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An Automated Wire Rope Inspection System Based on Image Processing and Anomaly Detection

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Abstract – **Wire ropes are essential load-bearing components in construction machinery, elevators, cranes, and other heavy industrial systems, where their structural integrity directly influences operational safety and reliability. Detecting defects such as wire breakage at an early stage is critical for preventing equipment failure and minimizing the risk of severe accidents. However, conventional inspection procedures are predominantly performed through manual visual examination, making the inspection process dependent on operator experience, environmental conditions, and available working time. These limitations often lead to inconsistent inspection quality and reduce the reliability of damage assessment. This paper presents an image processing-based framework for automated wire rope damage detection that minimizes dependence on human expertise while providing a practical and efficient inspection solution. The proposed methodology investigates two complementary image analysis techniques: an Autoencoder-based anomaly detection model and a Gabor filter-based feature extraction approach for identifying wire breakage and other surface abnormalities. The Autoencoder is trained exclusively using normal wire rope images to learn the visual characteristics of undamaged ropes, allowing abnormal regions to be identified through reconstruction error analysis. Additionally, a Convolutional Autoencoder (CAE) is evaluated to examine its capability for anomaly reconstruction, while connectivity analysis combined with Otsu thresholding is employed to improve the detection of wear-related defects. The Gabor filter method exploits local frequency characteristics of wire rope textures to identify minute wire breakage with high sensitivity. Experimental evaluation demonstrates that the Autoencoder-based approach is effective for identifying wear regions through connectivity analysis, whereas the Gabor filter successfully detects fine wire breakage that is difficult to identify using reconstruction-based methods alone. The proposed framework provides a practical, cost-effective, and image-based inspection strategy that supports safer and more reliable wire rope monitoring in construction environments.**

Keywords - **Wire Rope Inspection, Image Processing, Anomaly Detection Automated Inspection System, Computer Vision, Defect Detection**

I. INTRODUCTION

Wire ropes serve as one of the most important mechanical components in numerous industrial applications, particularly within construction machinery, tower cranes, mobile cranes, elevators, lifting equipment, and heavy transportation systems. These structures continuously experience high tensile loads, repeated bending, abrasion, environmental exposure, and fatigue during normal operation. Since wire ropes frequently support heavy suspended loads, any structural deterioration may lead to catastrophic equipment failure, resulting in significant economic losses, operational downtime, and potential threats to human safety. Consequently, regular inspection and timely detection of wire rope damage are essential for ensuring safe operation, extending service life, and preventing unexpected mechanical failures.

Traditionally, wire rope inspection has been performed through manual visual examination, where experienced inspectors evaluate the rope surface according to established maintenance guidelines and disposal standards. During inspection, operators identify defects such as broken wires, wear, corrosion, deformation, and surface deterioration by visually observing the rope while it is stationary or slowly moving. Although manual inspection remains widely adopted because of its simplicity and low equipment cost, the overall inspection quality is highly dependent on the inspector's experience, concentration, and working conditions. Environmental factors such as poor illumination, dust, vibration, weather conditions, restricted accessibility, and limited inspection time further reduce the reliability and consistency of visual assessments. As a result, manual inspection procedures often fail to provide objective and repeatable damage evaluation across different operators and construction sites.

To overcome these limitations, researchers have investigated numerous non-destructive testing (NDT) techniques for wire rope condition monitoring. Electromagnetic inspection methods, magnetic flux leakage sensors, acoustic emission techniques, ultrasonic guided wave testing, and radiographic inspection have demonstrated the ability to identify internal defects that are difficult to observe visually. Although these techniques provide valuable structural information, they frequently require specialized sensors, complex calibration procedures, expensive equipment, and skilled personnel for operation. Furthermore, measurement accuracy often depends on the distance between the sensor and the wire rope, sensor alignment, rope movement, and

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environmental noise, making continuous inspection under practical construction site conditions difficult to achieve. These challenges have motivated the search for alternative inspection techniques that provide both high accuracy and practical field applicability.

Recent advances in computer vision, digital imaging, and image processing have created new opportunities for developing intelligent wire rope inspection systems. Modern image sensors provide high-resolution visual information at relatively low cost while enabling completely non-contact measurement. Combined with powerful image processing algorithms, these sensors can automatically identify surface defects without physically interacting with the wire rope. Compared with traditional electromagnetic inspection methods, image-based approaches offer several practical advantages, including simple installation, reduced maintenance requirements, lower equipment cost, improved portability, and intuitive visualization of inspection results. These characteristics make image processing particularly attractive for deployment within construction environments where inspection equipment must operate reliably under varying environmental conditions.

Several image-based wire rope inspection methods have been proposed in recent years. Early approaches primarily relied on template matching, handcrafted texture descriptors, and model-based image analysis to recognize surface damage. Although these techniques achieved acceptable performance under controlled laboratory conditions, they generally required predefined templates or accurate wire rope models that limited their ability to detect previously unseen defects. More recently, supervised learning and object detection methods have been introduced to classify wire rope damage using labeled image datasets. However, supervised approaches require large collections of defect images representing every possible damage type. Since severe wire rope defects occur relatively infrequently because damaged ropes are usually replaced during routine maintenance, collecting sufficient training data for supervised learning remains a significant challenge.

