MATEC Web of Conferences **413**, 05004 (2025)
MAIQS 2025
https://doi.org/10.1051/matecconf/202541305004

LSTM based SCC detection using ultrasonic testing based data

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Abstract. Recent trends in the field of structural integrity highlight the integration of Artificial Intelligence (AI) with related domains such as Structural Health Monitoring (SHM), Non-Destructive Evaluation (NDE), and the assessment of Stress Corrosion Cracking (SCC). AI plays a pivotal role in developing intelligent solutions to complex challenges, particularly in the detection and characterization of SCC. While several techniques are available, this paper focuses on the Ultrasonic Testing (UT) based Non-Destructive Testing (NDT) method integrated with Artificial Intelligence (AI), making it a robust Industry 4.0 solution. Deep learning, a subset of Artificial Intelligence and Machine Learning, is already considered as a key technology in Industry 4.0 solutions. This paper discusses the detection of SCC in steel using UT based data and deep learning. The trained neural network model will be used for the detection of SCC in the steel.

1 Introduction

Structural Health Monitoring (SHM) is vital for maintaining and enhancing structural integrity by enabling real-time or periodic assessment of a structure's conditions [1]. It integrates various sensing technologies and data analysis methods to evaluate performance and detect potential damage or anomalies. SHM addresses a wide range of defects, broadly categorized into material, manufacturing, construction, service-induced, environmental, operational, design, maintenance, and welding-related issues [1]. For the purpose of this analysis, the focus is specifically on service-induced and environmental defects, which encompass corrosion, fatigue cracks, wear and abrasion, weathering, erosion, and stress corrosion cracking (SCC) [2, 3], among others.

The ongoing analysis and research place specific emphasis on SCC, a form of degradation that occurs due to the combined effect of static tensile stress, a corrosive environment, and a susceptible material [4]. This unique interplay of factors makes SCC a critical subject within structural integrity and materials science. SCC is particularly unsafe because it can develop and propagate rapidly, often without visible warning, ultimately leading to catastrophic structural failure. As such, the timely detection and mitigation of SCC are essential for ensuring the safety and reliability of engineering structures and their components.

There are various methods for detecting Stress Corrosion Cracking (SCC), which can be broadly classified into two categories: destructive testing and non-destructive testing (NDT) [5]. Ultrasonic testing (UT) is one of the important NDT methods which uses high-frequency sound waves to inspect materials and detect defects without causing damage. UT is a type of volumetric inspection, meaning it can reveal flaws within the material, not just on the surface.

1.1 UT method and the concept for defect detection

UT is one of the most used non-destructive evaluation (NDE) method for the detection of SCC. It uses the concept of sound wave reflection and interaction with material discontinuities. Sound energy is transmitted into the material as waves, which travel through it. When these waves encounter a discontinuity, such as a crack, a portion of the energy is reflected back from the defect [6]. This reflected wave is then converted into an electrical signal by the transducer and displayed on a screen. The graph shows the crack pulse, initial echo, back surface echo etc., as shown in Figure 1 with its details to be explained in later part of this paper.

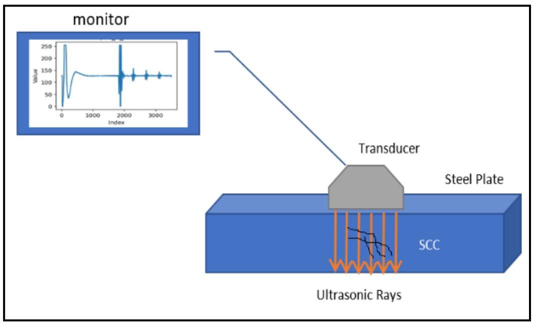

Figure 1: UT based detection method

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1.2 Role of deep learning in the detection of SCC

Deep learning is a significant branch of AI, which is helping in shifting the industry processes towards Industry 4.0. The deep learning capabilities enable the data-driven approaches, holistic insights and heightened efficiency. Here, the deep learning uses the same UT based data that already has the information about the SCC in the steel plates. It will enhance the efficiency as well as the sophistication of the detection process.

