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Evaluation of Bolt Corrosion Degree Based on Non-Destructive Testing and Neural Network

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Abstract: Anchor bolt corrosion is a complex and dynamic system, and the prediction and identification of its corrosion degree are of significant importance for engineering safety. Currently, non-destructive testing using ultrasonic guided waves can be employed for its detection. Building upon the analysis of anchor bolt corrosion mechanisms, this paper proposes a method for evaluating the corrosion degree of anchor bolts based on multi-scale convolutional neural networks (MS-CNNs) that address the multi-mode propagation and dispersion effects of ultrasonic guided wave signals in non-destructive testing. Electrochemical experiments were conducted to simulate anchor bolt corrosion, and ultrasonic guided wave non-destructive testing was performed every 12 h to obtain waveform data. An MS-CNN was then utilized to accurately diagnose the corrosion degree of the anchor bolts. The test results demonstrate that this method effectively detects and diagnoses the extent of anchor bolt corrosion, facilitating timely troubleshooting and preventing potential safety accidents.

Keywords: multi-scale convolutional neural networks; ultrasonic guided waves; non-destructive testing; anchor bolt corrosion



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1. Introduction

An anchor bolt is an important component widely used in geotechnical engineering and rock support, which can withstand tensile and shear forces by bonding with concrete, rock, and other structures. However, in practical applications, anchor bolts may suffer from corrosion, leading to damage to their mechanical performance and service life. Through the use of non-destructive testing, the early detection and evaluation of anchor corrosion can be achieved, allowing for appropriate maintenance and repair measures to be taken in order to ensure the safety and reliability of the structure. Anchor bolt corrosion is a chemical reaction process that occurs on the metal surface due to chemical changes in different media. In particular, the corrosion of chloride ions severely affects the durability of the structure [1]. This chemical reaction can destroy the protective layer on the metal surface, exposing it to harsh environments such as oxygen, moisture, acidic or alkaline substances and triggering further corrosion reactions [2]. To investigate the corrosion of anchor bolts, it is necessary to acquire corrosion test samples. Wang et al. [3] accelerated the corrosion of anchor bolts using a self-developed stress corrosion apparatus for grouted rock anchor bolts, conducting corrosion tests under different working stresses, corrosion environments, and corrosion times. Wei et al. [4] used low-coherence fiber optic interferometry to monitor the corrosion of rock anchor bolts and obtained corrosion specimens through electrochemical-accelerated corrosion experiments. Ding et al. [5] studied the deteriorating effect of the shear performance of prestressed anchor bolts in jointed rock masses under different corrosion levels using electrochemical-accelerated corrosion tests and direct shear

tests. Typically, corrosion studies on anchor bolts are completed under accelerated corrosion in indoor environments, yielding results in a relatively short period of time.

Anchor bolt corrosion typically occurs within the internal structure of the anchor bolt and is not directly observable. In considering the requirement for structural integrity, a significant amount of research has been conducted on non-destructive testing (NDT) methods, with ultrasonic guided wave technology gaining increasing attention and application due to its advantages of a long monitoring distance and wide coverage range [6]. Guided wave technology is sensitive to corrosion and is suitable for monitoring interface changes caused by corrosion at certain frequencies [7]. The signal propagates in the form of an elastic wave in the bolt, and experiences scattering, reflection, refraction, and diffraction in the bolt, concrete, and rock mass, and finally forms guided wave. In tracking and comparing the changes in signals at different time periods, the corrosion degree of the anchor bolt can be identified. Majhi et al. [8] applied an improved time–frequency method based on the S-transform to analyze the received signals. Sriramadasu et al. [9] used ultrasonic guided wave scattering technology to detect and evaluate local damages in the form of corrosion pits on bare bars at an early stage. The results showed that the proposed damage index method can be successfully used to monitor the axial extent and strength of steel rebar pitting corrosion. Talakokula V et al. [10] proposed that the corrosion process, including three stages of initiation, progression, and reduction in diameter, can be successfully monitored using a longitudinal guided wave mode.

Although the aforementioned studies have promoted the development of the non-destructive testing and monitoring of corrosion using ultrasonic guided wave technology, the complexity of the internal structure of anchor bolt anchoring systems in practical situations and the high complexity of propagated guided wave signals pose challenges in processing reflected signals. Zhang et al. [11] combined the empirical mode decomposition method with the multi-scale entropy method to analyze guided wave signals and quantify the number of internal defects in anchor bolt anchoring systems. Li et al. [12] studied resin bolts with different anchorage defects (disbonding length and notch size). The influence of the L-mode defect detection ability and defect size parameters on the amplitude of guided wave signal was analyzed. The experimental results showed that the L-mode can be used to detect bolt defects, and the amplitude of the defect back wave represents the defect size. Zhang et al. [13] trained six machine learning models using ultrasound detection data and predicted the influence of the deterioration and corrosion levels of rubber concrete on ultrasound features. However, research on the corrosion identification of bolt anchoring systems using ultrasonic guided waves is limited, and current NDT data analysis primarily relies on digital signal processing techniques such as fast Fourier transforms (FFTs), wavelet transforms, correlation analyses, and adaptive filtering. Neural networks, on the other hand, possess strong learning and generalization capabilities and can automatically learn the internal structural features of anchor bolts, obtaining more accurate prediction results through sample training [14]. In the process of actual bolt detection, the neural network exhibits the capability to handle extensive amounts of data simultaneously, enabling the real-time evaluation of bolt quality, minimizing the requirement for manual intervention and adjustments, and enhancing problem-solving efficiency.

The main contributions of this study are reflected in two aspects:

- (1) The analysis of the corrosion mechanism of anchor bolts and the propagation mechanism of ultrasonic guided waves in anchor bolts through practical experiments;
- (2) The design of a multi-scale convolutional neural network (MS-CNN) model for classifying and identifying ultrasonic guided wave signals, capturing local features of different degrees and improving the expressive ability of the model for features in ultrasonic guided wave data.

The structure of the rest of this paper is as follows: Section 2 introduces the theoretical background, Section 3 presents the propagation mechanism of guided waves in anchor bolts and non-destructive testing experiments, and Section 4 discusses the experimental results.

