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RESEARCH ARTICLE

An Implementation of the Convolutional Neural Network Algorithm for Detecting Crack in 150 kV Transmission Line Insulator

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Abstract
To ensure the reliability of 150 kV transmission lines, routine inspections of insulators are essential, as these components can deteriorate over time. Recently, these inspections have been enhanced using Unmanned Aerial Vehicles (UAVs) or drones, allowing for faster and safer data collection. However, the rapid increase in image data has created a challenge in terms of analysis speed and accuracy. This study proposes a Convolutional Neural Network (CNN)-based algorithm capable of classifying drone-captured insulator images into two categories: normal and damaged. The developed model achieved a validation accuracy of 99.09%, with a precision of 99.44%, recall of 99.50%, and F1-score of 99.46%. The model was evaluated using three different test datasets. For Test Data 1 and Test Data 2, it correctly classified all 10 images in each set. In Test Data 3, the model achieved 9 correct predictions out of 10. These results demonstrate the proposed system's potential to accelerate image-based analysis in UAV-assisted inspections and contribute to more efficient maintenance of high-voltage transmission infrastructure.

Keywords: CNN, fault, insulator, UAV

I. Introduction

High-voltage power transmission systems play a vital role in delivering electrical energy from generation units to distribution networks [1]. The reliability and continuity of these systems depend heavily on the physical condition of main components, such as transmission towers, conductors, and especially insulators. Insulators are designed to electrically isolate high-voltage lines from supporting structures. Any physical damage, contamination, or degradation of insulators can lead to faults, line outages, and serious reliability issues [2].

To ensure reliable operation, transmission operators routinely conduct inspections as part of their preventive maintenance strategies. Conventional inspection methods typically involve manual climbing of transmission towers—commonly referred to as Climb Up Inspection (CUI)—allowing maintenance personnel to visually examine insulators and other components [1]. Although this method enables close-range observation, it is time-consuming, labor-intensive, and poses safety risks, particularly in high structures or remote areas.

With advancements in aerial imaging and robotics, drones have emerged as an efficient alternative for conducting visual inspections of transmission lines [3]. UAVs offer multiple advantages, including reduced inspection time, enhanced safety, and access to difficult or hazardous locations. Drone-based inspections enable the rapid collection of high-resolution imagery across large transmission segments without interrupting power delivery [4].

Insulators are critical components in high-voltage transmission systems [1]. One of the most common issues with insulators is physical damage, such as cracks or breakage, which can occur due to mechanical stress, corrosion—particularly in coastal or dusty areas—or lightning strikes. Damaged insulators can reduce insulation performance and lead to faults or outages, making early detection critical for system reliability.

Glass insulators are widely used due to their high mechanical strength, good resistance to electrical degradation, and transparency, which allows damage to be easily identified. They also tend to shatter completely when broken, making failures more noticeable during inspection. Critically, each disc in an insulator string contributes to the overall dielectric strength; even a single broken disc can lower the voltage withstand capability below safe limits, especially in polluted or high-humidity environments. As such, prompt replacement of damaged insulators is essential to prevent flashover events and maintain the operational reliability of the transmission system.

Due to the high frequency of lightning strikes in many regions, visual inspections of insulators are conducted frequently to ensure system reliability [2]. In recent years, the use of UAV or drones has become a common method for performing these inspections efficiently and safely [5]. However, this practice has introduced a new challenge: the large volume of images generated during each inspection session requires substantial time and effort for manual analysis. To address this issue, this study proposes the development of an automated classification system based on CNN, capable of distinguishing between normal and broken insulator images captured by drones. This approach aims to

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accelerate the inspection process while maintaining high accuracy and consistency in fault detection.

