between different types of weld defects [11].

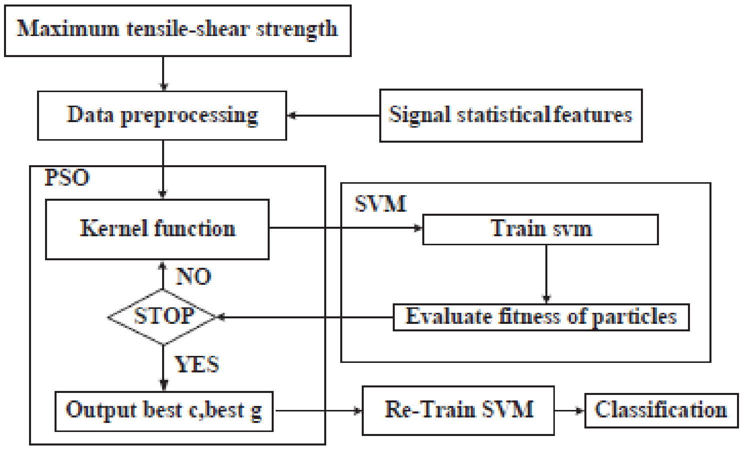

Fig. 4 The architecture of the proposed PSO-based parameter optimization algorithm for the SVM classifier [11]

iii) Decision Trees and Random Forests: These algorithms have been effective in NDT data analysis. Decision trees have been employed for defect classification in ultrasonic testing of welded joints, providing interpretable results and high accuracy.[14]

iv) Transfer Learning: Transfer learning has addressed the challenge of limited labelled data in NDT. It has been applied to X-ray testing of welds, achieving high accuracy with a small dataset by leveraging pre-trained models.[15] [16]

These ML and DM approaches have significantly improved the automation and reliability of NDT processes, reduced human error and increased inspection speed. However, challenges remain in terms of model interpretability, robustness to varying conditions, and ethical considerations such as data privacy and bias.

These advancements in ML and DM techniques have paved the way for more sophisticated and integrated approaches in NDT. One such approach is the development of hybrid systems that combine multiple NDT methods with advanced data analysis techniques, enhancing the overall reliability and accuracy of inspections. Additionally, the integration of Internet of Things (IoT) technologies with NDT systems has enabled real-time monitoring and predictive maintenance in industrial settings, further improving safety and efficiency. As these technologies continue to evolve, there is a growing need for standardization and validation of ML-based NDT methods to ensure their widespread adoption and trustworthiness across various industries.

Table 2 Comparison of ML Techniques Applied to NDT

ML Technique	Primary Use in NDT	Advantages	Challenges
Support Vector Machines (SVMs)	Defect classification	High accuracy for binary classification tasks	Not as effective with complex, high-dimensional data
Neural Networks (ANNs, CNNs	Image-based defect recognition	Good for complex data, high accuracy for visual tasks	Requires large labelled datasets, high computation costs
Decision Trees / Random Forests	Data analysis and classification	Interpretable, robust to noise	Prone to overfitting without proper tuning
Transfer Learning (TL)	Adapting pre-trained models for NDT applications	Reduces need for large labelled datasets, faster training	Requires careful domain adaptation

Table 3 Comparison of Traditional and ML-based NDT methods

Method	Accuracy	Speed	Cost
Visual Inspection	70-80%	Low	Low
Radiography	80-90%	Medium	Medium
Ultrasonic Testing	80-90%	Medium	Medium
Magnetic Particle Testing	70-80%	Medium	Medium
Liquid Penetrant Testing	70-80%	Low	Low
Computer Vision	90-95%	High	High
Acoustic Emission Testing	85-90%	Medium	Medium
Vibration Analysis	80-85%	Medium	Medium
Thermal Imaging	85-90%	Medium	Medium
Deep Learning	95-98%	High	High