2. Corrosion Mechanism and Experimental Study of Anchor Bolts

2.1. Corrosion Theoretical Model of Anchor Bolts

The corrosion process model is an important reference for identifying the corrosion of anchor bolts in rock masses. The corrosion forms of anchor bolts include uniform corrosion, pitting corrosion, and stress corrosion, among others. As shown in Figure 1, when anchor bolts are used for a long time in environments with high chloride ion content, they are prone to corrosion by chloride ions. The evolutionary process of anchor bolts being corroded by chloride ions is as follows.

Initial stage: Chloride ions infiltrate the interior of the anchor bolt anchoring system, eroding the surface of the anchor bolt and gradually breaking down the protective layer of the anchor bolt.

Accelerated stage: The deterioration of the protective layer on the surface of the anchor bolt intensifies, resulting in an increased exposed area of the anchor bolt. Chloride ions continuously penetrate and migrate, further corroding the anchor bolt.

Stable stage: The sectional area of the anchor bolt reaches a certain extent, causing a reduction in the cross-sectional area of the anchor bolt and resulting in a loss of the load-bearing capacity.

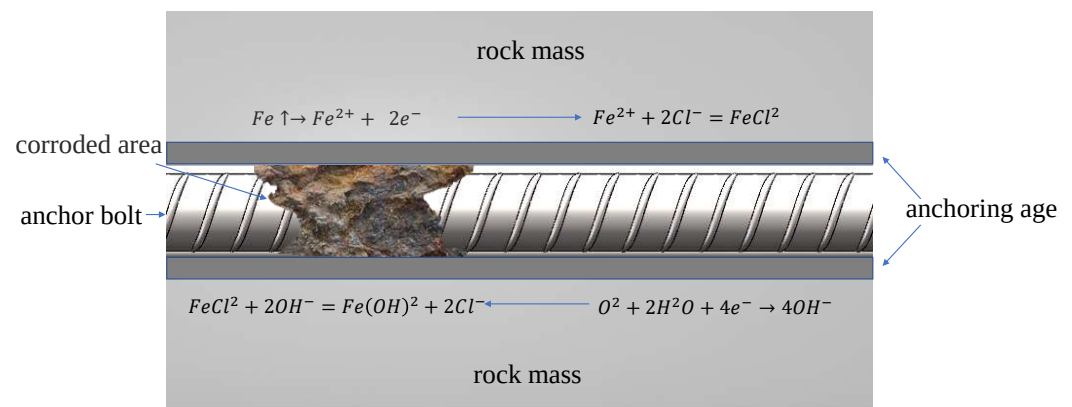


Figure 1. Schematic of anchor bolt corrosion.

2.1.1. Electrochemical Corrosion Principle

Due to the slow corrosion rate in natural environments, electrochemical corrosion methods are commonly used to accelerate the corrosion process [15]. The following reactions describe the principles of electrochemical corrosion.

Anodic reaction:



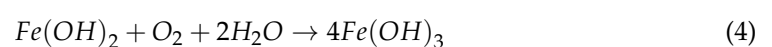
Cathodic reaction:



The equation for the secondary reaction occurring in the anodic region is

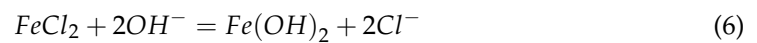


Unstable $Fe(OH)_2$ will continue to oxidize in a humid environment and form $Fe(OH)_3$ in the following reaction:



The presence of chlorides increases the hygroscopicity of anchoring agents, decreases their resistivity, and accelerates the corrosion of anchor bolts. Free chloride ions combine with the passive film on the surface of steel reinforcement to form water-soluble complexes, which react with alkaline substances to generate iron hydroxides and release chloride ions.

Chloride ions act as catalysts in this process. The chemical reaction can be represented by the following equations:



2.1.2. Corrosion Current Calculation

The constant-current-accelerated corrosion method was employed in this study to accelerate the corrosion rate of the anchor bolt by applying a constant electric current to its corroded surface. Specifically, this current can be calculated using the following equation:

$$I = is = i\pi dl \quad (7)$$

where i represents the current density on the corroded surface of the anchor bolt, s represents the area of that surface, d represents the diameter of the anchor bolt, and l represents the length of the anchor bolt. In this experiment, the constant current method was employed with a current magnitude of 2.5 A and a corrosion contact area of 5942 mm². The calculation yields an average corrosion current density of 0.04 A/cm².

2.2. Electrochemical-Accelerated Corrosion Experiment

Electrochemical-accelerated corrosion is a method used to simulate the corrosion process and accelerate the corrosion rate of the anchor bolt. In this study, an anchor bolt with a length of 1.5 m was selected, with a free segment length of 50 cm and an anchored segment length of 100 cm. An anchoring agent with a length of 8 cm was applied in the middle of the anchored segment prior to the experiment. After curing the sample, the bolt specimen was submerged in a 3.5% NaCl solution for a duration of 12 h to ensure the full penetration of the NaCl solution into the anchoring agent. Subsequently, the anchor agent was also immersed in a 3.5% NaCl solution to facilitate accelerated corrosion testing. The choice of 3.5% NaCl concentration is widely adopted by researchers due to the solubility properties of NaCl, aligning this range with safe laboratory conditions and reflecting real-world scenarios. The corrosion period was set at 12 h, maintaining room temperature throughout. Following corrosion, the anchor was retrieved and subjected to surface cleaning before undergoing ultrasonic guided wave testing. A total testing duration of 72 h was conducted to replicate potential corrosion conditions that the bolt might encounter in an authentic environment. The specimen is shown in Figure 2. The connection for the electrochemical-accelerated corrosion test is illustrated in Figure 3.



Figure 2. The corroded anchor bolt specimen.

In this study, a DC stabilized power supply with an adjustable range of 0–32 V and 0–3 A was used to achieve the accelerated corrosion process. Each specimen was subjected to a constant current of 2.5 A for corrosion. Specifically, the anchor bolt was used as the anode, and a copper rod was used as the cathode. A DC regulated power supply was employed to apply the corrosion current, with a current density of 40 mA/cm² on the surface of the anchor bolt. During the testing process, water was periodically replenished, while maintaining a constant NaCl solution concentration.