2 Related work

Kaseko et al. (1993) [7] worked on single images which may contain multiple defects but the defective regions in an image are generally demarcated by rectangular bounding boxes, which do not trace the defect boundaries accurately and therefore are not very useful for defect quantification. Abdel-Qader et al. (2006) [8] demonstrated the use of principal component analysis for crack identification on concrete bridge deck images. Shi et al. (2016) [9] developed an ensemble learning technique using random forest based on decision trees and it was later put to use by the research community for automatic image-based crack classification. Unlike the traditional ML-based models, convolutional neural network (CNN)-based DL methods can automatically learn the damage-sensitive features in the input data and are, in general, more accurate. One of the first few studies in this direction can be attributed to Zhang et al. (2016) [10], who proposed a novel CNN architecture called ConvNet for identifying crack patches in road inspection images. They demonstrated that CNN-based models can outperform support vector machine (SVM) and Boosting-based classifiers [11]. This approach was later extended to crack identification on concrete surfaces by Cha et al. (2017) [12]. Liu et al. (2019) [13] resorted to a SVM to identify cracks in tunnel inspection images. An initial crack map was first obtained by using intensity and gradient-based thresholding strategy. Chen et al. (2017) [14] proposed a Naive Bayes-based multi-view data fusion scheme which was incorporated into a CNN-based crack classification framework enabling accurate and robust inspection of nuclear power plant components. The research by Gopalakrishnan et al. invoked the idea of transfer learning to address this issue of limited training data [15]. It has been observed that the features extracted by the early convolutional layers are largely class-agnostic. So, the authors used a CNN pre-trained on the large ImageNet dataset [16] to initialize the parameters of a CNN for identifying crack patches on hot-mix asphalt and port land cement concrete pavement surface images leading to accurate predictions.

One of the prominent examples by Ren et al. (2015) of modelling approach is Faster RCNN [17]), where an input image is first processed by a series of convolutional layers. The feature map generated by the last convolutional layer is sent to a region proposal network to produce a number of interest regions. The interest regions are finally classified, and the corresponding bounding boxes are refined using a CNN module [18], explained by Cha et al. (2018); demonstrated the efficiency of this approach through the detection of a variety of defects such as concrete crack, steel corrosion, bolt corrosion, and steel delamination in building and bridge structures.

The analysis of related work shows that there is no noteworthy work done on UT based data using AI algorithms and their prime focus is images but the proposed research has scope to work on raw data as well advance deep learning algorithms e.g. RNN (Recurrent Neural Network).

3 Equipment and experimental setup

This section elaborates on the equipment utilized and the experimental setup employed for data acquisition.

3.1 Inducing SCCs in the lab environment

To collect the UT data of SCCs, we had to induce the SCCs in steel plates in the lab environment. The lab environment is to mimic the real-world conditions based on temperature, chemical reaction and pressure that leads to SCC, as shown in Figure 2.

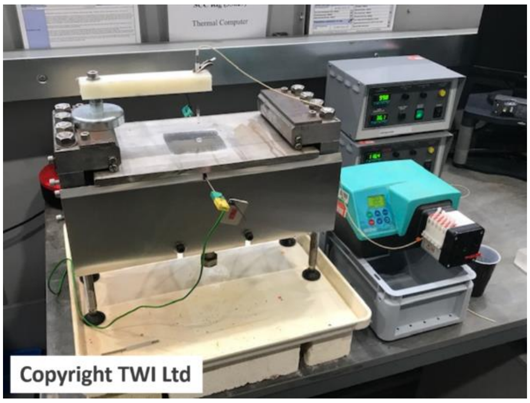

Figure 2: SCC test rig

3.2 LTPA

The instrument used to collect the data is a MicroPulse LTPA, which is an advanced ultrasonic testing (UT) equipment designed for the inspection of materials. It is used to collect data to detect internal defects such as cracks, porosity, or corrosion. It works with conventional single element transducers (as used in this paper) and with phased array transducers.

3.3 UT Transducer

An UT transducer was an immersion type that is a specialized UT probe used in NDT applications. This type of probe is designed to transmit and receive ultrasonic waves without requiring direct physical contact with the test surface. It enables precise, non-invasive inspection.