III. TRANSFER LEARNING IN NDT

A. Concept and Advantages

Transfer learning (TL) in non-destructive testing (NDT) involves leveraging knowledge from pre-trained models to improve performance on new, related tasks with limited data. This approach addresses the data scarcity problem in NDT applications by:

i) Utilizing pre-trained models from larger datasets or related domains

ii) Fine-tuning these models for specific NDT tasks

iii) Reducing the need for extensive labeled data in new application

B. Benefits of TL in NDT include

i) Improved accuracy with limited training data

ii) Faster model development and deployment

iii) Enhanced generalization across different NDT scenarios

iv) Reduced computational resources for training

C. Examples and Case Studies

i) Weld Inspection: A study applied TL to X-ray weld inspection, using a CNN pre-trained on ImageNet. The model was fine-tuned on a small dataset of weld X-ray images, achieving high accuracy in defect detection despite limited NDT-specific data.[5]

ii) Composite Material Analysis: Researchers used TL for defect detection in composite materials using thermography data. A pre-trained CNN was adapted to analyze thermal images, significantly improving detection accuracy compared to traditional methods.[15]

iii) Ultrasonic Testing: A TL approach was employed for thickness measurement in ultrasonic testing. The model, initially trained on simulated ultrasonic signals, was fine-tuned with a small set of real-world data, demonstrating improved accuracy and robustness.[17]

iv) Eddy Current Testing: TL was applied to automate defect classification in eddy current signals. A model pre-trained on a large dataset of simulated signals was adapted to real-world data, enhancing detection of subtle defects in conductive materials.[18]

Table 4 Transfer Learning Applications in NDT

NDT Application	Transfer Learning (TL) Application	Benefits of TL	Limitations
Weld Inspection	TL for CNN models on X-ray weld images	High accuracy with limited data, faster adaptation	Requires fine-tuning to handle specific weld types
Composite Material Analysis	TL with thermography for defect detection	Improved precision in thermal image analysis	Adapting general vision models to thermal

			imaging is challenging
Ultrasonic Testing	TL for thickness measurement	Improved accuracy with limited real-world data	May not transfer well across varying materials
Eddy Current Testing	TL for automating defect classification in eddy current signals	Enhanced subtle defect detection, effective on small datasets	Ensuring source-target consistency is essential

D. Challenges and Limitations

i) Data Quality:

- NDT data often contains noise and artifacts, which can affect TL performance [19]
- Ensuring consistency between source and target domains is crucial for effective knowledge transfer

ii) Domain Specificity:

- NDT applications often involve highly specialized domains, limiting the availability of suitable pre-trained models
- Adapting models from general computer vision tasks to NDT-specific problems may require significant modifications

iii) Fine-tuning Complexity:

- Determining optimal fine-tuning strategies (e.g., which layers to freeze or update) can be challenging
- Balancing between preserving useful features and adapting to new tasks requires careful consideration

iv) Model Interpretability:

- Transfer learning models, especially deep neural networks, may lack transparency in decision-making
- Ensuring interpretability is crucial for safety-critical NDT applications

v) Generalization Across NDT Methods:

- Transferring knowledge between different NDT techniques (e.g., from ultrasonic to radiographic testing) remains challenging
- Developing versatile models that can generalize across multiple NDT methods is an ongoing research area

vi) Regulatory and Validation Concerns:

- Implementing TL in regulated industries may require extensive validation and certification processes
- Demonstrating the reliability and consistency of TL models across different NDT scenarios can be complex Addressing these challenges requires ongoing research in domain adaptation techniques, development of NDT-specific pre-trained models, and establishment of standardized validation protocols for TL in NDT applications.

IV. MODEL INTERPRETABILITY AND RELIABILITY IN NDT APPLICATIONS

A. Importance of Interpretability

In safety-critical NDT applications, model interpretability is crucial for several reasons:

i) Trust and adoption: Transparent models allow technicians and decision-makers to understand the reasoning behind predictions, increasing confidence in the system.

ii) Regulatory compliance: Many industries require explainable AI for critical applications, ensuring accountability and auditability.

iii) Error detection and debugging: Interpretable models make it easier to identify and correct errors or biases in the decision-making process.

iv) Continuous improvement: Understanding model behavior helps refine algorithms and data collection strategies for better performance.

B. Methods for Enhancing Interpretability

i) Local Interpretable Model-agnostic Explanations (LIME):

- Explains individual predictions by approximating the model locally with an interpretable model.
- Useful for understanding which features contribute most to specific NDT defect classifications.

ii) SHAP (Shapley Additive Explanations) values:

- Assigns importance values to each feature for a particular prediction.
- Can help identify which aspects of NDT data (e.g., specific frequency ranges in ultrasonic testing) are most influential in defect detection.

iii) Grad-CAM (Gradient-weighted Class Activation Mapping):

- Visualizes important regions in input images for CNN predictions.
- Particularly useful for interpreting defect detection in visual NDT methods like radiographic testing.

