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An Intelligent Wireless Ultrasound Platform for Nondestructive Testing (NDT) and Structural Monitoring (SM)

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Abstract: With recent advances in internet of things (IoT), software technology, and artificial intelligence (AI), these emerging technologies have become increasingly accessible and attractive for NDT and SM. Meanwhile, the integration of these new technologies into NDT and SM has become a major trend within nondestructive evaluation (NDE) 4.0, and numerous publications have demonstrated the potentials of AI enabled NDT/SM systems, IoT based NDT/SM platforms, and large language model (LLM)-assisted NDT/SM methodologies. However, most of the existing work remains largely confined to academic research, where the integration and deployment of these advanced technologies typically require substantial expertise and specialized technical knowledge. This constraint has hindered the rapid and widespread adoption of new technologies within the broader NDT community. To bridge this gap, this study presents a versatile wireless ultrasound platform for NDT and SM, which is affordable and user friendly. The capabilities of the proposed work are demonstrated through two representative benchmark applications: corrosion monitoring and defect inspection/monitoring. Furthermore, the deployment of AI models on the platform and model prediction results are illustrated, including the implementation of a deep autoencoder-based unsupervised learning model and a convolutional neural network (CNN)-based supervised classification model for autonomous defect detection. The wireless ultrasonic platform provides an integrated framework that serves as a one-step solution for intelligent inspection and monitoring, thereby offering new solutions to NDT/SM challenges.

Keywords: Ultrasound, Nondestructive Testing, Structural Monitoring, Internet of Things, Machine Learning

1. Introduction

Artificial intelligence (AI) has emerged as one of the most disruptive technologies across a wide range of engineering and industrial domains. Although the adoption of AI in industrial manufacturing remains relatively limited compared with other application areas, AI-enabled nondestructive testing (NDT) and structural monitoring (SM) have experienced rapid development in recent years. Deep learning-based approaches have been successfully applied for discontinuity identification and classification in visual testing, radiographic testing, thermography, magnetic particle testing, and ultrasonic testing [1–7]. Owing to the inherent architecture of convolutional neural networks (CNNs) and the image-oriented output of many NDT systems, most existing studies primarily utilize image-based data for model development and evaluation. However, in ultrasonic testing, A-scan signals remain fundamentally important because they preserve the original waveform information associated with material characteristics and defect responses. Accordingly, autonomous defect detection using ultrasonic A-scan data and deep learning techniques, such as deep autoencoder models and one-dimensional CNN (1D-CNN) architectures, has also been reported [5,8]. Hence, deep learning exhibits significant capabilities for autonomous defect detection.

The performance and reliability of machine learning models strongly depend on the availability of high-quality data for training and validation. However, due to the proprietary nature of many commercial NDT systems, direct transfer of inspection data to centralized data lakes or cloud repositories is often inconvenient and inefficient, particularly for large-scale data acquisition and storage. Furthermore, most existing academic studies primarily focus on machine learning model development, training, and algorithmic performance evaluation, while comparatively less attention has been given to practical machine learning deployment for industrial applications, especially in production-scale environments.

To address these limitations, this study develops a wireless ultrasonic platform intended to serve as a comprehensive one-step solution for the NDT/SM research communities. The proposed platform enables direct wireless transfer of ultrasonic inspection data to cloud-based database while simultaneously providing a framework for deploying user-trained machine learning models. In addition, the platform allows users to visualize and analyze machine learning prediction results through a web-based application, thereby facilitating intelligent, scalable, and deployable NDT/SM solutions.

2. Wireless Ultrasound Platform

The architecture of the proposed wireless ultrasonic testing (UT) platform is illustrated in Figure 1. The platform consists of integrated hardware and software components designed for automated data acquisition, cloud-based data management, and intelligent data analysis. After users define the inspection application and corresponding technical parameters, the UT system automatically acquires ultrasonic A-scan data and wirelessly transfers the data to a cloud-based database. Upon user request, the web-based application initiates a processing pipeline that includes signal preprocessing, feature extraction, and data analytics. The processed signals are then fed into a trained AI inference model for prediction or classification, and eventually the inspection and monitoring results are presented on the graphical user interface.