To address these limitations, unsupervised anomaly detection has emerged as a promising alternative. Instead of learning the characteristics of damaged wire ropes directly, unsupervised models learn only the visual appearance of normal wire ropes and subsequently identify deviations from normal behavior as potential defects. Autoencoders, a class of unsupervised deep learning models, have demonstrated considerable success in anomaly detection because they reconstruct normal input images accurately while producing larger reconstruction errors for abnormal regions. Consequently, reconstruction error maps can be utilized to localize damaged areas without requiring explicit defect annotations during training. This learning strategy significantly reduces the dependency on large labeled datasets while improving the ability to detect previously unseen damage patterns.

In addition to deep learning-based anomaly detection, traditional image processing techniques continue to provide valuable complementary information. Among these methods, the Gabor filter has proven particularly effective for analyzing texture orientation and local spatial frequency characteristics. Since wire rope strands exhibit regular directional patterns under normal conditions, local disturbances caused by broken wires introduce high-frequency discontinuities that can be effectively identified using Gabor-based filtering. Combining texture analysis with anomaly detection therefore provides a more comprehensive inspection framework capable of identifying both localized wire breakage and larger wear-related defects.

Motivated by these challenges, this study proposes an intelligent image processing framework for automated wire rope damage detection that integrates Autoencoder-based anomaly detection, Convolutional Autoencoder (CAE) analysis, Gabor filter-based texture feature extraction, connectivity analysis, and Otsu thresholding. The Autoencoder is trained exclusively using normal wire rope images to learn undamaged visual characteristics, while reconstruction error analysis identifies abnormal regions associated with potential damage. The CAE is additionally evaluated to investigate its reconstruction capability for anomaly localization. Furthermore, Gabor filtering analyzes local frequency variations to detect extremely fine wire breakage, and connectivity analysis improves the localization of wear defects extracted from reconstruction error images.

The primary objective of this research is to develop a practical, reliable, and automated wire rope inspection framework capable of operating effectively under real construction site conditions while minimizing dependence on operator experience. By integrating unsupervised deep learning, classical image processing, and texture analysis within a unified inspection system, the proposed methodology contributes toward improving inspection accuracy, reducing manual effort, enhancing operational safety, and supporting the development of intelligent maintenance systems for construction machinery and other industrial lifting equipment.

II. LITERATURE SURVEY

The reliability and safety of wire ropes are of critical importance in construction machinery, elevators, cranes, mining systems, cable transportation, and numerous industrial lifting applications. Because wire ropes operate continuously under heavy mechanical loads and harsh environmental conditions, they are highly susceptible to deterioration caused by fatigue, corrosion, abrasion, deformation, and wire breakage. Failure to detect these defects at an early stage may result in severe equipment damage, production interruptions, financial losses, and serious safety hazards. Consequently, considerable research has focused on developing intelligent inspection techniques capable of automatically identifying wire rope defects with high accuracy while minimizing dependence on manual inspection. Traditional inspection approaches have gradually evolved from manual visual assessment toward advanced image processing, computer vision, and deep learning techniques that provide more reliable and objective defect detection.

Conventional manual visual inspection remains one of the most widely adopted methods for wire rope condition assessment. During inspection, experienced operators visually examine the rope surface to identify broken wires, wear, corrosion, strand deformation, and other visible defects. Although manual inspection requires minimal equipment and can be performed in diverse working environments, its effectiveness depends heavily on the knowledge, experience, concentration, and judgment of the inspector. Environmental factors such as inadequate lighting, dust, vibration, weather conditions, and limited accessibility further reduce inspection reliability. As a result, identical wire ropes inspected by different operators may produce inconsistent evaluations, motivating researchers to develop automated inspection systems that provide objective and repeatable assessments.

To overcome the limitations of visual inspection, researchers have investigated various non-destructive testing (NDT) methods for wire rope monitoring. Electromagnetic inspection, magnetic flux leakage (MFL), acoustic emission analysis, ultrasonic guided wave techniques, and radiographic inspection have demonstrated the capability to identify both internal and external defects. These technologies offer valuable structural information beyond surface-level observations. However, they generally require specialized sensors, sophisticated instrumentation, precise calibration procedures, and trained personnel. Furthermore, inspection accuracy is often influenced by sensor alignment, rope movement, environmental interference, and installation complexity, limiting the practicality of these techniques for continuous field deployment in construction environments.

Recent advances in computer vision have encouraged the adoption of image-based inspection systems for industrial defect detection. Digital cameras provide high-resolution visual information at relatively low cost while enabling completely non-contact inspection. Combined with image processing algorithms, these systems can automatically analyze surface characteristics and detect defects without interrupting machine operation. Compared with sensor-based NDT techniques, image-based inspection offers advantages including simple installation, reduced maintenance requirements, intuitive visualization, portability, and lower operational cost. Consequently, image processing has become an increasingly attractive solution for automated wire rope monitoring.

Early image processing approaches primarily relied on edge detection, threshold segmentation, template matching, and texture analysis to identify damaged regions. Classical algorithms extracted handcrafted image features describing intensity variation, local texture, geometric structures, and directional patterns associated with wire rope surfaces. Although these techniques demonstrated acceptable performance under controlled laboratory conditions, they frequently exhibited limited robustness when confronted with illumination changes, surface contamination, complex backgrounds, or previously unseen defect patterns. Such limitations motivated researchers to explore more adaptive machine learning and deep learning approaches capable of automatically learning discriminative image representations.

Among traditional texture analysis methods, the Gabor filter has received considerable attention because of its ability to analyze local spatial frequency and orientation characteristics. Gabor filters effectively extract directional texture information by emphasizing frequency components associated with repetitive structural patterns. Since normal wire rope strands exhibit highly regular directional textures, localized disturbances caused by broken wires produce significant changes in local frequency responses that can be detected through Gabor-based filtering. Several investigations have demonstrated that Gabor filters successfully identify fine surface defects that are difficult to observe using conventional edge detection methods. Their robustness to illumination variation further enhances their applicability within industrial inspection systems.