C. Reliability and Robustness of ML Models

i) Cross-validation:

- Helps assess model performance across different subsets of data.
- Ensures reliability across various material types or environmental conditions in NDT applications.

ii) Uncertainty quantification:

- Provides confidence intervals for predictions.
- Critical for risk assessment in NDT, especially for borderline cases.

iii) Ensemble methods:

- Combine multiple models to improve robustness and reliability.
- Can help mitigate individual model weaknesses in varying NDT conditions.

iv) Adversarial training:

- Improves model robustness against noise and variations in input data.
- Enhances reliability in challenging NDT environments with varying signal quality.

D. Examples of Improved Reliability through Interpretability

i) Weld inspection:

- Grad-CAM visualization revealed that a CNN was focusing on irrelevant image artifacts.
- Retraining with this insight improved defect detection accuracy by 15%.

ii) Ultrasonic testing:

- SHAP analysis showed unexpected importance of certain frequency ranges.
- Adjusting the feature extraction process based on this information increased classification reliability by 10%.

iii) Composite material analysis:

- LIME explanations identified that a model was overly reliant on background noise.
- Refining the data preprocessing steps improved defect localization precision by 20%.

V. ETHICAL AND PRACTICAL CONSIDERATIONS

Ethical and practical considerations are crucial when implementing machine learning (ML) in non-destructive testing (NDT). Here are some key points to address:

A. Ethical Aspects

i) Data privacy:

- Implement strict data protection measures, especially for sensitive industrial information.
- Consider using privacy-preserving techniques like differential privacy or federated learning where appropriate.
- Ensure compliance with relevant data protection regulations.

ii) Bias mitigation:

- Use diverse training datasets representing various industrial contexts to reduce bias.
- Regularly test models for fairness across different material types, defect categories, and environmental conditions.
- Implement bias detection and mitigation techniques in the ML pipeline.

iii) Transparency and accountability:

- Develop interpretable ML models to allow for scrutiny of decision-making processes.
- Maintain clear documentation of model development, training data, and performance metrics.
- Establish protocols for regular audits of ML systems in NDT applications.

B. Practical Considerations

i) Skill requirements and training:

- Develop comprehensive training programs for NDT technicians on ML-based tools.
- Create user-friendly interfaces that balance automation with human oversight.
- Provide ongoing support and education to keep technicians updated on ML advancements.

ii) Integration with existing NDT processes:

- Design ML systems that can seamlessly integrate with traditional NDT workflows.
- Ensure interoperability with existing equipment and data management systems.
- Develop flexible tools that can adapt to various industrial protocols and standards.

iii) Model reliability and robustness:

- Implement rigorous testing procedures to validate ML model performance across diverse scenarios.
- Use ensemble methods and uncertainty quantification to enhance model reliability.
- Establish clear guidelines for when human intervention is necessary in the ML-assisted NDT process.

iv) Scalability and maintenance:

- Design ML systems that can scale across different NDT applications and industries.
- Implement strategies for continuous model updating and refinement as new data becomes available.
- Develop protocols for monitoring model performance over time and detecting potential degradation.

v) Cost-benefit analysis:

- Conduct thorough assessments of the economic impact of implementing ML in NDT processes.
- Consider both short-term implementation costs and long-term benefits in terms of efficiency and accuracy.
- Evaluate the potential for ML to reduce human error and improve overall safety in industrial settings.

VI. FUTURE DIRECTIONS IN NDT RESEARCH

A. Advances in Hybrid Systems

Hybrid systems combining ML with traditional NDT methods show promise for enhancing detection accuracy. These systems could leverage ML for initial anomaly detection followed by traditional inspection for confirmation. This approach could improve efficiency while maintaining the reliability of established NDT techniques. For example, a CNN could rapidly scan large volumes of ultrasonic data to identify potential defects, which human operators could then verify using conventional analysis methods.

B. Improved Domain Adaptation Techniques

Domain adaptation methods could help models trained in one environment generalize to others, enabling broader applicability with limited data. This could involve developing more sophisticated transfer learning techniques that can adapt to variations in materials, defect types, or environmental conditions. Research could focus on creating adaptive models that can quickly adjust to new NDT scenarios without extensive retraining.