Figure 1. System schematic of the wireless ultrasonic platform.

The developed prototype of the wireless ultrasonic testing (UT) platform is presented in Figure 2. The system consists of an ultrasonic acquisition board integrated with low-power control electronics, enabling compact and energy-efficient operation. The platform can be powered either through a conventional electrical power supply or through renewable energy sources, such as solar or wind energy systems, thereby enhancing its adaptability for both laboratory and field-deployed applications under diverse operating conditions. Wireless communication is supported through Wi-

Fi and 4G/5G cellular networks, allowing remote data transmission and low-latency system accessibility.
The corresponding user interface of the web-based application is also illustrated in Figure 2. Users select a pre-defined inspection/ monitoring task according to the target application scenario. The backend server of the web application subsequently retrieves and processes the acquired ultrasonic data and presents the analysis results through the graphical user interface. The platform additionally supports AI-enabled workflows, including machine learning-based data analysis and prediction, to facilitate intelligent inspection and autonomous defect evaluation.

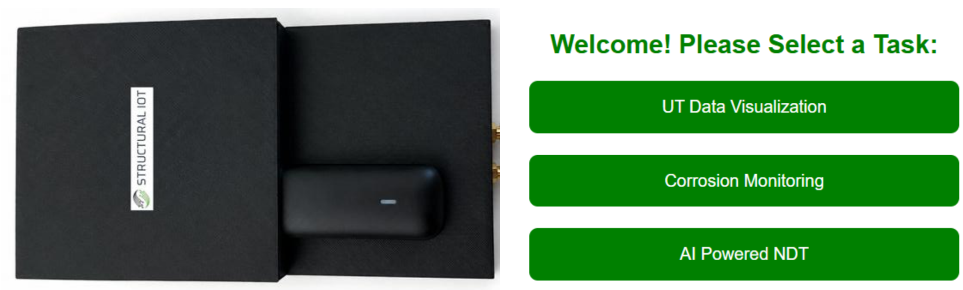

Figure 2. The wireless UT hardware (left) and corresponding web application (right).

3. Application examples of the wireless ultrasound platform

To demonstrate the functionality and effectiveness of the proposed wireless ultrasonic testing (UT) platform, two representative application examples are presented in this section: corrosion inspection/monitoring and autonomous defect detection. These case studies are employed to validate the system capabilities in terms of ultrasonic data acquisition, wireless data transmission, cloud-based processing, and AI-assisted inspection/monitoring performance.

3.1 Corrosion inspection/monitoring

As a benchmark specimen, a five-step steel wedge with thicknesses of 0.22", 0.24", 0.26", 0.28", and 0.30" was utilized in conjunction with a straight-beam ultrasonic transducer. An additional step wedge was employed as a supporting fixture for both the wedge specimen and the ultrasonic transducer, as illustrated in Figure 3. During the experiment, the ultrasonic transducer was translated gradually from the left side to the right side of the specimen while ultrasonic A-scan data were continuously acquired over a total duration of one hour at one minute acquisition intervals.

Figure 3. Experimental setup for corrosion monitoring benchmark.

On the web-based application, the acquired ultrasonic data is retrieved and processed using built-in signal processing algorithms. For corrosion monitoring, the time-of-flight (TOF) of the A-scan signals is first analyzed and determined. Based on the material properties and ultrasonic wave velocity, the corresponding thickness measurements are computed, and the results are subsequently visualized in Figure 4. The ultrasonic measurement results have great agreement with the actual thickness values for these five steps.