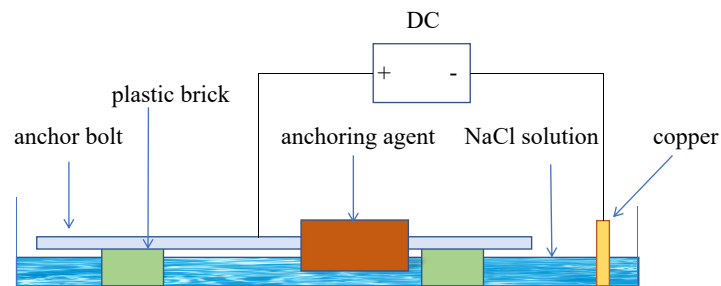


Figure 3. Electrochemical-accelerated corrosion test.

2.3. Electrochemical-Accelerated Corrosion Results

The same anchor bolt was used as the specimen in the experiment. In order to achieve the desired corrosion level promptly, the corrosion test was conducted for a total of six different durations, with a 72-h period and intervals of 12 h between each corrosion session. A visual assessment of the anchor bolts with varying corrosion rates is shown in Figure 4. The corrosion rate for each steel bar sample was calculated as follows: the initial mass of the non-corroded anchor bolt is denoted as m_0 , and the mass of the anchor bolt after corrosion is denoted as m_1 . The corrosion rate of the anchor bolt is

$$C_r = \frac{m_0 - m_1}{m_0} \times 100\% \quad (8)$$

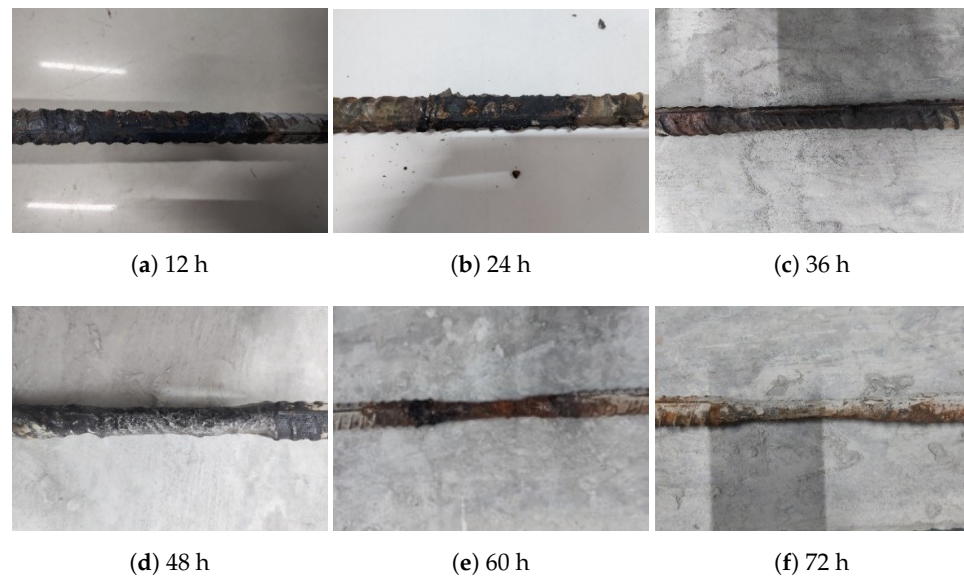


Figure 4. Samples with different degrees of corrosion.

During the process of electrochemical corrosion, the mass loss of particles can be estimated according to Faraday's Law:

$$\Delta m = \frac{Mit}{zF} \quad (9)$$

In the equation, Δm represents the mass loss of the anchor bolt. M stands for the molar mass, z refers to the absolute value of the total number of positive or negative valence states in a compound, F represents the Faraday constant with a value of $F = 9.65 \times 10^4 \text{ C/mol}$, I represents the current intensity, and t represents the time the current flows in seconds (s).

The corrosion products are mainly composed of Fe^{2+} and Fe^{3+} [16]. In this study, the theoretical mass losses of the anchor bolt after 12 h of accelerated corrosion were 31.25 g (for Fe^{3+}) and 20.84 g (for Fe^{2+}). In natural corrosion, the current density of the anchor bolt varies from $0.1 \mu\text{A}/\text{cm}^2$ to $10 \mu\text{A}/\text{cm}^2$. The value of $0.04 \text{ A}/\text{cm}^2$ used in this study was

400 times the maximum value of the range. The 12 h corrosion period in the experiment corresponds to over 200 days in real-life conditions. The corrosion time and mass loss are shown in Table 1.

Table 1. Corrosion results.

Corrosion Time (h)	Remaining Mass (g)	Mass Loss (g)	Corrosion Percentage	Corresponding Actual Corrosion Time (d)
0	3477.8	0	0	0
12	3452.7	25.1	0.72%	≥200
24	3424.2	53.6	1.54%	≥400
36	3394.6	83.2	2.39%	≥600
48	3369.4	108.4	3.12%	≥800
60	3345.2	132.6	3.81%	≥1000
72	3322.6	155.2	4.46%	≥1200

3. Propagation Mechanism and Signal Processing of Guided Waves in Anchor Bolts

3.1. Propagation of Ultrasonic Guided Waves in Anchor Bolts

In assuming that the concrete is an isotropic elastic medium and the cylindrical body is axially symmetric and infinitely long, the axis of the cylinder coincides with the z -axis. In this configuration, guided waves can propagate along the cylinder and form three primary wave modes: a longitudinal wave L , transverse wave T , and torsional wave F . The longitudinal wave L propagates along the axis of the cylinder (i.e., the z -axis), with its vibration direction being parallel to the direction of wave propagation. The transverse wave T propagates radially or tangentially along the cylinder, with its vibration direction perpendicular to the direction of wave propagation. The torsional wave F is a wave mode that rotates the cylinder around its axis without significant radial or axial displacement. A schematic of guided wave propagation is presented in Figure 5, and the propagation equations are given in (10) to (15) [17].