3.4 Servostep controller

A servostep motor controller is an integrated system with hardware and software that can control the movements of axes of an immersion tank. The water tank has axes that can move the UT probe left, right, upward and downward. The vertical axis holds the transducer in the water tank, as shown in Figure 3.

The water works as couplant which allows ultrasonic rays to cross the medium.

3.5 Experimental setup

The transducer was fixed onto the vertical axis in water tank and connected to the LTPA. On the other side, the servostep controller is connected to the water tank to control the movement of the transducer.

Both LTPA and servostep controller are connected to a computer system which is used to control the LTPA and servostep controller (Figure 3). The LTPA sends data to computer system in the form of text file.

Figure 3: Experimental setup

4 Data acquisition & graphical analysis

The transducer captures the UT data from the plates for every millimetre from the marked area on the steel plate. The experimental arrangement will capture a text file with numerical data for each millimetre. There are 7150 text files for each plate. Each file has 3500 entries, which depends on the configuration of LTPA. Figure 4 presents an example scan contained in the text file.

By analysing multiple text files, it can be observed that on the X-axis, initial spike in the graph from 0 to 2000 is common in all the text files, therefore this part of the data can be eliminated. The second spike is for the front surface and third spike is for the back surface. Since the SCCs are on the back surface, only the part from 2000 to 2500 is relevant to use.

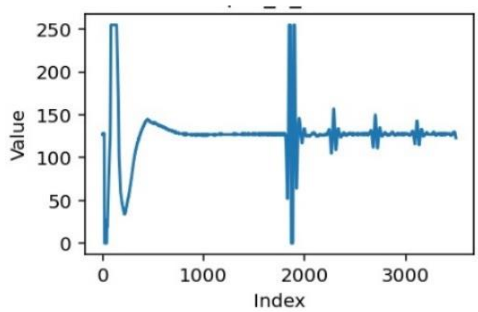

Figure 4: Graphical representation of data from one position

5 Proposed idea

The proposed approach involves acquiring UT data and leveraging AI techniques particularly deep learning for effective classification. Specifically, the focus is on using deep learning architectures that have the capacity to automatically extract meaningful features from raw UT signals and perform accurate classification without the need for handcrafted feature engineering. The current objective centres on the detection of cracks, with an emphasis on identifying SCC in steel plates. The goal is to determine whether a given steel plate shows signs of SCC using the collected UT data.

To achieve this, an RNN with Long Short-Term Memory (LSTM) units will be implemented. This architecture is well-suited for analysing sequential data, such as UT signal patterns, by capturing both short- and long-term dependencies in the time series. Once trained on labelled datasets, the RNN-LSTM model will be employed to classify new steel plate samples, indicating the presence or absence of SCC.

6 RNN-LSTM

We initially began our experiments using an RNN to model the sequential UT data. However, we encountered the vanishing gradient problem — a common limitation in traditional RNNs — which severely hindered the model's ability to learn long-range dependencies. As a result, the network failed to converge effectively during training, leading to suboptimal performance.

To overcome this challenge, we transitioned to an LSTM architecture [19]. LSTM networks are specifically designed to address the vanishing gradient issue by incorporating memory cells and gating mechanisms, which help preserve and regulate information across longer sequences. This change significantly improved the learning stability and prediction accuracy. The model was better to capture the underlying temporal patterns in the UT data, which is crucial for tasks like crack detection and structural integrity assessment.

7 Results

The results are as follows when the LSTM model was applied on UT based data for classification. The LSTM model demonstrated excellent performance throughout training, validation, and testing stages. Over training epochs, both the training and validation accuracy (Figure 5) exhibited a steady and consistent improvement, culminating in final values of 0.9904 and 0.9942, respectively.

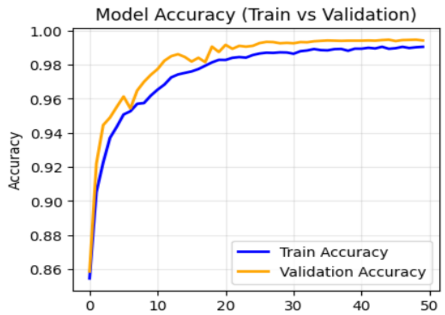

Figure 5: Model accuracy

The minimal gap of 0.0037 between training and validation accuracy indicates strong generalization with negligible overfitting.

