Detection of components on power lines using images captured by UAVs

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***Abstract*—Preventive maintenance of power poles, including component inspection, is essential to ensure the continuous supply of electricity to cities. Despite its importance, the current practice of visually identifying issues demands considerable time and effort. To address this challenge, this study proposes the use of automatic methods for power pole inspection, aiming to reduce inspection time and predict potential component replacements. The investigation leverages convolutional neural networks based on Faster R-CNN to automatically evaluate power pole conditions. A dataset was generated from 848 images obtained from a repository available on the internet. The resulting neural network from the training process has an average precision of 98.7% with an Intersection over Union (IoU) of 50% and 98.2% with an IoU of 75% for high-voltage electrical network components.**

***Index Terms*—Convolutional neural networks, Power line inspection, Unmanned aerial vehicle assisted inspection**

I. Introduction

In the modern world, the consumption of electricity has become essential for human existence and development [1]. Electricity is used twenty-four hours a day in many devices, such as healthcare industry, food, and other products widely used in people's daily lives. In order to enjoy the benefits of electricity, equipment is needed to transport the energy from power plants, where it is generated, to the end consumer. To achieve this, wires made of conductive materials (such as copper) are used to ensure its transport over long distances, as well as other components such as insulators and transformers. However, a large amount of equipment also requires frequent maintenance and inspections [2].

Insulators are components usually made of porcelain or glass and serve to maintain the insulation distance between two structures with different electrical potentials, preventing undesired circulation of current [3]. Due to being made from fragile materials such as porcelain, insulators tend to break easily as they are subject to vandalism and weather events such as lightning strikes, manufacturing defects, third-party interference and design and maintenance failures [4]. Thus periodic inspections are necessary for each insulator on each pole.

Despite being necessary, periodic inspections of power lines are very time-consuming, where the energy company responsible for each pole uses a truck that carries a ladder so an electrician can reach the insulator and visually inspect it and then replace the component in case of any defect. In addition to being time-consuming, power line maintenance is generally corrective, where the replacement of a component is made only after it is damaged. This results in losses due to power outages and possible damage to other components in the system itself.

Due to problems with the current inspection of power lines, this work proposes the use of a Region-based Convolutional Neural Network (Faster R-CNN) for identification and classification of power pole components, as well as possible defects of the component, in order to facilitate, speed up and reduce the cost of power line inspections, enabling preventive maintenance. Experiments were conducted on 848 images captured by UAVs with the aim of identifying insulators and their defects. As results, an average precision of 98.7% was achieved with an IoU of 50%, 98.2% with an IoU of 75%, and 79.7% with an IoU ranging from 50% to 95%.

In the following sections of this paper, we will delve into a comprehensive exploration of the subject matter. Section II describes the literature review, providing valuable insights and context for our study. In Section III, we detail the materials and methods employed in our research. Moving forward to Section IV, we present our experimental approach and the subsequent results, while Section V presents the conclusions.

II. Literature Review

In this section, the main literature review that serve as models for consultation and assistance in understanding the proposal of the work will be addressed. The literature review was conducted by evaluating articles published since 2003, within the areas according to the proposal of the work. The research was made through Google Scholar. The articles were categorized according to the techniques of image collection, applied Artificial Intelligence techniques, and results obtained.

A. *Solutions for power line inspection problem.*

The inspection of power lines with unmanned vehicles began around the 1990s, using equipment such as line-following robots and UAVs (Unmanned Aerial Vehicles) [5]. These vehicles were utilized to collect images, which were then sent to human inspectors for visual analysis of components and identification of potential defects.

However, over the years, there has been an evolution of devices and an increase in computational power [6], which has enabled the advancement of new software technologies. These advancements now make it possible to combine unmanned vehicle inspections with modern hardware and software technologies, thereby facilitating the development of completely automated power line inspection systems using UAVs and vision-based inspections with the assistance of Deep Learning [2].