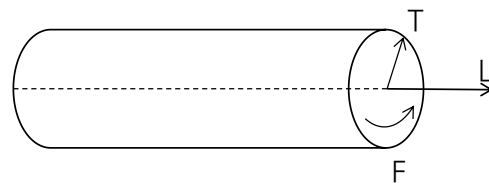


Figure 5. Propagation of guided waves in anchor bolts.

For longitudinal waves in a cylinder, the displacement field propagates along the axis of the cylinder. The wave velocity of the longitudinal wave is given by the following equation:

$$c_L = \sqrt{((\lambda + 2\mu)/\rho)} \quad (10)$$

where ρ represents density, λ and μ are Lamé constants, and C_L denotes the longitudinal wave velocity in the cylindrical body. The dispersion equation for longitudinal waves in a cylindrical body is given by the following equation:

$$k^2 + (\omega^2/c_L^2) = 0 \quad (11)$$

where k is the wave number and ω is the angular frequency. For transverse waves in a cylinder, the displacement field propagates perpendicular to the axis of the cylinder. The wave velocity of the transverse wave is given by the following equation:

$$c_T = \sqrt{\mu/\rho} \quad (12)$$

The dispersion equation for transverse waves in a cylindrical body is as follows:

$$k^2 + (\omega^2/c_T^2)(1 + (J'_n(kr))^2/(J_n(kr))^2) = 0 \quad (13)$$

where J_n and J'_n are the derivatives of the first-kind and second-kind Bessel functions, respectively, and r is the radius of the cylinder.

For torsional waves in a cylinder, the displacement field forms a helical pattern and propagates along the axis of the cylinder. The wave velocity of the torsional wave is given by the following equation:

$$c_F = \sqrt{(\mu/(\rho + 4\mu/3))} \quad (14)$$

The dispersion equation for torsional waves in a cylindrical body is given by

$$k^4 + (\omega^2/c_S^2)(k^2 + 1.5k^2(J'_n(kr)/J_n(kr))^2) = 0 \quad (15)$$

During the propagation of guided waves, there are three modes of waves: $L(0,m)$, $T(0,m)$, and $F(1,m)$. Here, ' m ' represents the mode order, while '0' and '1', respectively, denote symmetric and asymmetric wave fields. The dispersion curve of a 20 mm diameter anchor bolt was plotted using MATLAB R2021b software, and these dispersion curves are shown in Figure 6. From the dispersion curves, it can be observed that within the frequency range of 0–1000 kHz, the $L(0,1)$ mode exhibits a frequency band with the fastest group velocity and minimal variation, spanning from 20 to 40 kHz, as depicted in Figure 5. This characteristic enables the $L(0,1)$ mode to arrive at the receiving sensor first among all echo signals, without waveform distortion, making it easily identifiable and distinguishable in the time domain. Additionally, this frequency band falls below the cut-off frequency of other modal guided waves, thus ensuring that the $L(0,1)$ mode does not generate higher-order modal guided waves during detection. A five-cycle Hanning window-modulated pulse with a center frequency of 30 kHz was chosen as the driving signal.

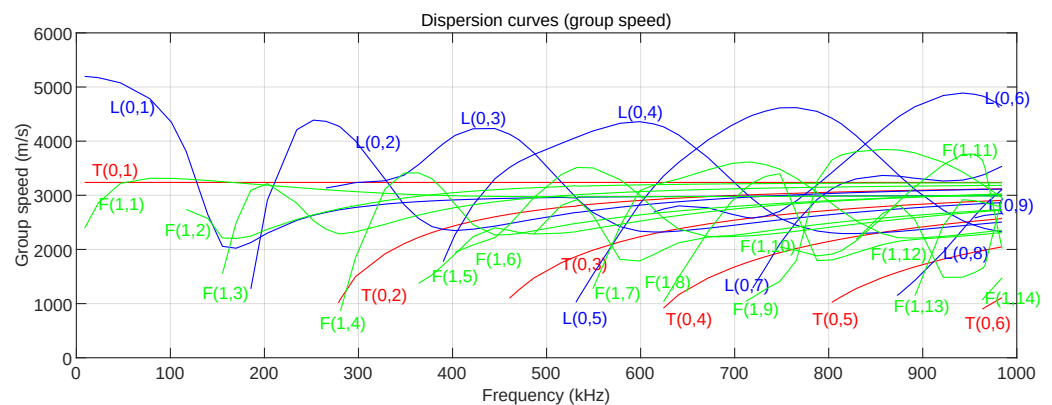


Figure 6. Group velocity dispersion curve of 20 mm ribbed anchor bolts.

3.2. Propagation of Guided Waves in Anchor Bolts with Corrosive Defects

When guided waves penetrate the corroded area on the surface of an anchor bolt, the reductions in the cross-sectional area and material damage in that region result in energy focusing and scattering, leading to changes in the distribution of energy density. Additionally, the propagation velocity and direction of guided waves within the rod are influenced by factors such as the properties of the medium and the geometric shape. Consequently, the change in the propagation path caused by corrosive defects also affects the velocity and direction of the wave propagation. The propagation of guided waves in anchor bolts with corrosive defects is illustrated in Figure 7.

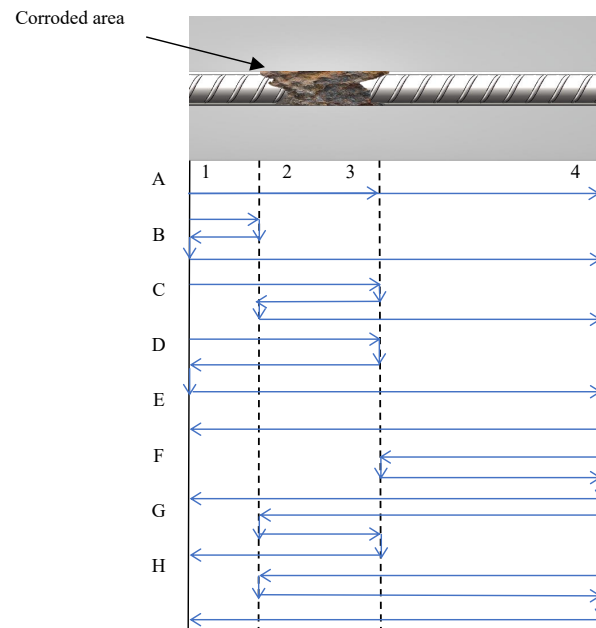


Figure 7. Schematic of guided wave propagation: (A) wave transmission; (B) wave reflections at boundaries 2 and 1; (C) waves are reflected from boundaries 3 and 2; (D) wave reflections at boundaries 3 and 1; (E) wave transmission; (F) wave reflections at boundaries 3 and 4; (G) wave reflections from borders 2 and 3; and (H) wave reflections from borders 2 and 4.

