Application of Artificial Vision Based on Convolutional Neural Networks for Predictive Detection of Faults in Electrical Distribution Line Insulators

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Abstract *– Insulators play a crucial role in transporting and distributing electrical energy. They separate the energized conductor from the metal structure and support the conductors against adverse weather conditions such as winds and rains. However, these devices lose their insulating and mechanical properties when exposed to climatic factors such as sun exposure, rain, dust, and environmental pollution. This is due to the forming of a cover of organic matter and breaks and fissures, which can trigger adverse effects such as generating electric arcs. For this reason, it is essential to identify these failures effectively. In this research, an innovative solution is proposed that involves the use of artificial vision integrated into uncrewed vehicles, using the YOLOv5 object detection technology based on convolutional neural networks, to analyze 3000 images of the insulators in search of signs of deterioration, such as the presence of organic matter, breaks or cracks. The results showed an accuracy of over 90% in detecting failures. Deploying YOLOv5 alongside an uncrewed vehicle allows for faster and more accurate inspection of insulators along power distribution lines in real-time. Furthermore, by using this artificial vision technology, detailed data on the condition of the insulators can be collected in an automated manner, which facilitates the planning of preventive and corrective maintenance actions. This not only reduces the costs associated with the maintenance of distribution lines but also contributes to improving the reliability and efficiency of the electrical system.*

Keywords: *electrical energy, artificial vision, efficiency, mechanical properties*

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1. INTRODUCTION

The conventional electrical system comprises three main stages: generation, transmission, and distribution. The distribution stage is crucial since it brings electrical energy to commercial and residential users [1], [2]. This system comprises structures (poles and towers) that support the conductors, which have metallic elements directly connected to the ground. Consequently, insulating elements are required to prevent leakage currents caused by surges or atmospheric discharges [3], [4], [5]. Insulators are essential components in distribution and transmission lines. Therefore, it is vital to carry out maintenance work because exposure to various weather factors can reduce their useful life, such as industrial pollution, dust, and acid rain. [1], [6], [7]. These factors cause the loss of its insulating characteristics, and due to this, there is a risk of leakage currents and unwanted electric arcs, which are one of the causes that cause the flow of electrical energy to be cut off. This would affect residential and large customers and the operation of the electrical power system. Therefore, it is essential to detect faults in the insulator.

Currently, different techniques are used for the inspection of insulators; for example, in remote locations, the inspection of insulators is carried out through visual observation and the operator's judgment [5], [8], [9]. On distribution lines, basket cars are used whenever there is a nearby access road, while on transmission lines, the inspection is carried out when the operator climbs the tower [10], [11], [12]. These activities require considerable time, especially considering the distribution lines in rural areas that are inaccessible to the use of the basket car. This approach is inefficient due to the travel time of the operators and the necessary equipment, as well as its economic implications. It is essential to highlight that the high number of insulators in the distribution lines makes continuous inspection of these elements complex [10], [11], [13]. Therefore, maintenance takes a corrective approach in most cases, with inspections performed following a catastrophic insulator failure [7], [14].

The electrical insulator must have highly resistive properties so as not to allow the circulation of electric current. Among the materials with these characteristics are porcelain, glass, and teflon. Currently, porcelain is one of the most used materials in the manufacture of insulators for distribution lines due to its outstanding dielectric properties [15], [16], [17] and its low production cost. There are various types of insulators, such as rigid or pin type and suspension type, the latter being the most commonly used in distribution lines [18].

Advanced techniques based on artificial intelligence (AI) are some of the tools developed to monitor insulator status, improve fault detection, and reduce operator dependence. The use of vision artificial intelligence for analyzing images provided by uncrewed vehicles is presented as an innovative solution. However, creating a database is a complex task that requires many images representing the insulators' possible states that could cause faults in the distribution lines. In addition, it is crucial to consider the limitations, such as the safety distances from the energized conductors. According to the Arconel regulation 001/018 [19], it is established that for a voltage level of 13.8 kV, a minimum distance of 6 meters must be maintained to avoid electromagnetic interference with the operation of the drone. The advancement of AI has improved the accuracy and efficiency of image analysis, especially with the use of deep learning (DL). Training data is collected and analyzed to diagnose the insulators' condition, significantly reducing analysis time.