Several studies have applied image-based analysis for condition monitoring in high-voltage transmission systems [6]. For instance, previous research has focused on detecting physical damage on transmission conductors, such as strand breakage and corrosion, using UAV imagery combined with deep learning approaches [3]. These studies demonstrate the effectiveness of computer vision techniques in identifying critical faults that could lead to outage. However, most of these methods are tailored for conductor-related anomalies and do not address issues in other key components such as insulators. In contrast, this study targets the detection of broken insulator discs, which are equally critical in ensuring system reliability. This study aims to expedite the processing of visual inspection images, enabling faster identification of insulator defects in high-voltage transmission systems.

The main contribution of this study is addressing the inefficiencies associated with conventional visual inspection workflows, where images captured by Unmanned Aerial Vehicles (UAVs) are manually reviewed by human operators. This manual process is not only time-consuming but also susceptible to inconsistencies and errors, particularly due to operator fatigue when analyzing large volumes of data. To mitigate these issues, this research introduces an automated classification framework based on a Convolutional Neural Network (CNN) capable of distinguishing between normal and broken insulator conditions. The proposed system facilitates rapid and reliable defect identification, thereby enhancing the overall efficiency and accuracy of condition monitoring in high-voltage transmission systems.

II. Method

This research applies a Convolutional Neural Network (CNN) to enhance the analysis process of visual inspection results on glass insulators, transforming what has traditionally been a manual task into an automated classification system. The developed program categorizes insulators into two classes: normal and broken. This binary classification is justified by the typical failure characteristics of glass insulators, which tend to shatter completely when subjected to significant damage, especially from lightning strikes.

A. Dataset

In this study, the dataset consists of images obtained from drone-based visual inspections of 150 kV overhead transmission line insulators. The images specifically capture the condition of glass insulators and are categorized into two classes: normal and cracked, which can be seen in Fig. 2. This classification serves as the foundation for training and evaluating the proposed image classification model.

A total of 1,169 images of glass insulators were used, consisting of 1,017 images of insulators in normal condition and 152 images showing cracked or broken insulators. The detailed distribution of the dataset is presented in Table I.

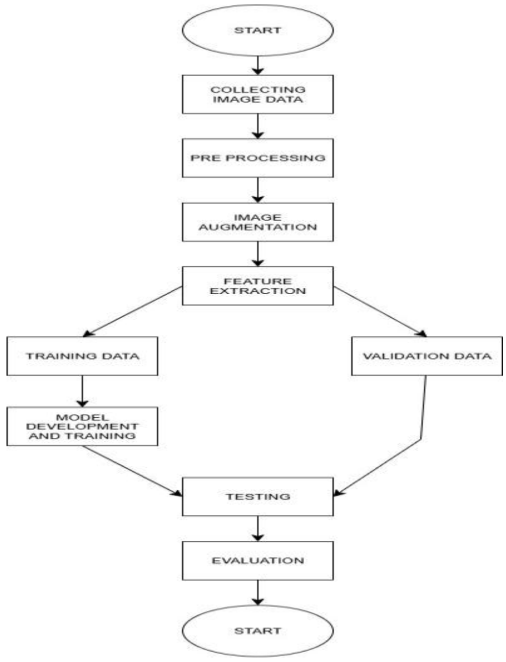

Fig. 1. Research Workflow

Fig. 2. Example of dataset, crack (left) and normal (right)

TABLE I. Quantity of Dataset Images

Dataset Images	
Normal	**Crack**
1017	152

B. Pre Processing

To ensure uniformity in input dimensions, all images underwent a pre-processing stage in which they were resized to 150 × 150 pixels with three RGB color channels, resulting in a standardized shape of (150, 150, 3). This resolution was selected to maintain essential visual features while reducing computational overhead. This resolution was chosen to retain critical visual features while minimizing computational cost. With over 1,000 images in the dataset, higher resolutions would have significantly increased memory usage and training time, thus affecting model efficiency.

C. Image Augmentation

Image augmentation is a data engineering technique employed to enhance the model's reliability in detecting objects under varying visual conditions. This approach enables the model to maintain accurate predictions despite differences in image orientation—such as portrait and landscape modes—and variations in visual characteristics, including contrast and rotation. The application of augmentation is particularly important in this study due to the lack of standardized benchmarks across the diverse data sources utilized. The augmentation techniques applied include horizontal flip, vertical flip, 90-degree rotation, -90-degree rotation, gamma contrast, sigmoid contrast, and linear contrast.