4. Multi-Scale Convolutional Neural Networks for Anchor Bolt Corrosion Recognition

4.1. CNN for 1D Signals

A CNN is generally used in the fields of computer vision, image recognition, and so on. In dimensional data processing, a 1D-CNN can analyze numbers of fixed length, especially when the data feature is not highly correlated with the location of the data. However, the corresponding characteristics can be obtained effectively. In order to prevent anchor bolt failure caused by corrosion and provide early fault diagnosis, an AI-based intelligent decision-making mechanism can be developed [18]. Unlike traditional machine learning algorithms, a convolutional neural network (CNN) architecture offers effective solutions for classification problems with its powerful self-learning capabilities and state-of-the-art performance. The CNN is an important algorithm in the field of deep learning and operates through convolutional layers, pooling layers, and fully connected layers. In the convolutional layer, neurons gather data from different input regions and share the same set of weights. In assuming that the input image matrix is denoted as X , the convolutional kernel matrix as W , the activation function as f , the bias matrix as b , and the output pixel matrix as Y , the calculation formula for the convolutional layer is as follows:

$$Y = f(X \otimes W + b) \quad (16)$$

where $\otimes$ represents the convolution operation. In practice, the bias term b is obtained through training. The size of the output feature map depends on the size of the filter and the stride. For instance, when the convolutional kernel size is $F \times F$ and the stride is S , for an input image of size $H \times H$, the output size is $W \times W$.

The pooling layer is used to reduce the resolution of the previous feature maps and can operate based on methods like maximum or average pooling. If an input of size $W \times W$ is fed into the pooling layer, the output size is determined by the following formula:

$$W' = (W - F)/S + 1 \quad (17)$$

Convolutional neural networks (CNNs) typically consist of multiple fully connected layers at the top, similar to feed-forward neural networks, aiming to extract global features from the input. The last layer is a softmax classifier used to estimate the posterior probability of the input sample across K different classes.

In summary, a CNN extracts features and performs pattern learning through operations such as convolution, pooling, and fully connected layers. It holds a significant position in the field of deep learning and has achieved remarkable results in areas such as time-series data recognition.

4.2. Multi-Scale Convolutional Neural Network Model Design

4.2.1. Construction of MS-CNN

Considering the inherent multi-scale characteristics of complex patterns in measured signals for corrosion diagnosis, this paper proposes an MS-CNN fault diagnosis method for improving accuracy corrosion diagnosis. Although CNN models improve their feature self-learning ability by learning the vibration characteristics in raw signals, the robustness of the model may be poor if it does not consider these complex patterns present at multiple time scales. In this section, a new improved multi-scale procedure based on traditional multi-scale analysis methods is proposed to extract more information at multiple time scales. The structure and parameter settings of the MS-CNN model are shown in Table 2. Two new convolution branches are added in series within the 3×3 kernel convolution layer, as low-level convolutions have small-size filters. These branches include mid-high-level convolution kernels with 4×4 and 5×5 kernels to extract multi-scale signal features from the input. The use of a convolution kernel divided into three different scales for extracting ultrasonic conduction wave characteristics of bolt corrosion may be motivated by the need to capture corrosion conditions at varying scales. In ultrasonic guided wave detection, corrosion typically exhibits characteristics at different scales, including local fine corrosion and large areas of corrosion. Additionally, batch normalization (BN) is added after the convolutions to avoid overfitting and improve the convergence speed of the network. The network structure design is shown in Figure 8.

Table 2. The structure and parameter settings of the MS-CNN model.

Layer Number	Structure Type	Parameter
1	Input layer	762 waveforms
2	Convolutional layer 1	3×1
3	Convolutional layer 2	4×1
4	Convolutional layer 3	5×1
5	Concat layer	—
6	Convolutional layer 4	3×1
7	Dropout layer	Probability is 0.5
8	Fully connected layer	—
9	Output layer	—

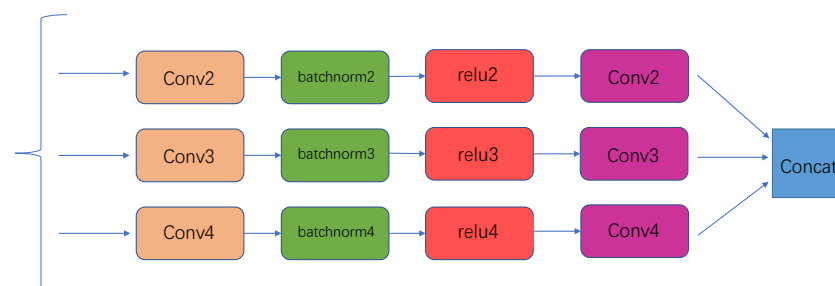


Figure 8. The framework of the MS-CNN model consists of three pathways that can extract features at different time scales.

4.2.2. MS-CNN Network Architecture

Each pathway in the CNN network has a similar structure. It consists of four convolutional layers, four pooling layers, and two fully connected layers, as shown in Figure 9. To reduce overfitting during training, a dropout layer with a dropout rate of 50% is introduced between the remaining two fully connected layers.

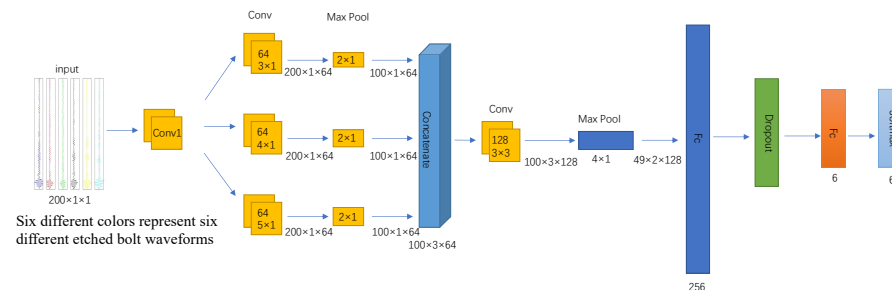


Figure 9. MS-CNN framework.