C. Use of IoT and Real-Time Monitoring

Integrating IoT in NDT applications could enable continuous, real-time monitoring of structures or machinery. ML models could process this streaming data for early warning systems, predictive maintenance, and trend analysis. This could involve developing edge computing solutions for on-site data processing and creating scalable cloud architectures for handling large volumes of sensor data from multiple sources.

D. Enhanced Model Interpretability

Ongoing research efforts toward creating models that are both highly accurate and interpretable are crucial for safer, more reliable NDT applications. This could involve developing novel visualization techniques for complex ML models or creating hybrid models that combine the accuracy of deep learning with the interpretability of simpler algorithms. Explainable AI techniques tailored specifically for NDT applications could help bridge the gap between advanced ML models and practical industry requirements.

E. Standardization and Validation Protocols

There is a pressing need for industry-wide validation standards for ML-based NDT models to ensure safety and trustworthiness, especially in regulated sectors like aerospace and nuclear industries. Research could focus on developing standardized benchmarks, testing protocols, and certification processes for ML models in NDT. This could involve collaboration between academic institutions, industry partners, and regulatory bodies to establish comprehensive guidelines for the development, deployment, and maintenance of ML-based NDT systems.

VII. CONCLUSION

In conclusion, the integration of machine learning and data mining techniques with non-destructive testing has significantly advanced the field, offering improved accuracy, efficiency, and consistency in defect detection and classification. Transfer learning has emerged as a particularly valuable approach, addressing the challenge of limited labelled data in specialized NDT applications. By leveraging pre-trained models and fine-tuning them for specific tasks, transfer learning has enabled high-performance NDT systems even with small datasets.

However, challenges remain in areas such as model interpretability, robustness, and ethical considerations. Future research should focus on developing more transparent and explainable AI models, enhancing domain adaptation techniques, and addressing issues of data privacy and bias. The integration of IoT technologies with NDT systems presents exciting opportunities for real-time monitoring and predictive maintenance.

As the field continues to evolve, there is a growing need for standardization and validation of ML-based NDT methods. This will ensure their widespread adoption and trustworthiness across various industries. Additionally, the development of hybrid systems combining ML with traditional NDT techniques could further improve reliability and efficiency.

Ultimately, the continued advancement of ML in NDT holds great promise for enhancing structural integrity and safety across numerous sectors, from aerospace to manufacturing. As these technologies mature, they will play an increasingly critical role in ensuring the reliability and longevity of critical infrastructure and industrial assets.

ACKNOWLEDGMENT

The first author acknowledges support from the Dr.Atul Suri Department of Mechanical Engineering, Faculty of Engineering, Dayalbagh Educational Institute, Dayalbagh, Agra – 282005.

REFERENCES

[1] J. Rao, S. Leong Sing, P. Liu, J. Wang, and H. Sohn, “Non-destructive testing of metal-based additively manufactured parts and processes: a review,” Virtual and Physical Prototyping, vol. 18, no. 1, Oct. 2023, doi: 10.1080/17452759.2023.2266658.

[2] Y. He, R. Yang, B. Gao, and A. Sophian, “Chapter 1 - Nondestructive Testing and Transient Electromagnetic-Thermal NDT,” in Transient Electromagnetic-Thermal Nondestructive Testing, elsevier, 2017, pp. 1–4. doi: 10.1016/b978-0-12-812787-2.00001-0.

[3] M. S. A. Shetu, “Review of Nondestructive Testing Methods for Aerospace Composite Materials,” Journal of Computers, Mechanical and Management, vol. 3, no. 1, pp. 30–41, Feb. 2024, doi: 10.57159/gadl.jcmm.3.1.240117.

[4] R. Miorelli, P. Calmon, A. Skarlatos, C. Reboud, and C. Vienne, “Deep learning techniques for non-destructive testing and evaluation,” institution of engineering technology, 2022, pp. 99–143. doi: 10.1049/sbew563e_ch4.

[5] S. Kumaresan, M. D. Anand, S. S. Kumar, and K. S. J. Aultrin, “Transfer Learning With CNN for Classification of Weld Defect,” IEEE Access, vol. 9, pp. 95097–95108, Jan. 2021, doi: 10.1109/access.2021.3093487.