Several works, such as [2] and [7], have highlighted the application of Neural Networks in identifying distinct elements of power lines by leveraging imagery acquired via Unmanned Aerial Vehicles (UAVs). Within this procedure, UAVs capture images of the target utility poles, which are subsequently relayed to a computer system for in-depth analysis. These methodologies will be elaborated upon and examined in conjunction with programming approaches within the upcoming subsections.

B. Data collection techniques for inspection

The use of unmanned vehicles employed in power line inspections, coupled with advancements in robotics and electronic technologies, facilitate the incorporation of multiple sensors and other components that can help in the inspection process In the study conducted by Cantieri et al. [5], a camera was mounted on a UAV to enable the collection of images of streetlight poles, enabling the identification of their components.

In the study conducted by Junior et al. [8], a camera equipped with a temperature sensor was mounted on an inspection robot that travels on rails. This setup aimed to identify possible instances of component overheating on the pole. Chen et al. [9] (2013) demonstrated the visualization of imperfections, such as corona discharges, which are invisible to the naked eye. This was achieved by using cameras equipped with ultraviolet light sensors.

The research conducted by Nguyen et al. [2] emphasizes the use of UAVs as a promising approach for autonomously inspecting power pole components visually. This approach is considered cost-effective, as it offers low-cost inspections. The work also shows that UAVs are capable of flying in close proximity to the poles, and with advancements in battery and fuel cell technologies, modern UAVs can achieve significant autonomy.

C. Data analysis techniques for inspection.

Once the data has been collected, the prospect of identifying potential failures in electrical systems through the application of Artificial Intelligence (AI) becomes viable. Among the key methodologies are Hough Transform, Convolutional Neural Network (CNN), and Artificial Neural Network (ANN).

Hough Transform was used as a method for detecting easily parameterizable shapes [2]. Typically, the transform is applied after edge detection and can be combined with a neural network to improve the detection accuracy.

Artificial Neural Network (ANN) was used to classify collected samples into four major groups [2]: Poles, Crossarms, Vegetation, and Others. This classification enables easier inspection of each pole and simplifies the model training process.

For images, Convolutional Neural Networks can be used to reduce the need for handcrafted solutions for each potential sub-task in power pole inspection [2]. CNNs are feed-forward neural networks that can learn directly from raw data without extensive preprocessing.

III. Materials and Methods

In this section, we discuss the tools and techniques used to obtain images of power pole components and train the convolutional neural networks capable of identifying them.

A. Dataset

The dataset is a fundamental tool in any AI project, as it serves as the foundation for training, testing, and validating. To create the dataset, images of insulators used in high-voltage power networks were downloaded from an internet repository created in [10]. These images were captured using UAVs, and some of them show insulators with common defects such as cracks. For each image, there is a corresponding XML file that contains annotations specifying the positions of the components within the image. These XML files are particularly valuable during the neural network training phase. The dataset contains 848 images of insulators, 600 normal and 248 defective. All of the images have the dimensions of 1152 by 864 pixels.

Fig. 1. Normal Power Line Insulator Example.

Fig. 2. Defective Power Line Insulator Example.

B. Object Detection Method

To perform the detection of components on power lines, a Faster R-CNN (Faster Region-based Convolutional Neural Network) was created, which is an object detection method based on region intersection comparison, followed by classification in a single pipeline [11]. A Faster R-CNN is a fast method for image detection that combines the concepts of the Region Proposal Network (RPN) for generating region proposals and the Fast Region-based Convolutional Neural Network (Fast R-CNN) for region classification.

An RPN (Region Proposal Network) is a convolutional network capable of simultaneously predicting object boundaries and their corresponding scores. It generates region proposals that are further analyzed by the Faster R-CNN itself. A Fast R-CNN is a training model based on Convolutional Neural Network (CNN) that, in the context of Faster R-CNN, incorporates the results from the RPN as part of its training process.

C. Metrics of Evaluation

For evaluating the quality and accuracy, two metrics were considered: IoU (Intersection over Union) and AP (Average Precision). These criteria are used to determine the accuracy of an object detection and the percentage of correct predictions made by the neural network, respectively.