5. Experiment Results and Analysis

5.1. Experiment on Non-Destructive Testing of Anchor Bolts

5.1.1. Anchor Bolt and Anchoring

The experimental anchor bolts had a diameter of 20 mm and a length of 1500 mm. The anchoring section had a length of 1000 mm, and the performances of the anchor bolt and anchoring parameters are listed in Table 3. The anchor bolt protrudes 500 mm from one end of the rock mass for the installation, excitation, and measurement of the ultrasonic guided wave device. The length of the corrosion zone was set to 80 mm.

Table 3. Corrosion results.

Type	Length/m	Diameter/mm	Poisson Ratio	Elasticity Modulus/GPa	Density kg/m ³
Anchor Bolt	1.5	20	0.3	210	7850
Anchor agent	1.0	32	0.2	25	2300
Surrounding rock	1.0	200	0.25	60	2600

5.1.2. IEPE Piezoelectric Acceleration Sensor

In this study, the Tektronix AFG3052C signal generator (From China Tektronix Technology Co., Ltd., Shanghai, China) was employed to generate a five-period sine wave with an excitation frequency of 30 kHz as the excitation signal. The excitation signal is emitted from point A, the transmitting end of the sensor, and received at point B, the receiving end of the sensor. Subsequently, it is transmitted to the DHDAS dynamic signal acquisition system. The signal acquisition process is finalized after passing through a modulated Butterworth filter for effective filtering. The non-destructive testing process of the anchor bolt is shown in Figure 10. After 12, 24, 36, 48, 60, and 72 h of corrosion, the specimens were subsequently positioned within the anchoring system and securely affixed using an anchoring agent. Then, ultrasonic guided wave detection was conducted, wherein the resulting waveforms were meticulously documented. The actual signal acquisition experiment is illustrated in Figure 11.

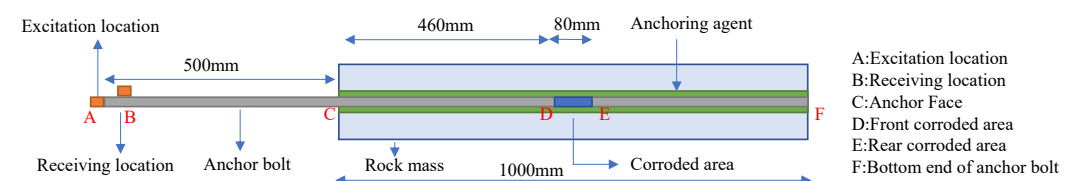


Figure 10. Schematic of non-destructive testing process.



Figure 11. Actual signal acquisition.

5.2. Ultrasonic Guided Wave Test Waveform

5.2.1. Experimental Ultrasonic Guided Waveforms

From Figure 12, it can be observed that the signal waveform of an intact anchor bolt typically exhibits a clear and regular pattern, with the peak and center frequencies of its primary wave remaining stable and without additional reflected wave signals. In contrast, the signal waveform of a defective anchor bolt displays a complex pattern due to the superposition of a defect reflection wave signal, resulting in a shift in the peak and center frequencies of its primary wave. This superposition also leads to a certain degree of phase shift in the received waveform.

In the figure, the second wave packet represents the echo reflected from the corrosion defect on the anchor bolt, while the third wave packet corresponds to the echo reflected from the bottom surface of the anchorage. In measuring the time intervals between each wave arrival, the position of the anchor bolt corrosion defect and the length of the free segment and anchorage section can be calculated. The first wave peak occurs at 0.120 ms, the echo from the anchorage surface arrives at 0.29 ms, the echo from the corrosion defect arrives at 0.474 ms, and the echo from the bottom of the anchorage arrives at 0.671 ms. Based on the calculation of group velocity from the time-domain waveform, the propagation speeds of the guided wave in the free section and the anchored section of the anchor bolt are 5748 m/s and 4959 m/s, respectively. Therefore, the free segment of the anchor bolt was determined to be 48.86 cm, the position of the corrosion defect was at 89.27 cm, and the length of the anchorage section was 100.02 cm. The calculation yielded a 2.97% error in the position of the defect and a total length of 148.88 cm with a 0.75% error.

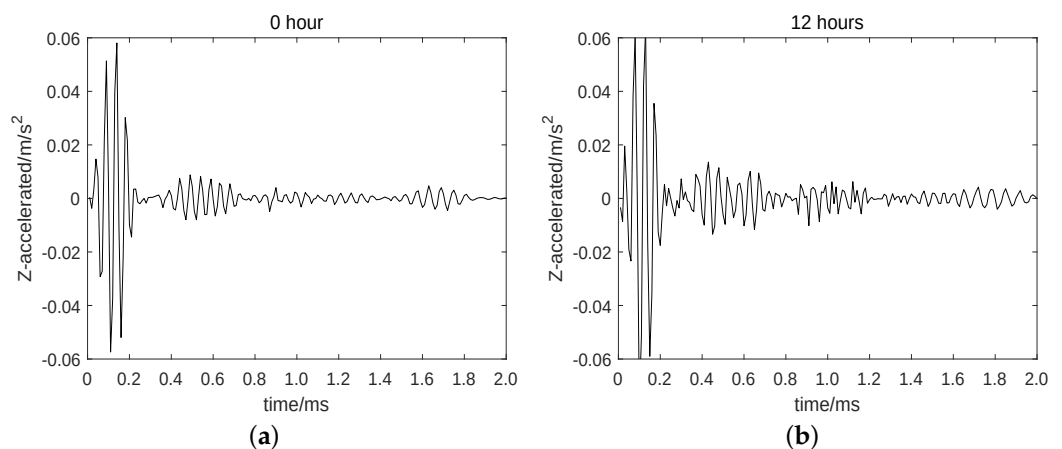


Figure 12. Ultrasonic guided wave waveform diagram for anchor bolt non-destructive testing. (a) Normal anchor bolt Waveform graph. (b) Waveform graph of anchor bolt after 12 h of corrosion.