The rapid development of Deep Learning has significantly advanced industrial image inspection. Instead of relying on manually designed image features, deep neural networks automatically learn hierarchical visual representations directly from training data. Among various neural architectures, Autoencoders have become particularly popular for unsupervised anomaly detection. Autoencoders are trained using only normal images and learn to reconstruct defect-free samples with high accuracy. When abnormal images containing defects are presented, the network produces larger reconstruction errors within damaged regions because it has not learned their appearance during training. The resulting reconstruction error maps provide valuable information for localizing anomalies without requiring manually annotated defect images. This capability is especially advantageous in industrial applications where abnormal samples are scarce or difficult to collect.

Researchers have further improved anomaly detection performance through the development of Convolutional Autoencoders (CAE). Unlike conventional fully connected Autoencoders, CAEs utilize convolutional layers that preserve spatial relationships within images while learning hierarchical feature representations. The encoder compresses visual information into a compact latent representation, and the decoder reconstructs the original

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image from this compressed feature space. Because convolutional operations effectively capture local texture patterns and structural characteristics, CAEs generally provide superior reconstruction quality for industrial image analysis. Their ability to learn spatially meaningful features makes them well suited for detecting subtle wire rope defects.

In addition to deep learning, researchers have investigated image segmentation techniques to improve defect localization. Among these methods, Otsu thresholding has become one of the most widely adopted automatic threshold selection algorithms. Otsu's method determines an optimal threshold by maximizing the variance between foreground and background image regions, thereby enabling reliable separation of defect regions from surrounding textures. Combined with reconstruction error maps generated by Autoencoders, Otsu thresholding facilitates automatic extraction of candidate defect areas without requiring manually selected threshold values.

Following segmentation, connectivity analysis provides an additional mechanism for improving defect identification. Connected component analysis groups neighboring pixels belonging to the same segmented region according to predefined connectivity relationships such as 4-connectivity or 8-connectivity. By analyzing the size, shape, and distribution of connected regions, connectivity analysis enables the elimination of isolated noise while highlighting larger abnormal areas corresponding to wear or structural damage. Consequently, combining Autoencoder reconstruction with threshold segmentation and connectivity analysis improves the reliability of industrial anomaly detection systems.

Despite significant progress in image processing and deep learning for industrial inspection, several challenges remain. Conventional image processing methods frequently struggle to detect extremely small defects under varying illumination conditions, while deep learning approaches often require large computational resources and careful network design. Furthermore, Autoencoder-based anomaly detection may successfully identify large wear regions but sometimes exhibits reduced sensitivity to very fine wire breakage because of reconstruction smoothing effects. These limitations suggest that combining complementary inspection techniques may provide more comprehensive wire rope monitoring than relying on a single detection algorithm.

Motivated by these research challenges, the present study proposes an integrated image processing framework that combines Autoencoder-based anomaly detection, Convolutional Autoencoder (CAE), Gabor filter-based texture analysis, Otsu thresholding, and connectivity analysis for automated wire rope damage detection. The proposed methodology utilizes 3,870 normal wire rope images resized to 64 × 64 pixels, employs the Adam optimizer, ReLU and Sigmoid activation functions, Mean Squared Error (MSE) loss, and 100 training epochs to develop an intelligent anomaly detection model. By integrating reconstruction-based learning with classical texture analysis, the proposed framework aims to improve the detection of both wear-related defects and fine wire breakage while providing a practical, reliable, and automated inspection solution for construction machinery and industrial lifting systems.

III. PROPOSED METHODOLOGY

The proposed framework presents an intelligent image processing-based wire rope inspection system for automatically detecting wire breakage, surface wear, and other visual abnormalities in wire ropes used in construction machinery. The methodology combines Autoencoder-based anomaly detection, Convolutional Autoencoder (CAE), Gabor filter-based texture analysis, Otsu thresholding, and connectivity analysis to identify damaged regions without relying on extensive manually labeled defect datasets. Unlike conventional supervised classification techniques that require numerous defect images, the proposed framework learns the visual characteristics of normal wire ropes and identifies abnormal regions through reconstruction error analysis. The integration of deep learning and classical image processing enables accurate localization of surface defects while maintaining computational efficiency and practical applicability for industrial inspection.

The methodology begins with the image acquisition stage, where wire rope images are collected under controlled imaging conditions. The dataset consists of 3,870 normal wire rope images, which are utilized for training the anomaly detection models. Since abnormal wire rope images are relatively scarce in practical industrial environments, only defect-free samples are employed during model learning. This unsupervised learning strategy enables the proposed framework to recognize deviations from normal wire rope appearance without requiring explicit annotation of damaged regions. The acquired images are resized to 64 × 64 pixels, providing a consistent input dimension suitable for efficient deep learning model training while preserving sufficient structural information required for defect detection.

Following image acquisition, all images undergo comprehensive image preprocessing to improve visual consistency before feature learning. Initially, the captured images are resized to the predefined input resolution, followed by normalization to standardize pixel intensity values. Image normalization improves training stability by reducing variations caused by illumination differences and camera acquisition conditions. The preprocessed images are subsequently divided into training and testing datasets. The training dataset contains only normal wire rope images used for learning the visual characteristics of undamaged ropes, whereas testing includes both normal and defective wire rope images to evaluate anomaly detection performance.