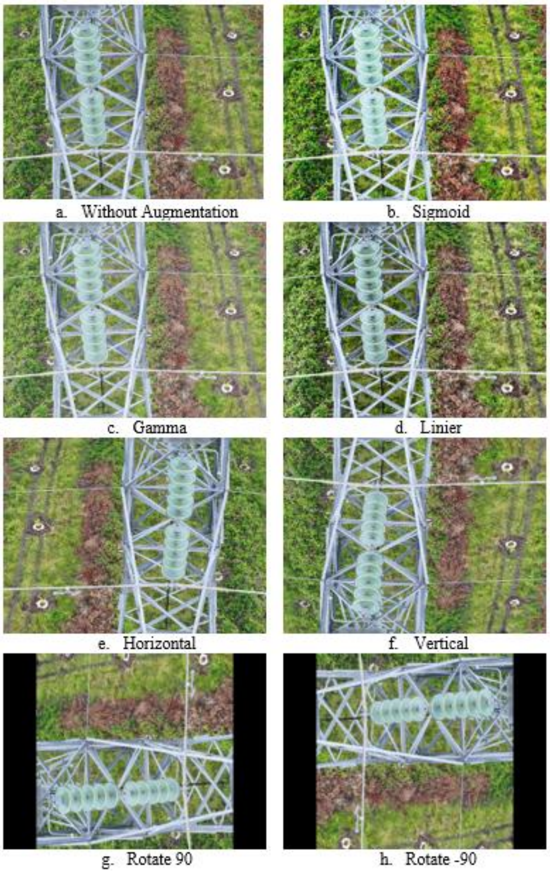

Fig. 3. Augmentation

Following the augmentation process, the number of images representing normal insulators increased to 8136, while the number of images depicting broken insulators reached 1216.

D. Data Set Splitting

In this study, the dataset was partitioned into training and validation subsets to facilitate model development and performance evaluation. A standard 80:20 split ratio was adopted, with 80% of the total images used for training the CNN model and the remaining 20% reserved for validation. This approach ensures that the model learns effectively from a majority of the data while maintaining a separate set for unbiased performance assessment.

TABLE II. DATA SPLITTING

	Train	**Validation**
Normal	6513	1623
Crack	968	248

E. CNN Architecture

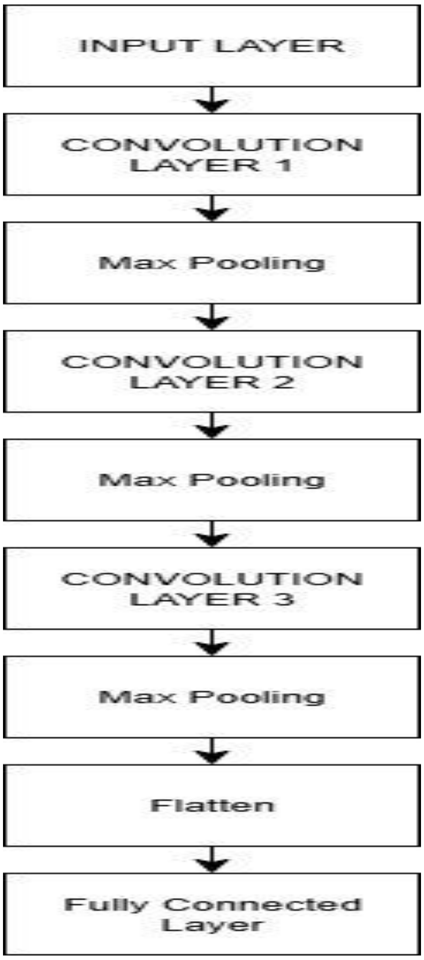

Fig. 4. CNN Architecture

The architecture begins with an input layer that receives RGB images with a fixed dimension of 150 × 150 × 3. The first convolutional layer (Conv1) applies 32 filters with a kernel size of 3 × 3 and uses 'same' padding to maintain the original image size. The ReLU activation function is used to introduce non-linearity [7][8]. This is followed by a MaxPooling2D layer with a pool size of 2 × 2, which reduces the spatial dimensions by half and helps extract the most important features.