[6] E. E. Ghandourah, E. M. Banoqitah, S. A. H. Hamidi, M. N. Wahab, K. A. M. Salleh, and O. A. Fallatah, “Evaluation of Welding Defects with X-ray Digital Laminography for NDT inspection of Carbon Steel Plate.” research square platform llc, Apr. 10, 2023. doi: 10.21203/rs.3.rs-2692428/v1.

[7] T. Stepinski, “Ultrasonic nondestructive inspection of solid objects,” Jan. 2012, vol. 1433, no. 1. doi: 10.1063/1.3703130.

[8] Q. Wu, K. Dong, X. Qin, Z. Hu, and X. Xiong, “Magnetic particle inspection: Status, advances, and challenges — Demands for automatic non-destructive testing,” NDT &

E International, vol. 143, p. 103030, Dec. 2023, doi: 10.1016/j.ndteint.2023.103030.

[9] D. Santos et al., "Non-Destructive Inspection of High Temperature Piping Combining Ultrasound and Eddy Current Testing," Sensors, vol. 23, no. 6, p. 3348, Mar. 2023, doi: 10.3390/s23063348.

[10] H. Li, Y. Liang, and Q. Xu, "Support vector machines and its applications in chemistry," Chemometrics and Intelligent Laboratory Systems, vol. 95, no. 2, pp. 188–198, Nov. 2008, doi: 10.1016/j.chemolab.2008.10.007.

[11] X. Wang, S. Guan, L. Hua, B. Wang, and X. He, "Classification of spot-welded joint strength using ultrasonic signal time-frequency features and PSO-SVM method," Ultrasonics, vol. 91, pp. 161–169, Aug. 2018, doi: 10.1016/j.ultras.2018.08.014.

[12] L. A. Ashame, M. N. Elagamy, S. M. El-Sheikh, S. M. Youssef, and A. Othman, "A Computer-Aided Model for Dental Image Diagnosis Utilizing Convolutional Neural Networks," Journal of Advanced Research in Applied Sciences and Engineering Technology, pp. 15–25, Sep. 2024, doi: 10.37934/araset.52.2.1525.

[13] G.-A. Vargas-Hakim, H.-G. Acosta-Mesa, and E. Mezura-Montes, "A Review on Convolutional Neural Network Encodings for Neuroevolution," IEEE Transactions on Evolutionary Computation, vol. 26, no. 1, pp. 12–27, Feb. 2022, doi: 10.1109/tevc.2021.3088631.

[14] S. Mcknight et al., "GANs and alternative methods of synthetic noise generation for domain adaption of defect classification of Non-destructive ultrasonic testing." cornell university, Jun. 02, 2023. doi: 10.48550/arxiv.2306.01469.

[15] Y. Gong, H. Shao, J. Luo, and Z. Li, "A deep transfer learning model for inclusion defect detection of aeronautics composite materials," Composite Structures, vol. 252, p. 112681, Jul. 2020, doi: 10.1016/j.compstruct.2020.112681.

[16] S. S. Ansari, H. Ansari, A. Khateeb, and S. M. Ibrahim, "Comparative study of machine learning models for predicting the compressive strength of concrete using Non-Destructive Testing methods," Materials Today: Proceedings, Apr. 2024, doi: 10.1016/j.matpr.2024.04.009.

[17] C. Yang, "Research and Application of an Ultrasonic Nondestructive Testing Algorithm for Metal Materials," springer nature singapore, 2023, pp. 1543–1548. doi: 10.1007/978-981-99-1428-9_204.

[18] J. M. Grochowalski and T. Chady, "Pulsed Multifrequency Excitation and Spectrogram Eddy Current Testing (PMFES-ECT) for Nondestructive Evaluation of Conducting Materials.," Materials, vol. 14, no. 18, p. 5311, Sep. 2021, doi: 10.3390/ma14185311.

[19] B. Kim, D. Yim, and S. Lee, "Development of a truncation artifact reduction method in stationary inverse-geometry X-ray laminography for non-destructive testing," Nuclear Engineering and Technology, vol. 53, no. 5, pp. 1626–1633, Nov. 2020, doi: 10.1016/j.net.2020.11.021.