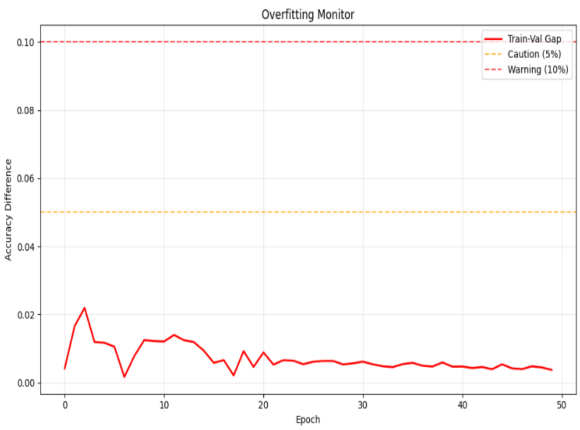

Figure 6: Overfitting monitor

This observation is further supported by the overfitting monitor as shown in Figure 6, which shows that the accuracy difference remained consistently below the 5% caution threshold throughout the training process. The normalized loss trend closely mirrors the accuracy curve, indicating that as the model's confidence increased, the error reduced significantly.

The learning rate schedule followed a step decay approach, progressively decreasing from an initial rate of 10^{-3} to a final rate of 3.13×10^{-5}, as shown in Figure 7.

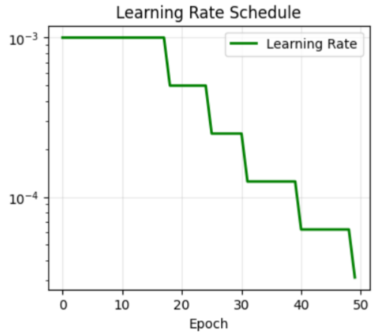

Figure 7: Learning rate schedule

This strategy allowed the model to converge smoothly, especially in the later epochs. Using an independent test set, the model achieved a test accuracy of 0.9946, reaffirming its ability to generalize to unseen data. Notably, the model retained this performance after being reloaded from saved weights, demonstrating its stability and reproducibility.

=== DETAILED CLASSIFICATION REPORT ===

	precision	recall	f1-score	support
No Crack	0.9937	0.9956	0.9946	4290
Crack	0.9956	0.9937	0.9946	4290
accuracy			0.9946	8580
macro avg	0.9946	0.9946	0.9946	8580
weighted avg	0.9946	0.9946	0.9946	8580

Figure 8: Classification report

A detailed classification report further validated the model's effectiveness. For the binary classification task distinguishing between "Crack" and "No Crack," the precision, recall, and F1-score for both classes were all 0.9946, indicating balanced and high-quality predictions (Figure 8). These metrics are visually summarized in a bar chart, where all values exceed the 0.9 threshold, falling in the "excellent" performance range. Overall, the results confirm that the LSTM model is highly reliable and effective for crack detection, exhibiting both high accuracy and robust generalization with minimal overfitting.

8 Conclusion and future work

In this paper, an LSTM-based model was developed and tuned for the crack detection in steel plates, reaching good performance across all training and evaluation metrics. The model demonstrated a high degree of accuracy, with a final test accuracy of 0.9946 and consistency between training, validation, and testing phases. The training process showed stable convergence with minimal overfitting, helped by a well-designed learning rate schedule. The precision, recall, and F1-scores for both classes were nearly identical, reflecting the model's robustness and ability to generalize effectively. These results confirm the suitability of LSTM architectures for SCCs detection, especially when combined with appropriate training strategies and monitoring.

While the current model performs well, there are several directions for future work. First, incorporating transformer-based modules could potentially enhance the model's ability to focus on subtle crack features. Furthermore, unsupervised learning could reduce the labelling burden and make the model more efficient. These enhancements will further strengthen the practicality and scalability of deep learning approaches in automated structural health monitoring applications.

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