The second convolutional layer (Conv2) increases the number of filters to 64, again using 3 × 3 kernels and ReLU activation. A second MaxPooling2D layer is applied to further downsample the feature maps. Next, the third convolutional layer (Conv3) uses 128 filters, followed by another MaxPooling2D layer to compress the data even more.

After the convolutional and pooling stages, a Flatten layer is used to convert the 3D feature maps into a 1D vector.

This output is then passed through two fully connected (Dense) layers with 256 and 128 neurons, respectively, both using ReLU activation. Finally, the output layer consists of 2 neurons with a softmax activation function, which generates the probability distribution for the two classes: normal and broken insulators.

This architecture is designed to extract and learn spatial features from images effectively. The use of multiple convolutional and pooling layers helps reduce the input size gradually, while still capturing important visual patterns. The softmax function at the end ensures that the model can classify input images into one of the two target categories with probabilistic output [9].

III. RESULT

The training process in this study was conducted over 25 epochs, utilizing an early stopping mechanism to prevent overfitting. Upon achieving satisfactory training and validation accuracy, along with low loss values, the model was evaluated using three distinct test datasets. Each test set comprised 10 randomly selected images, including 7 images of normal insulators and 3 images of broken insulators. This testing phase aimed to assess the model's ability to accurately classify insulator conditions based on unseen data samples.

A. *Training Result*

The training accuracy trend was obtained as illustrated in figure below :

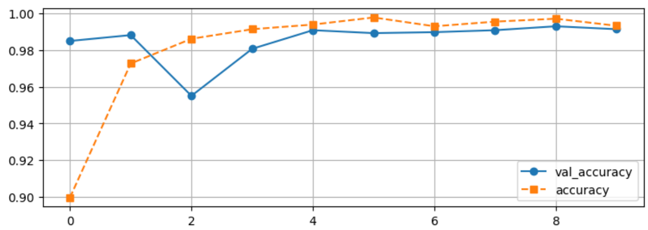

Fig. 5. Accuracy graph

Fig. 5 illustrates the model's accuracy throughout the training process over 25 epochs, with early stopping enabled. The early stopping mechanism was configured with a patience value of 5, allowing the training to halt if the validation accuracy did not improve or began to decline. As observed, training was terminated after the 10th epoch due to a stagnation in validation performance.

During the initial phase of training, both the training and validation accuracy curves exhibited a strong upward trend, indicating that the model rapidly learned basic patterns from the dataset. The training accuracy continued to rise, eventually reaching near-perfect levels and remaining stable throughout the remaining epochs. This suggests that the model successfully captured the training data characteristics.

The validation accuracy followed a similar trend, despite a slight drop at epoch 2. This temporary decline is likely attributed to the model's early struggle to adapt to data augmentation variability and initial feature complexity, even though training loss remained low. Subsequently, the validation accuracy improved and stabilized within the range of 98% to 99%.

The close alignment between the training and validation curves indicates that the model generalized well to unseen data, with no signs of overfitting. The corresponding loss trend observed during training is presented in Fig. 6.