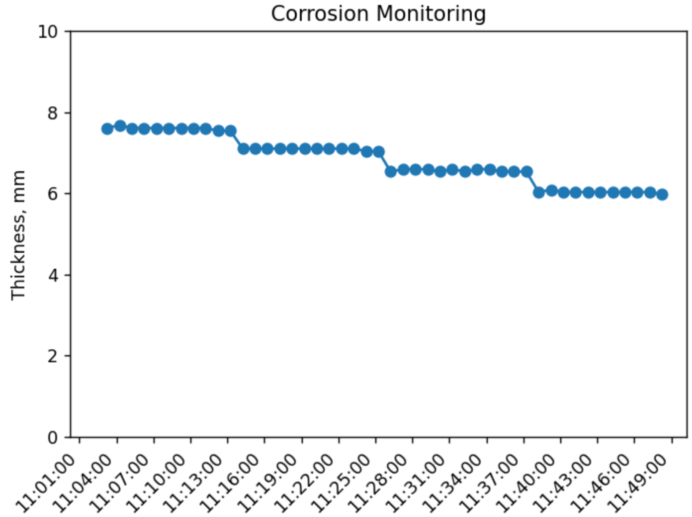

Figure 4. Corrosion monitoring results on graphic user interface with data point decimation.

3.2 AI empowered autonomous defect detection

A Navy calibration block containing side-drilled holes (SDHs) at varying depths was employed to acquire training datasets for the training of machine learning models, as shown in Figure 5. UT data was collected at different locations on the top surface of the block. The collected dataset is summarized in Table 1, and 87 datasets are prepared for model training and validation.

Table 1. Data set use for training and testing.

Training/Testing	Number of datasets	Length of each set
Dataset (no SDH)	46	4096
Dataset (with SDH)	41	4096

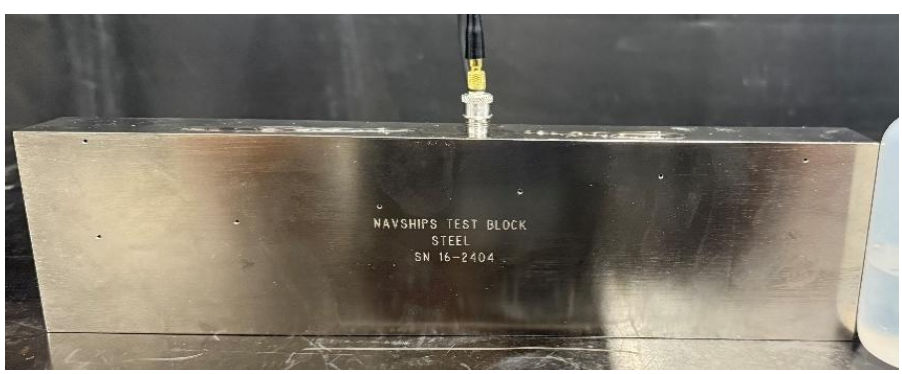

Figure 5. Experimental setup for defect detection benchmark.

Using available UT data, a deep autoencoder and a 1D convolutional neural network (CNN) model were trained for defect detection and evaluation. The training process was conducted in a local computing environment. Both models achieved classification accuracies exceeding 98% on the evaluation dataset. For the autoencoder-based model, a reconstruction error threshold of 0.032 was defined and used as the decision criterion for anomaly and defect detection. The loss curves for the deep autoencoder model and CNN model are shown in Figure 6, where both training and validation loss decay steadily across epochs. The trained models were subsequently deployed within the web application to enable automatic, AI-assisted ultrasonic data analysis and defect identification.