The first major component of the proposed framework is the Autoencoder-based anomaly detection model. An Autoencoder is an unsupervised neural network consisting of two primary components: an encoder and a decoder. During training, the encoder compresses the input image into a compact latent representation that preserves essential visual information. The decoder subsequently reconstructs the original image from this compressed feature space. Since the Autoencoder is trained exclusively using normal wire rope images, it learns to reconstruct defect-free surfaces with high accuracy. When abnormal images containing broken wires or wear are presented during testing, the reconstruction quality deteriorates around damaged regions, resulting in larger reconstruction errors that indicate potential anomalies. These reconstruction error maps serve as the foundation for automatic defect localization.

To further improve spatial feature learning, the methodology additionally investigates a Convolutional Autoencoder (CAE). Unlike fully connected Autoencoders, the CAE utilizes convolutional layers that preserve spatial relationships among neighboring pixels while extracting hierarchical texture features. The encoder progressively compresses the wire rope image through convolutional operations and feature map generation, whereas the decoder reconstructs the original image using deconvolution operations. The proposed CAE employs ReLU activation functions throughout the hidden layers and a Sigmoid activation function at the output layer to generate reconstructed grayscale images. Model optimization is performed using the Adam optimizer, while Mean Squared Error (MSE) serves as the reconstruction loss function. According to the experimental configuration, the network is trained for 100 epochs, enabling effective learning of normal wire rope appearance.

After image reconstruction, the proposed framework calculates the reconstruction error image by measuring pixel-wise differences between the original input image and the reconstructed output generated by the Autoencoder or CAE. Normal wire rope regions generally produce minimal reconstruction error because they closely resemble the training data. Conversely, damaged regions such as wire breakage and excessive wear generate larger reconstruction errors because the model has not learned these abnormal visual patterns during training. Consequently, the reconstruction error image effectively highlights candidate defect locations requiring further analysis.

To isolate abnormal regions from reconstruction error images, the methodology incorporates Otsu thresholding. Otsu's method automatically determines an optimal threshold value that separates foreground defect regions from background reconstruction noise by maximizing inter-class variance. Compared with manually selected threshold values, automatic threshold determination improves robustness and eliminates operator dependency. The resulting binary image clearly distinguishes potential defect regions from normal background textures, providing a suitable input for subsequent connectivity analysis.

Following threshold segmentation, the proposed framework performs connectivity analysis to improve defect localization accuracy. The methodology utilizes 4-connectivity analysis to identify connected pixel regions corresponding to candidate anomalies. Small isolated regions generated by reconstruction noise are eliminated, while larger connected components representing genuine surface defects are preserved. Connectivity analysis therefore reduces false detections while improving localization of wear-related abnormalities identified by the Autoencoder reconstruction process.

In parallel with deep learning-based anomaly detection, the proposed methodology incorporates a Gabor filter-based image processing module for identifying fine wire breakage. Gabor filters analyze local spatial frequency and orientation information associated with the regular strand patterns of wire ropes. Since broken wires disrupt these regular directional textures, Gabor filtering produces strong responses around defect locations. The extracted texture responses are subsequently analyzed to identify localized structural discontinuities that may not be sufficiently emphasized by reconstruction-based anomaly detection alone. The integration of Gabor filtering therefore complements the Autoencoder by improving sensitivity to minute surface defects and individual broken wires.

The outputs generated by the Autoencoder, Convolutional Autoencoder, and Gabor filter are comparatively analyzed to evaluate their effectiveness for different categories of wire rope damage. Reconstruction-based methods primarily identify wear-related abnormalities through anomaly localization, whereas Gabor filtering demonstrates superior capability for detecting fine wire breakage because of its sensitivity to local texture orientation changes. This comparative evaluation enables objective assessment of the strengths and limitations associated with each image processing technique.

Finally, the proposed framework produces the wire rope inspection result, where abnormal regions are highlighted and classified as potential damage requiring maintenance or replacement. The combination of anomaly detection, texture analysis, threshold segmentation, and connectivity analysis enables accurate localization of defects while minimizing false alarms. Since the methodology relies exclusively on normal training images, the framework significantly reduces the effort associated with collecting large annotated defect datasets while remaining capable of identifying previously unseen damage patterns.

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Overall, the proposed methodology establishes a comprehensive automated inspection framework by integrating image acquisition, image preprocessing, Autoencoder, Convolutional Autoencoder (CAE), Gabor filter-based texture analysis, Otsu thresholding, 4-connectivity analysis, and anomaly localization within a unified image processing architecture. The coordinated interaction among these components enables reliable detection of wire breakage and surface wear while providing an efficient, scalable, and practical solution for intelligent wire rope inspection in construction machinery and industrial lifting applications.

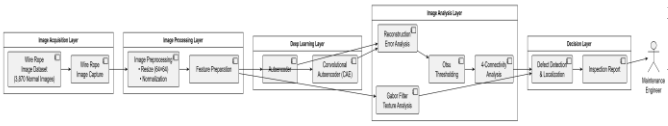

Fig. 1. Proposed System Architecture

IV. SYSTEM ARCHITECTURE

The proposed system architecture is designed as an intelligent image processing-based inspection framework for automatically detecting wire rope defects in construction machinery through the integration of deep learning, image enhancement, and classical computer vision techniques. The architecture combines image acquisition, preprocessing, anomaly detection, texture analysis, segmentation, connectivity analysis, and defect localization within a unified inspection pipeline. Unlike conventional manual inspection methods that depend heavily on operator experience, the proposed architecture performs automated analysis of wire rope images using Autoencoder, Convolutional Autoencoder (CAE), Gabor filtering, Otsu thresholding, and connectivity analysis, thereby improving inspection consistency, reliability, and operational efficiency.