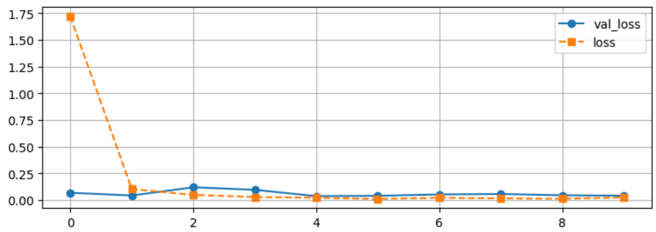

Fig. 6. Loss graph

Fig. 6 illustrates the loss values observed during the model training process over 25 epochs, displaying two primary curves: training loss (orange line) and validation loss (blue line). At the beginning of training (epoch 0), the training loss was recorded at 1.75. However, after just one epoch, the loss value dropped significantly and approached near-zero levels. In subsequent epochs, the loss remained consistently low and stable for both training and validation datasets. The small gap between training and validation loss indicates that the model was not only able to fit the training data effectively but also generalize well to unseen validation data. These results suggest that the model did not exhibit signs of overfitting.

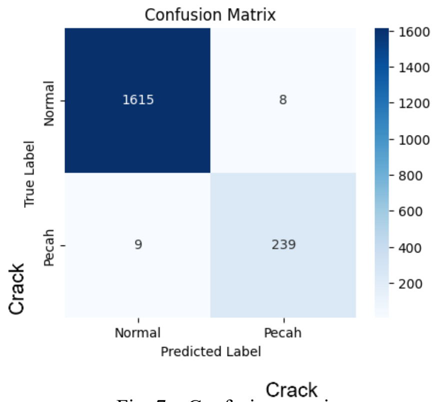

Fig. 7. Confusion Matrix

As shown in Fig. 7, the model successfully classified 1,615 out of 1,623 normal insulator images as normal (True Positive), while misclassifying 8 images as cracked (False Negative). Among the 248 cracked insulator images, 239 were correctly identified as cracked (True Negative), with 9 images incorrectly classified as normal (False Positive).

Overall, the model demonstrates strong performance, with a high correct classification rate across both classes. The number of misclassifications is relatively low, particularly for the normal class, where only 8 out of 1,623 predictions were incorrect. This indicates that the model exhibits good sensitivity to the majority class and satisfactory accuracy in recognizing the minority class (cracked). However, there is a slight tendency for the model to classify cracked insulators as normal, as reflected by the higher number of false positives (9 instances).

Further evaluation can be conducted using performance metrics such as accuracy, precision, recall, and F1-score. The accuracy derived from the confusion matrix is calculated as follows [10]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Accuracy = \frac{1615 + 239}{1615 + 9 + 239 + 8} \tag{1}$$

$$Accuracy \approx 99.09\%$$

The proposed model achieved a classification accuracy of 99.09%, indicating a high level of performance in correctly identifying the condition of insulators from the test images. This result demonstrates the model's ability to generalize well and accurately reflect the true condition of the data. Notably, the model also performed well in recognizing the minority class—cracked insulators—with 239 out of 248 images correctly classified. This highlights the model’s effectiveness in detecting damaged insulators, which is critical for ensuring the reliability and safety of transmission systems.

$$Precision = \frac{TP}{TP + FN}$$

$$Precision = \frac{1615}{1615 + 9} \tag{2}$$

$$Precision \approx 99.44\%$$

Meanwhile, the precision of the developed model reached 99.44%, which is particularly important in the context of this application. Minimizing false positives—i.e., cases where damaged insulators are incorrectly classified as normal—is critical, as such misclassifications could result in undetected faults that may compromise the reliability and safety of the power transmission system.

$$Recall = \frac{TP}{TP + FN}$$

$$Recall = \frac{1615}{1615 + 8} \tag{3}$$

$$Recall \approx 99.50\%$$

The recall of the developed model reached 99.50%, indicating the model’s strong ability to correctly identify insulators in the positive (normal) condition, which aligns with the primary objective of this study.

$$F1 - score = 2x\frac{Precision\ x\ Recall}{Precision + Recall}$$

$$F1 - score = 2x\frac{0.9944\ x\ 0.9950}{0.9944\ +\ 0.9950} \tag{4}$$

$$F1 - score \approx 99.46$$

The F1-score, which represents the harmonic mean of precision and recall, was recorded at 99.46%. This value indicates that the model not only achieved high precision but also demonstrated strong capability in identifying all positive cases, reflecting a well-balanced and robust classification performance.