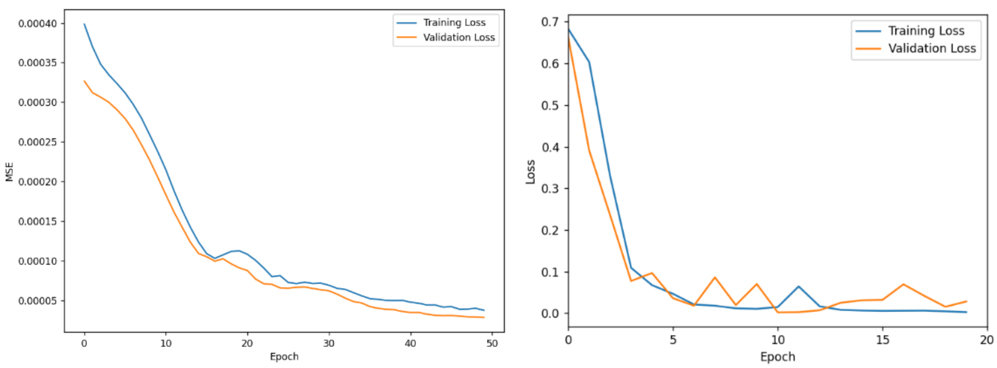

Figure 6. Loss curves for the deep autoencoder model (left) and the CNN-based model (right).

With collected ultrasonic testing (UT) datasets and the deployed 1D CNN machine learning models, the AI-based classification results that exhibit on the web application are represented in Figure 7. In this figure, UT signals corresponding to defect-free conditions and those containing side-drilled holes (SDHs) at different depths are classified accordingly. The predicted labels from the proposed machine learning model show excellent agreement with the ground truth labels, demonstrating the effectiveness of the developed AI-based classification tool.

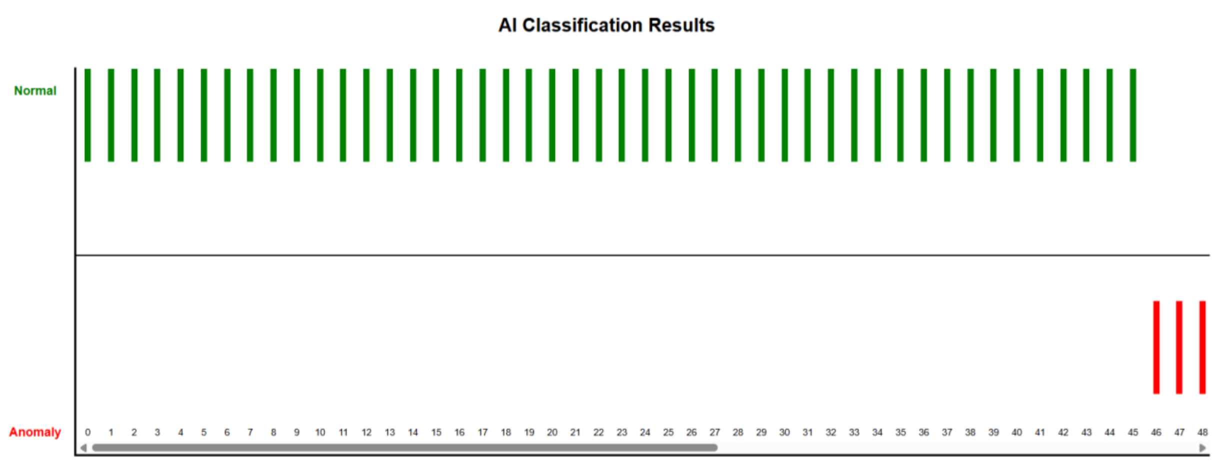

Figure 7. Results of autonomous defect detection using the trained CNN-based classification model deployed in the web application.

4 Conclusions

A wireless ultrasonic testing (UT) platform integrating both hardware and software components has been developed as a unified solution for end-to-end workflows, including ultrasonic data acquisition, time-series data streaming, signal processing, and AI-based defect detection. Additionally, machine learning models, including an unsupervised model and a supervised model, have been trained using prepared UT data and deployed in the web application. Two representative case studies with promising experimental results, namely corrosion monitoring and AI-enabled autonomous defect detection, are presented to demonstrate the capabilities and effectiveness of the proposed platform. This work establishes a solid foundation for future research and applications of AI-integrated nondestructive testing (NDT) and structural monitoring (SM) systems.

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