The inspection process begins with the Image Acquisition Module, where high-resolution images of wire ropes are captured using a digital imaging system. The collected dataset consists of 3,870 defect-free wire rope images, which are used for training the deep learning models. Since damaged wire rope images are relatively limited in practical maintenance environments, the proposed framework adopts an unsupervised anomaly detection strategy, allowing the learning process to depend exclusively on normal images. This approach enables the system to recognize abnormal visual patterns during testing without requiring manually labeled defect samples.
Following image acquisition, all images enter the Image Preprocessing Module, where several enhancement operations are performed before feature extraction. Initially, every image is resized to 64 × 64 pixels to provide a standardized input dimension for the neural network. Image normalization is then performed to reduce variations caused by illumination differences and camera acquisition conditions. These preprocessing operations improve training stability while preserving important structural characteristics of the wire rope surface. The processed dataset is subsequently divided into training and testing subsets, with only normal images used for model learning and defective images reserved for evaluation.

The preprocessed images are then forwarded to the Autoencoder Learning Module. The Autoencoder consists of two major components: an encoder, which compresses the input image into a compact latent representation, and a decoder, which reconstructs the original image from the encoded features. During training, the network learns the visual characteristics of defect-free wire ropes by minimizing the reconstruction error between the original and reconstructed images. The optimization process utilizes the Adam optimizer, while Mean Squared Error (MSE) serves as the reconstruction loss function. According to the experimental configuration, the Autoencoder is trained for 100 epochs, allowing the network to effectively model normal wire rope appearance. To improve spatial feature learning, the proposed architecture also incorporates a Convolutional Autoencoder (CAE). Unlike the conventional Autoencoder, the CAE replaces fully connected layers with convolutional operations that preserve spatial information within the image. The encoder progressively extracts hierarchical texture features through convolutional layers using ReLU activation functions, while the decoder reconstructs the original image using corresponding deconvolution operations and a Sigmoid activation function at the output layer. The convolutional structure enables the CAE to capture local spatial characteristics of wire rope textures more effectively, thereby improving reconstruction quality for normal images.

After reconstruction, the outputs generated by both Autoencoder models are transferred to the Reconstruction Error Analysis Module. The system computes the pixel-wise difference between the original input image and its reconstructed version to generate an error map. Regions exhibiting low reconstruction error are considered normal because they closely resemble the training data. Conversely, damaged areas produce significantly higher reconstruction errors since the trained network cannot accurately reconstruct visual patterns that were absent during training. The resulting reconstruction error image therefore highlights potential defect locations requiring further analysis.

The proposed architecture subsequently performs Image Segmentation using Otsu thresholding. Otsu's algorithm automatically determines an optimal threshold value that separates foreground anomaly regions from background reconstruction noise. Compared with manually selected thresholds, automatic threshold estimation provides greater robustness and improves adaptability across different inspection conditions. The binary segmentation output clearly isolates candidate defect regions while suppressing minor reconstruction artifacts.

Following segmentation, the architecture applies 4-connectivity analysis to improve defect localization. Connected component analysis identifies groups of neighboring pixels belonging to the same abnormal region. Small isolated regions caused by image noise are eliminated, whereas larger connected regions corresponding to wear or structural damage are preserved for further evaluation. Connectivity analysis therefore improves localization accuracy while reducing false-positive detections generated during threshold segmentation.

Parallel to anomaly detection, the proposed architecture incorporates a dedicated Gabor Filter Analysis Module. The Gabor filter extracts local texture and orientation information from wire rope images by analyzing spatial frequency responses. Since normal wire ropes exhibit highly regular strand textures, broken wires introduce localized directional discontinuities that generate strong Gabor responses. Consequently, the Gabor filter effectively detects fine wire breakage that may not produce sufficiently large reconstruction errors within Autoencoder-based anomaly detection. The combination of deep learning reconstruction and texture analysis therefore provides complementary inspection capabilities for different defect categories.

The outputs generated by the Autoencoder, Convolutional Autoencoder, and Gabor Filter are subsequently integrated within the Decision Module, where detected anomalies are comparatively analyzed. Reconstruction-based methods primarily identify larger wear regions and surface deterioration, whereas the Gabor filter excels at recognizing individual broken wires and localized texture discontinuities. The combined evaluation enables the framework to provide more comprehensive wire rope inspection than relying on any individual technique alone.

Finally, the architecture produces the Inspection Result Module, where abnormal regions are highlighted and classified as potential wire rope defects requiring maintenance or replacement. The system displays localized defect regions together with processed inspection images, enabling maintenance personnel to rapidly evaluate wire rope condition and schedule appropriate corrective actions. Since the proposed methodology relies exclusively on normal training images, it significantly reduces dataset preparation effort while maintaining the capability to identify previously unseen defect patterns.

Overall, the proposed system architecture successfully integrates image acquisition, image preprocessing, Autoencoder, Convolutional Autoencoder (CAE), reconstruction error analysis, Otsu thresholding, 4-connectivity analysis, Gabor filtering, and automated defect localization into a unified intelligent inspection framework. The coordinated interaction among these modules enables accurate detection of wire breakage and wear-related abnormalities while improving inspection consistency, reducing manual effort, and supporting safer operation of construction machinery and industrial lifting equipment.