B. Testing

After the model was successfully developed and validated, a technical implementation was conducted to assess its capability in predicting unseen data. The testing was performed in three separate rounds, with each round involving ten input images. For each image, the model generated a classification output indicating whether the insulator depicted was in a normal or broken condition. The prediction results from the implemented model are summarized as follows.

TABLE III. DATA TEST 1 PREDICTION RESULT

File Name	Result	Assessment
1.1 Test.jpg	Normal	Normal
1.2 Test.jpg	Normal	Normal
1.3 Test.jpg	Normal	Normal
1.4 Test.jpg	Normal	Normal
1.5 Test.jpg	Normal	Normal
1.6 Test.jpg	Normal	Normal
1.7 Test.jpg	Normal	Normal
1.8 Test.jpg	Crack	Crack
1.9 Test.jpg	Crack	Crack
1.10 Test.jpg	Crack	Crack

As shown in Table 3, which presents a comparison between the program's simulation output and manual inspection results, the model achieved perfect classification performance, accurately predicting all 10 test images, resulting in an accuracy of 100%.

Table 4 presents a comparison between the program's predictions and manual inspection results. In this test, all 10 input images were correctly classified by the model, demonstrating a perfect match with human evaluation and yielding an accuracy of 100%.

TABLE IV. DATA TEST 2 PREDICTION RESULT

File Name	Result	Assessment
2.1 Test.jpg	Crack	Crack
2.2 Test.jpg	Normal	Normal
2.3 Test.jpg	Normal	Normal
2.4 Test.jpg	Normal	Normal
2.5 Test.jpg	Crack	Crack
2.6 Test.jpg	Normal	Normal
2.7 Test.jpg	Normal	Normal
2.8 Test.jpg	Normal	Normal
2.9 Test.jpg	Normal	Normal
2.10 Test.jpg	Crack	Crack

TABLE V. DATA TEST 3 PREDICTION RESULT

File Name	Result	Assessment
3.1 Test.jpg	Normal	Normal
3.2 Test.jpg	Normal	Normal
3.3 Test.jpg	Normal	Normal
3.4 Test.jpg	Crack	Crack
3.5 Test.jpg	Crack	Normal
3.6 Test.jpg	Crack	Crack
3.7 Test.jpg	Normal	Normal
3.8 Test.jpg	Crack	Crack
3.9 Test.jpg	Normal	Normal
3.10 Test.jpg	Normal	Normal

As shown in Table 5, which compares the program's output with manual inspection, the model misclassified one out of the ten test images—specifically, 3.5 Test.jpg was incorrectly predicted.

In the evaluation using Test Data 1 and Test Data 2, the model successfully predicted all images with perfect accuracy. However, during testing with Test Data 3, a single misclassification occurred. Overall, the average prediction accuracy across the three test sets reached 96.66%.

IV. CONCLUSION

This study successfully developed a CNN-based image classification model to detect the condition of glass insulators on 150 kV transmission lines, distinguishing between two classes: normal and crack. The designed architecture incorporates three convolutional layers, ReLU activation functions, max-pooling layers, and fully connected layers, resulting in excellent classification performance. Evaluation metrics indicate a validation accuracy of 99.09%, precision of 99.44%, recall of 99.50%, and an F1-score of 99.46%. These results demonstrate the model's effectiveness not only in identifying normal insulators but also in reliably detecting damaged ones.

The model was further evaluated using three separate test datasets. It achieved perfect predictions on both Test Data 1 and Test Data 2, correctly classifying all 10 images in each set. For Test Data 3, the model produced 9 correct predictions out of 10. While the overall performance remains high, these test results reveal that occasional misclassifications—both false positives and false negatives—still occur.

Therefore, despite its strong potential as an automated solution for visual condition monitoring of transmission insulators, further refinement is needed to improve the model's generalization capabilities, particularly in handling more diverse and complex damage scenarios.

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