Figure 13 shows the guided wave signals of anchor bolts with different degrees of corrosion in actual experiments. It can be observed that in practical situations, due to

uncertainties in corrosion and the presence of phenomena such as the dispersion and overlapping of guided waves, the amplitude, time delay, and frequency attenuation of the reflected guided wave signals become more complex. These variations also affect the resolution and identification accuracy of the signals. It is important to consider these influencing factors during data processing and analysis in order to improve the reliability and accuracy of the signals.

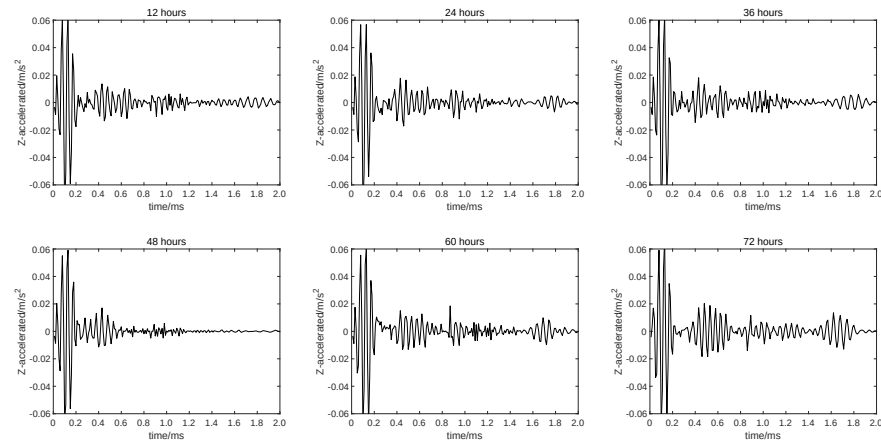


Figure 13. Guided wave signals of anchor bolts with different degrees of corrosion.

5.2.2. The Uncertainty of Waveforms at the Same Position

During the signal acquisition process of non-destructive testing experiments, the signal sensors continuously sample at a fixed sampling frequency. In this study, sequences with a length of 200 sampling points were used as the original samples. The dataset consisted of 127 groups of ultrasonic guided waveforms collected under different corrosion levels. As shown in Table 4, during the training process, the labeled dataset of 762 groups of data was randomly shuffled, and it was divided into a training set of 610 groups and a test set of 152 groups in an 8:2 ratio. During the actual detection process, multiple factors can affect the test results, such as sensor position, angle, coupling condition, environmental noise, etc. These factors introduce various distortions and interferences, increasing the complexity of the waveform. Figure 14 shows the guided wave signals collected at the same position, and it can be observed that even when the sensor remains stationary, there are significant differences in the reflected signals. This makes it more difficult to identify the characteristics of the waveforms.

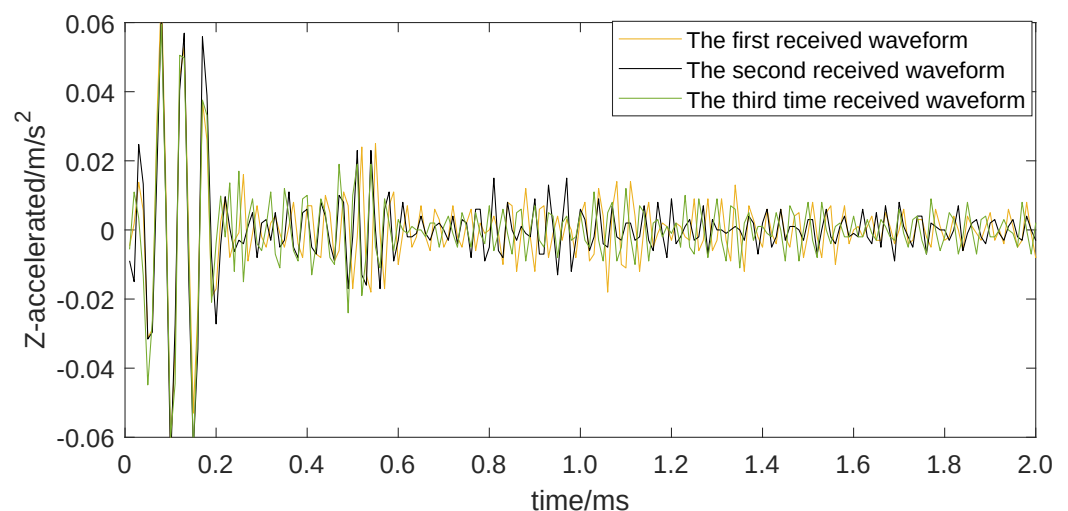


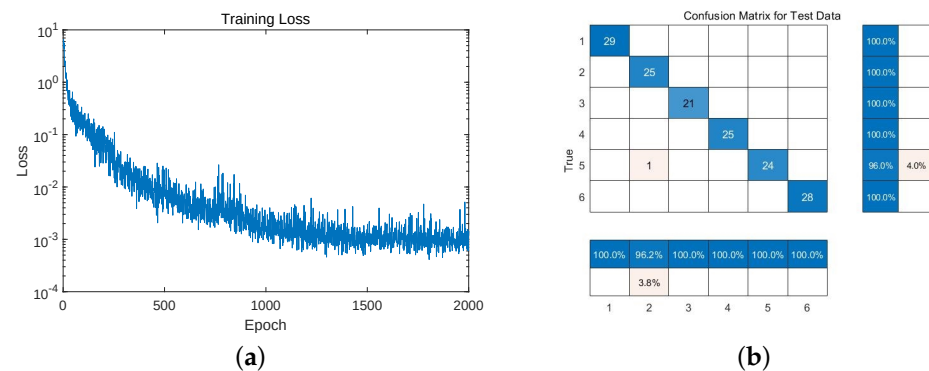
Figure 14. Corrosion ultrasonic guided wave signal collected at the same position after 72 h of corrosion.

Table 4. Dataset description.