IoU (Intersection over Union) constitutes a fundamental evaluation metric aimed at quantifying the efficacy of object detection. It measures the overlap between the predicted bounding box (detected by the neural network) and the ground truth bounding box (the actual object that should be detected). The IoU is calculated as the ratio of the intersection area to the union area between the predicted and ground truth bounding boxes as shown in Figure 3. In object detection, the establishment of an IoU threshold at 75% signifies a pivotal criterion. In practical terms, when the neural network detects an object like an insulator, for instance, the anticipation is that the overlap between the predicted bounding box and the Ground Truth should exceed 75%. This stipulation is fundamental, as it determines the accuracy of predictions, dictating that for a prediction to be validated, the prescribed overlap threshold must be met or exceeded.

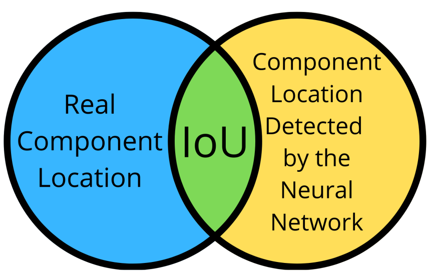

Fig. 3. IoU Visual Example

In the context of object detection methods, Average Precision (AP) serves as a vital metric for assessing performance. AP offers a comprehensive evaluation by considering the precision-recall curve, which reflects the trade-off between correct positive predictions and false positives. This metric accounts for the varying levels of confidence assigned to different predictions, providing a more nuanced view of a model's capability to discriminate between relevant and irrelevant detections. By calculating the area under the precision-recall curve, Average Precision condenses the overall performance into a single value.

D. Experimental Design

Before training, the dataset was divided in three groups, the biggest group containing 509 images was used for training, a second group of 169 images was used for testing, and the third group containing 170 images was used for validation of the neural network. Each image was associated to each group randomly. In the training of the CNN, data augmentation process was employed for mirroring, where each image had a 50% chance of being mirrored, effectively doubling the training dataset size. After mirroring, the images underwent normalization using the average color of 123.675, 116.28, and 103.53, respectively. After the normalization process, the training is performed using Stochastic Gradient Descent (SGD) with a learning rate of 0.02 for 20 epochs.

IV. Experiments and Results

In this section, the tests conducted with the convolutional neural network (CNN) and the corresponding results are discussed. Firstly, the values representing the evaluation metrics of the neural network are displayed, followed by some examples of detections to showcase the reliability of the obtained data.

Given the trained CNN, three tests were conducted on the dataset. In order to check the precision of the detection from each label individually, the mean Average Precision (mAP) was calculated for each label. The results, which include the average precision (AP) for each IoU can be seen in Table I.

TABLE I
Mean Average Precision rate of the Neural network

Object	**IoU**	
	50%	**75%**
Insulator	97,4%	96,3%
Defect	100%	100%
General	98,7%	98,2%

From the trained model, it was possible to calculate and plot the loss function, available in the Figure 4. The loss plot illustrates the convergence behavior of our model, showcasing its ability to progressively minimize the loss value with each iteration. A decrease in the loss function can be observed, indicating that the trained model effectively learns and adapts to the training data. This trend signifies the successful optimization of our model's parameters, ultimately leading to improved performance.

The mAP was also calculated separately for each insulator size (occupying medium or large space in the image). The results can be seen in Figures 5 and 6. As shown in the figures, it can be observed that the mAP for a large object in the image is higher, indicating that the model detects components more easily if they have been photographed from a closer distance.

According to the data in the table, the model was able to identify insulators with ease, even detecting visible defects

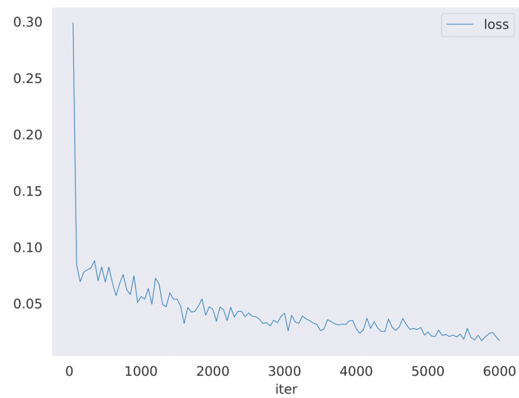

Fig. 4. Loss Function graph plot.