V. FEATURE ENHANCEMENT

The proposed wire rope inspection framework incorporates several enhancements that improve the accuracy, robustness, automation, and practical applicability of defect detection in construction machinery. By integrating Autoencoder-based anomaly detection, Convolutional Autoencoder (CAE), Gabor filter-based texture analysis, Otsu thresholding, and connectivity analysis, the framework provides a comprehensive image processing solution capable of identifying wire breakage, surface wear, and other visual abnormalities with minimal human intervention. Unlike conventional manual inspection procedures that depend heavily on operator expertise, the proposed framework automatically analyzes wire rope images and objectively identifies abnormal regions, thereby improving inspection consistency and operational safety.

One of the primary enhancements introduced by the proposed methodology is the implementation of an unsupervised anomaly detection strategy. Instead of requiring extensive collections of manually labeled defect images, the Autoencoder is trained exclusively using normal wire rope images. During testing, the model identifies abnormalities by analyzing reconstruction errors between the original and reconstructed images. This learning strategy significantly reduces dataset preparation effort while enabling the framework to detect previously unseen defects that were not explicitly represented during training. The ability to operate without defect annotations greatly improves the practicality of industrial deployment where abnormal samples are relatively scarce.

Another important enhancement is the incorporation of a Convolutional Autoencoder (CAE) for improved spatial feature learning. Unlike conventional Autoencoders that utilize fully connected layers, the CAE employs convolutional operations capable of preserving spatial relationships within the input image. The convolutional architecture effectively captures local texture patterns and structural characteristics associated with normal wire rope surfaces, resulting in improved image reconstruction quality. By utilizing ReLU activation functions, a Sigmoid output layer, the Adam optimizer, and Mean Squared Error (MSE) as the reconstruction loss function, the CAE achieves stable learning performance throughout 100 training epochs while maintaining efficient computational complexity.

The proposed framework further enhances inspection reliability through comprehensive image preprocessing. All captured wire rope images are resized to a standardized resolution of 64 × 64 pixels, followed by image normalization to reduce variations caused by illumination

conditions and camera acquisition differences. These preprocessing operations improve training stability while preserving important structural information required for anomaly detection. Standardized image representation also enables consistent performance across different inspection environments and simplifies subsequent feature extraction.
A significant enhancement of the proposed methodology is the integration of reconstruction error analysis for automatic defect localization. After reconstructing the input image, the framework computes the pixel-wise difference between the original image and its reconstructed counterpart. Regions exhibiting high reconstruction error are interpreted as potential anomalies because the trained Autoencoder cannot accurately reproduce image patterns that differ from the normal training data. This reconstruction-based anomaly detection mechanism provides an effective means of identifying wear-related defects without requiring explicit defect classification models.

To improve segmentation accuracy, the proposed framework incorporates Otsu thresholding for automatic binary image generation. Rather than selecting threshold values manually, Otsu's algorithm determines an optimal threshold by maximizing the variance between foreground and background image regions. Automatic threshold selection improves segmentation robustness while eliminating operator dependency during defect extraction. Consequently, the segmented images more accurately isolate abnormal regions corresponding to potential wire rope damage.

Another important enhancement is the implementation of 4-connectivity analysis following threshold segmentation. Connected component analysis groups neighboring pixels into continuous regions representing candidate defects while eliminating isolated noisy pixels that may otherwise generate false detections. This connectivity-based filtering improves localization accuracy for wear-related abnormalities by preserving only meaningful connected regions corresponding to actual structural damage. As a result, the framework significantly reduces false-positive detections while improving overall inspection reliability.

The proposed methodology also integrates a Gabor filter-based texture analysis module to improve sensitivity toward fine wire breakage. Wire ropes possess highly regular directional strand textures that generate characteristic spatial frequency patterns. Broken wires disrupt these patterns, producing localized texture variations that are effectively captured by Gabor filters. Unlike reconstruction-based anomaly detection, which primarily identifies larger abnormal regions, Gabor filtering excels at detecting very small structural discontinuities associated with individual broken wires. The complementary use of Gabor filtering therefore substantially enhances the framework's capability for detecting subtle surface defects that may otherwise remain undetected.

Another enhancement involves the comparative evaluation of multiple inspection techniques. Rather than relying exclusively on a single image processing algorithm, the proposed framework evaluates both Autoencoder-based anomaly detection and Gabor filter-based texture analysis. Experimental observations indicate that Autoencoder reconstruction effectively identifies surface wear through reconstruction error analysis, whereas the Gabor filter demonstrates superior performance for detecting localized wire breakage. This comparative strategy enables maintenance personnel to understand the strengths and limitations of each inspection method while supporting more reliable defect assessment.

The framework further improves computational efficiency by utilizing compact image dimensions and optimized neural network architecture. Training images are resized to 64×64 pixels, reducing computational complexity without significantly affecting defect visibility. The encoder-decoder architecture combined with efficient convolutional operations enables practical model training and inference suitable for industrial inspection systems where rapid analysis is desirable. Optimization using the Adam algorithm further accelerates network convergence while maintaining stable reconstruction performance.

An additional enhancement is the framework's modular architecture, which enables straightforward integration of future inspection technologies. Since the system consists of independent modules for image acquisition, preprocessing, Autoencoder learning, CAE analysis, Gabor filtering, threshold segmentation, connectivity analysis, and defect localization, additional image enhancement algorithms or deep learning architectures can be incorporated without major architectural modifications. This modular design improves system flexibility and facilitates future research involving transformer-based vision models, attention mechanisms, or advanced anomaly detection techniques.