	Training Set	Test Set	Degree of Corrosion
Dataset 1	101	25	0.72%
Dataset 2	101	25	1.54%
Dataset 3	101	25	2.39%
Dataset 4	101	25	3.12%
Dataset 5	102	26	3.81%
Dataset 6	102	26	4.46%

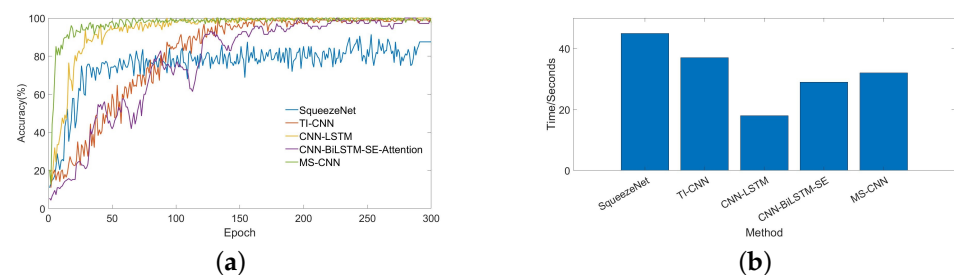
The randomness of the CNN network during the training process can lead to different recognition results that continuously change. In order to obtain a more objective and accurate recognition rate, it is common to increase the sample size and take the average of multiple experimental results to reduce the influence of objective conditions on the experimental results.

Under the prediction results of the CNN model, we can observe from Figure 15a that the loss function converges to the order of 10^{-3} . The classification recognition results of anchor bolt corrosion can be represented by the prediction accuracy and the final confusion matrix. The MS-CNN effectively extracts features from guided wave signals, achieving a prediction accuracy of 99.4% with only one waveform misclassified.

**Figure 15.** Training of MS-CNN. (a) CNN model training progress chart. (b) Confusion matrix results for multi-scale CNN model recognition.

5.3. Comparison with the Latest Methods

In order to evaluate our method better, we compared the MS-CNN with other models. Since there is limited research on the waveform recognition of anchor bolt corrosion, we selected methods that also recognize time series for comparison. The compared methods included SqueezeNet, TI-CNN [19], CNN-LSTM [20], and CNN-BiLSTM-SE [21], as shown in Figure 16 and Table 3. It should be noted that during the comparison process, due to the differences in dataset size between this study and the literature, we adjusted the convolutional kernel size and stride of some models. The training results for each method are shown in Table 5.

**Figure 16.** Comparison of training for different models. (a) Training accuracy of different methods based on raw signals. (b) Training time of different methods.

From the comparison results, it can be seen that MS-CNN has the highest recognition accuracy, reaching 99.4%. The CNN-LSTM has the fewest model parameters and takes only 18 s for training, with a recognition accuracy of 96.1%. The CNN-BiLSTM-SE model incorporates a bidirectional long short-term memory network (BiLSTM) to effectively model long-term dependencies in sequence data, achieving an accuracy of 98.6%. The recognition accuracy of the SqueezeNet model is not ideal, possibly because it fails to capture the temporal correlations in the ultrasonic guided wave recognition scenario sufficiently. The TI-CNN model shows slow improvement in accuracy at the beginning of training as it only introduces dropout to enhance the model's generalization ability, and it takes longer time than the MS-CNN to achieve the same 98% recognition accuracy. The multi-scale model requires doubling the number of convolutional kernels in adjacent paths, leading to a rapid increase in parameter count and training time as the number of paths increases. Although the MS-CNN does not show significant advantages in terms of model parameters and training time, it greatly improves the recognition accuracy.

Table 5. Predicted results of corrosion level types under different methods.

Method	Accuracy	MSE	Precision Ratio	Recall Ratio	F1 Score
SqueezeNet	92.3	3.293	0.934	0.913	0.919
TI-CNN	97.0	0.694	0.970	0.970	0.970
CNN-LSTM	96.1	0.568	0.960	0.961	0.960
CNN-BiLSTM-SE	98.6	0.262	0.989	0.988	0.988
MS-CNN	99.4	0.026	0.994	0.993	0.993

6. Conclusions

This study investigated the recognition of accelerated electrochemical corrosion defects in anchor bolts using convolutional neural networks through testing on anchor specimens with different corrosion periods. The conclusions are as follows:

(1) Guided waves propagate in multiple modes within the anchor bolts, and the energy of different modes propagates at different speeds. This allows guided waves to be influenced by different modes simultaneously. In the study of the 20 mm diameter bolt, using a 30 KHz signal excitation can ensure that only one modal $L(0,1)$ of longitudinal wave exists, which facilitates the analysis of the signal.

(2) The relationship between the ultrasonic guided wave waveform and the degree of corrosion in anchor bolts at different corrosion levels was studied. The propagation speed and reflection intensity of ultrasonic guided waves in the corroded region vary. The strength (i.e., high amplitude) or weakness (low amplitude) of the guided wave reflection signal is influenced by many factors, such as the shape, size, and roughness of the object surface. The corrosion degree of anchor bolt cannot be quantified solely based on the amplitude of the guided wave.

(3) A corrosion evaluation method for anchor bolts based on non-destructive testing and deep learning was proposed. This method utilizes a multi-scale convolutional neural network model to analyze the ultrasonic guided wave signals of corroded anchor bolts and quickly and accurately assess the degree of corrosion. On a dataset containing 608 waveform groups, the accuracy rate for identifying the corrosion degree of anchor bolts reached 99.4%, outperforming other comparative methods.

However, this study still has certain limitations. When analyzing the reflected ultrasonic guided waves, the uncertainty of the actual corrosion form should be taken into account. The signals of guided waves may be influenced by various factors, such as the diameter of the steel bar and the integrity of the anchoring agent. Further research is needed to incorporate the uncertainty of other influencing factors. Additionally, the corrosion form and degree in rock masses may differ from those in electrochemical corrosion, requiring further investigation.

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Abbreviations

The following abbreviations are used in this manuscript:

NDT	non-destructive testing;
FFT	fast Fourier transform;
MS-CNN	multi-scale convolutional neural network;
CNN	convolutional neural networks.

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