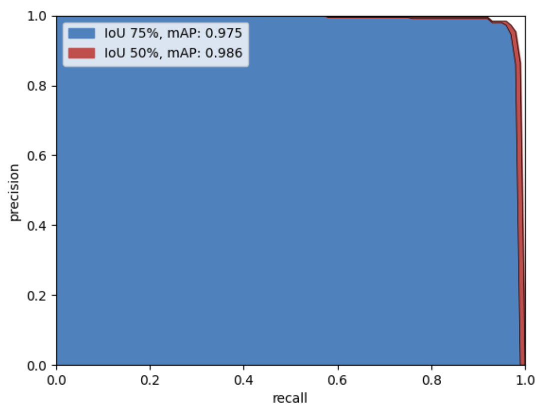

Fig. 5. Mean Average Precision rate of the model for large size insulators.

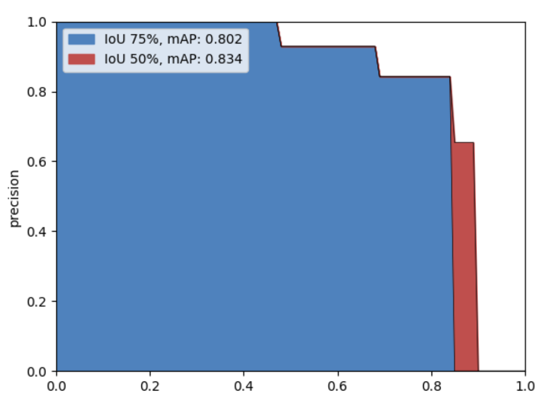

Fig. 6. Mean Average Precision rate of the model for medium size insulators.

such as cracks and breakages. This further demonstrates its precision in detecting high-voltage electrical insulators. Some examples of detections can be seen in Figures 7, 8, 9 and 10.

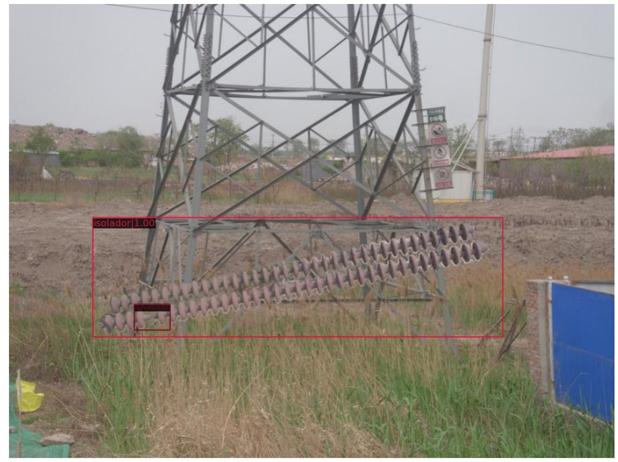

Fig. 7. High-Voltage Power Line Insulator and defect Detection Example.

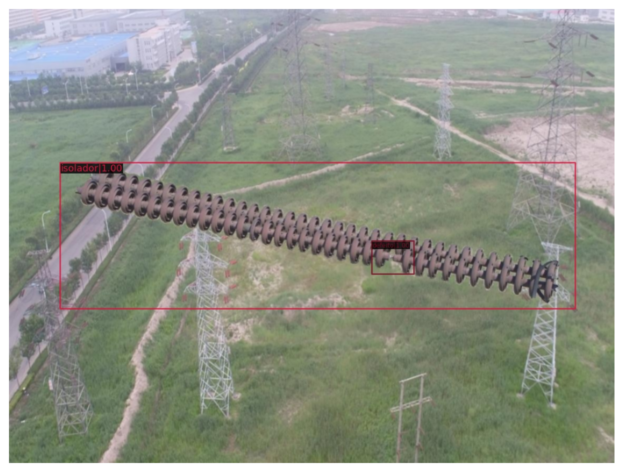

Fig. 8. High-Voltage Power Line Insulator and defect Detection Example.