Overall, the proposed feature enhancements establish a comprehensive and intelligent wire rope inspection framework by integrating image preprocessing, Autoencoder, Convolutional Autoencoder (CAE), reconstruction error analysis, Otsu thresholding, 4-connectivity analysis, Gabor filtering, and unsupervised anomaly detection within a unified image processing architecture. These enhancements significantly improve defect localization accuracy, reduce dependence on manually labeled datasets, minimize false detections, enhance computational efficiency, and provide a scalable solution for automated wire rope monitoring in construction machinery and industrial lifting applications.

VI. RESULTS AND DISCUSSION

The proposed wire rope inspection framework was experimentally evaluated to investigate the effectiveness of Autoencoder-based anomaly detection, Convolutional Autoencoder (CAE), and Gabor filter-based image

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processing for detecting wire rope defects under practical inspection conditions. The experiments were conducted using a dataset consisting of 3,870 normal wire rope images, which were employed for model training. Since the proposed methodology follows an unsupervised anomaly detection strategy, only defect-free images were used during training, while images containing wire breakage and wear defects were utilized exclusively during performance evaluation. The primary objective of the experiments was to assess the capability of each image processing technique to accurately identify abnormal regions while minimizing false detections and reducing dependence on manually labeled defect datasets.

Prior to model training, all collected images underwent comprehensive preprocessing to ensure consistent input representation. Each wire rope image was resized to 64 × 64 pixels, followed by normalization to reduce variations caused by illumination conditions and image acquisition settings. These preprocessing operations improved network convergence and enabled the Autoencoder models to learn representative visual features associated with defect-free wire rope surfaces. The training process was performed using the Adam optimizer, Mean Squared Error (MSE) as the reconstruction loss function, ReLU activation functions within hidden layers, a Sigmoid activation function for image reconstruction, and a total of 100 training epochs. The optimized training configuration enabled stable convergence while preserving important structural characteristics required for anomaly detection.

The first experimental analysis focused on evaluating the performance of the Autoencoder for anomaly detection. Since the Autoencoder was trained exclusively using normal wire rope images, it successfully reconstructed defect-free wire rope surfaces with minimal reconstruction error. During testing, images containing abnormal regions generated noticeably larger reconstruction errors because the learned model could not accurately reproduce visual patterns corresponding to wire damage. The resulting reconstruction error maps effectively highlighted regions associated with surface wear and other structural abnormalities. These findings demonstrate that reconstruction-based anomaly detection provides an efficient mechanism for identifying deviations from normal wire rope appearance without requiring explicitly labeled defect samples.

To improve spatial feature learning, a Convolutional Autoencoder (CAE) was subsequently evaluated. The convolutional architecture preserved spatial relationships among neighboring pixels while extracting hierarchical texture features through convolutional operations. Experimental observations indicated that the CAE generated higher-quality image reconstructions than the conventional Autoencoder for normal wire rope images. However, despite improved reconstruction capability, the CAE also reconstructed certain abnormal regions with relatively high accuracy, thereby reducing reconstruction error around some defects. Consequently, the localization of small anomalies became less distinct, limiting the effectiveness of CAE for identifying extremely fine wire breakage through reconstruction error analysis alone.

The proposed framework further incorporated Otsu thresholding to segment reconstruction error images automatically. Rather than relying on manually selected threshold values, Otsu's algorithm determined an optimal threshold that separated abnormal regions from background reconstruction noise. Experimental evaluation demonstrated that automatic threshold selection effectively isolated candidate wear regions while reducing operator dependency during segmentation. The resulting binary images provided a suitable foundation for subsequent connectivity analysis and defect localization.

Following segmentation, 4-connectivity analysis was employed to identify connected abnormal regions corresponding to potential wire rope defects. Small isolated regions generated by reconstruction noise were successfully eliminated, whereas larger connected components associated with actual surface deterioration were preserved. Experimental observations indicated that connectivity analysis significantly improved localization of wear-related defects while reducing false-positive detections caused by image noise. Consequently, the combination of Autoencoder reconstruction, Otsu thresholding, and connectivity analysis produced reliable identification of wear regions requiring maintenance attention.

The second major experimental investigation evaluated the performance of the Gabor filter-based image processing method. Unlike reconstruction-based anomaly detection, which identifies deviations from learned normal appearance, the Gabor filter analyzes local spatial frequency and directional texture information associated with wire rope strands. Experimental results demonstrated that the Gabor filter generated strong responses around localized wire breakage because broken strands disrupt the regular directional texture of the wire rope surface. These localized frequency variations were effectively emphasized through Gabor filtering, allowing small wire breakage to be detected more clearly than through Autoencoder reconstruction.

Comparative analysis revealed that the Gabor filter outperformed both the conventional Autoencoder and the Convolutional Autoencoder for detecting fine wire breakage. Although Autoencoder-based methods successfully identified relatively large abnormal wear regions through reconstruction error analysis, their sensitivity to individual broken wires remained limited because small structural discontinuities often produced only modest reconstruction differences. In contrast, the Gabor filter directly analyzed local texture orientation, making it particularly effective for identifying subtle wire discontinuities. These observations indicate that texture-

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based analysis provides important complementary information that enhances overall inspection capability.