To test component detection in adverse weather conditions, deliberate corruptions (noise generation) of the images were performed to simulate events such as winds affecting the UAV's positioning and fog, which can impair camera visibility in different severities [12]. The data obtained with each IoU for each noise level was divided by severity and entered into Table II and III.

As observed in the table, a decrease in accuracy can be noticed with an increase in severity due to reduced object sharpness. Nevertheless, the model managed to keep good precision even with noise in the images, except for the images with zoom blur, which decreased the mAP significantly.

V. Conclusion

This study presented a successful application of UAV-captured imagery for the detection of insulators and defective

Fig. 9. High-Voltage Power Line Multiple Insulator Detection Example.

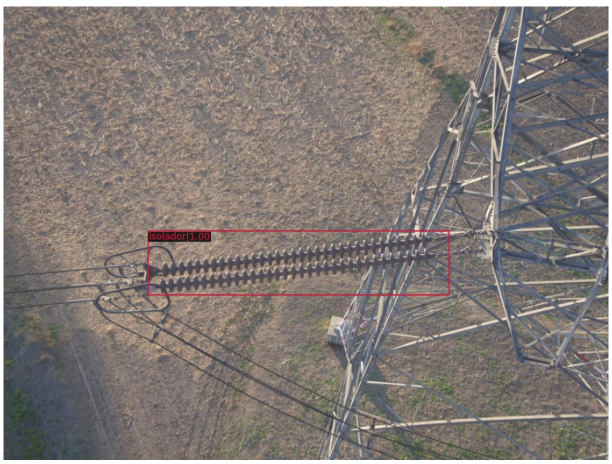

Fig. 10. High-Voltage Power Line Insulator Detection Example.

regions in power line infrastructure. The achieved results showcased a remarkable level of accuracy, with an average precision of 98.7% for an IoU threshold of 50% and 98.2% for an IoU threshold of 75%. These outcomes underscore the efficacy of the proposed methodology, which combines advanced object detection techniques with UAV technology. The utilization of IoU thresholds has proven pivotal in ensuring stringent evaluation criteria, effectively validating the accuracy of predictions. These findings hold substantial implications for the field of power line inspection, offering a potent tool to enhance the reliability and efficiency of maintenance procedures. As technology continues to advance, this research provides a solid foundation for further developments in autonomous inspection systems and underscores the potential of UAVs in revolutionizing the domain of infrastructure assessment and management.

CNNs are continuously demonstrating their capability of automating manual labor tasks that were previously performed by humans. There is still plenty of room for evolution in the field of power line maintenance, with the possibility of developing

TABLE II
MAP ON CORRUPTED IMAGES - IOU 50%

Severity	**Low**	**Medium**	**High**
Gaussian Noise	0.971	0.860	0.509
Shot Noise	0.947	0.816	0.551
Impulse Noise	0.968	0.812	0.607
Defocus Blur	0.934	0.864	0.620
Motion Blur	0.972	0.942	0.720
Zoom Blur	0.359	0.203	0.170
Fog	0.983	0.972	0.958

TABLE III
MAP ON CORRUPTED IMAGES - IOU 75%

Severity	**Low**	**Medium**	**High**
Gaussian Noise	0.911	0.756	0.385
Shot Noise	0.931	0.709	0.382
Impulse Noise	0.904	0.737	0.405
Defocus Blur	0.884	0.769	0.429
Motion Blur	0.958	0.808	0.428
Zoom Blur	0.179	0.080	0.048
Fog	0.971	0.914	0.841

additional concepts of neural networks capable of recognizing other pole components, such as fuse switches, for example. Additionally, the implementation of a fully autonomous system capable of performing necessary maintenance on power poles without human intervention, along with estimating the replacement time of components based on their installation date, holds great potential. Furthermore, the proposed idea for identifying components of low and medium voltage power lines holds should be taken into account.

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