The experiments also demonstrated that the proposed framework performs differently depending on the defect category being analyzed. Surface wear generally produced larger abnormal regions that were accurately localized through Autoencoder reconstruction combined with connectivity analysis. Conversely, individual wire breakage generated localized directional texture disturbances that were detected more effectively using Gabor filtering. Therefore, neither approach independently provides optimal performance for all defect categories. Instead, combining reconstruction-based anomaly detection with texture analysis enables more comprehensive wire rope inspection than relying on either technique alone.

The qualitative evaluation of inspection results further confirmed the effectiveness of the integrated framework. Visual comparison between original images, reconstructed images, reconstruction error maps, segmented defect regions, and Gabor filter responses demonstrated that each processing stage contributed to improved defect localization. The Autoencoder effectively highlighted abnormal wear areas, Otsu thresholding automatically extracted candidate defect regions, connectivity analysis eliminated isolated noise, and the Gabor filter successfully emphasized localized wire breakage. The complementary interaction among these techniques significantly improved inspection reliability while reducing false detections.

Overall, the experimental evaluation demonstrates that the proposed image processing framework provides an effective solution for automated wire rope inspection. The Autoencoder successfully identifies wear-related anomalies through reconstruction error analysis, the Convolutional Autoencoder improves image reconstruction quality, and the Gabor filter effectively detects fine wire breakage through texture analysis. The integration of Otsu thresholding, 4-connectivity analysis, and unsupervised anomaly detection further enhances localization accuracy while minimizing dependence on manually labeled datasets. These findings confirm that combining deep learning with classical image processing techniques offers a practical, scalable, and reliable approach for intelligent wire rope condition monitoring in construction machinery and industrial lifting applications.

VII. CONCLUSION

This paper presented an intelligent image processing-based framework for automated wire rope defect detection by integrating Autoencoder-based anomaly detection, Convolutional Autoencoder (CAE), Gabor filter-based texture analysis, Otsu thresholding, and connectivity analysis within a unified inspection system. The proposed methodology was developed to improve the reliability of wire rope inspection while reducing dependence on manual visual assessment and extensive labeled defect datasets. By utilizing only normal wire rope images for model training, the framework effectively identifies abnormal regions through reconstruction error analysis while complementing deep learning with classical image processing techniques for comprehensive defect localization.

The proposed inspection framework begins with image acquisition and preprocessing, where wire rope images are resized to 64 × 64 pixels and normalized before feature learning. The Autoencoder and Convolutional Autoencoder are trained using 3,870 normal wire rope images, employing the Adam optimizer, ReLU and Sigmoid activation functions, Mean Squared Error (MSE) as the loss function, and 100 training epochs. During testing, reconstruction error analysis successfully identifies abnormal regions by comparing the original input images with their reconstructed outputs. The incorporation of Otsu thresholding and 4-connectivity analysis further improves segmentation and localization of wear-related defects while reducing false-positive detections.

Experimental evaluation demonstrated that each image processing technique contributes unique advantages to the overall inspection framework. The Autoencoder effectively detects surface wear and larger abnormal regions through anomaly reconstruction, while the Convolutional Autoencoder improves image reconstruction quality by preserving spatial information using convolutional layers. However, the experiments also revealed that reconstruction-based methods exhibit limited sensitivity when identifying extremely fine wire breakage because subtle structural discontinuities may generate relatively small reconstruction errors.

The Gabor filter-based image processing method demonstrated superior capability for detecting fine wire breakage by analyzing local spatial frequency and directional texture information. Since broken wires disrupt the regular orientation patterns of wire rope strands, Gabor filtering effectively emphasizes localized texture discontinuities that are difficult to identify using reconstruction-based anomaly detection alone. The comparative analysis therefore confirms that combining deep learning with classical texture analysis provides more comprehensive inspection performance than relying on a single image processing technique.

An important contribution of the proposed research is the implementation of an unsupervised anomaly detection strategy, which eliminates the requirement for extensive collections of manually labeled defect images. Because only normal wire rope images are required during training, the framework significantly reduces dataset preparation effort while maintaining the ability to identify previously unseen abnormalities. This characteristic greatly enhances the practicality of deploying the proposed inspection system within industrial environments where abnormal samples are limited and continuously evolving.

The proposed framework offers considerable practical benefits for numerous industrial applications involving construction machinery, cranes, elevators, mining equipment, cable transportation systems, and other heavy lifting mechanisms. Automated inspection improves maintenance efficiency by providing objective defect identification, reducing operator workload, minimizing inspection time, and supporting preventive maintenance strategies that enhance equipment reliability and operational safety.

Overall, the proposed image processing framework establishes a practical, scalable, and reliable solution for intelligent wire rope inspection by integrating Autoencoder, Convolutional Autoencoder (CAE), Gabor filter, Otsu thresholding, 4-connectivity analysis, and unsupervised anomaly detection into a unified architecture. The coordinated interaction among these techniques enables effective detection of both surface wear and fine wire breakage, thereby improving inspection accuracy while reducing dependence on manual evaluation. The proposed methodology contributes toward safer operation of industrial lifting systems and demonstrates the effectiveness of combining deep learning with traditional image processing techniques for automated structural health monitoring.

Future research may focus on integrating Vision Transformers (ViT), attention-based deep learning architectures, YOLO-based real-time object detection, and multiscale feature extraction techniques to further improve defect localization accuracy and computational efficiency. Additionally, investigating higher-resolution imaging systems, real-time embedded deployment, multimodal sensor fusion, and adaptive anomaly detection algorithms may enhance inspection robustness under diverse industrial operating conditions, enabling the development of next-generation intelligent wire rope monitoring systems for practical field applications.

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