1.1. RELATED WORK

The YOLOV5 algorithm (You Only Look Once) has fast detection characteristics and high precision; this is a technique that is used in artificial vision [20], [18], [21]. This technique uses various sampling methods such as residual blocks, bounding boxes, loss function, and non-maximum suppression. This algorithm allows for extracting the essential characteristics and giving a prediction with a high percentage of precision. This data analysis technique has been used in several investigations. In [15], they proposed a model based on YOLOv5, which increases speed compared to previous versions by using complex backgrounds and the variation of the loss function. Analyzing insulators allowed a significant increase in fps (Frames Per Second). Compared to the original Yolo algorithm. In [22], they developed a model with RCNN, an RPN (Regional Proposal Network) model; this algorithm allows analyzing images more efficiently to detect objects' characteristics by adding a convolutional layer, and the precision improves considerably.

In [23], a model based on YoloV3 is developed, which uses a convolutional neural network composed of 53 layers to detect each of the images in the database in order; this allows increasing precision and detecting the desired characteristics. In [8], a study of the effects of insulators was developed using a Fast R-CNN model, which is based on three stages of feature extraction, analysis, and search in the regression layer, which allowed the detection speed to be improved at approximately 40 fps. In [24], an OTSU segmentation method is used to detect insulator failures, separating the pixels of the objects within the image and the background pixels, allowing the images to be decomposed and their characteristics better analyzed. In [10], an InsuDet model is proposed based on a feature pyramid (FPN), which contains multi-scale feature maps from an input image, which is especially useful for detecting objects of different sizes within the same image. In [25], an analysis of insulators in a transmission line is conducted using the convolutional neural network ResNeSt (Residual Network with Split-Attention) to predict the damage that insulators sustain due to ultraviolet (UV) radiation. Table 1 shows the precision and sensitivity of each classifier mentioned above.

Table 1. Evaluation of classifier types

Model	Accuracy (%)	Sensitivity (%)
ResNeSt [26]	94.2	93.4
Fast R-CNN [13]	92.1	81.1
YoloV3 [27]	92.67	86.10
YoloV5 [9]	96.47	89.2
InsuDet [10]	71.5	64.05

When analyzing the artificial vision methods suitable for detecting faults in insulators, it is observed that there are several options, but each of them has advantages and disadvantages; therefore, in this work, it was decided to use YOLOV5, taking into consideration the multiple benefits it has, the main benefit is its processing speed that can reach up to 45 fps. The deep learning object detection algorithm should be able to eliminate complex background interference when imaging. Considering the complex background of image data, we integrate the HorBlock module into the original base network to improve the network's ability to extract each image's features and increase the network's detection accuracy for minor insulator defects. Additionally, the algorithm's precision is a great advantage when analyzing the insulators in real-time, as it helps determine what type of maintenance the operator should perform (corrective, preventive, or none of the above).

1.2. WORK ORGANIZATION

To address the problems raised, a series of stages will be developed, allowing the failure detection process in the insulators to be carried out more simply. The stages contemplated in this investigation are described below.

- A database covering the central states of the insulators of the distribution lines in the cities of Salcedo and Latacunga was created. Images were captured using a drone in diverse environments, with different backgrounds and angles, to obtain a varied sample that faithfully represents actual conditions. This database comprises 3,000 images collected over three months to validate the possible changes that may occur in each of the elements every quarter.
- To optimize feature detection, a convolutional layer was incorporated into the deep learning process. This addition allows for exhaustive analysis of the images, facilitating the identification of potential states and improving the model's accuracy. The convolutional layer significantly improves the efficiency of feature extraction from input images, resulting in more efficient hierarchical learning and improved object detection at various contexts and scales. Furthermore, by learning relevant rather than specific features from the training images, the model better generalizes to new images in situations other than those in the training.
- The neural network is designed to analyze videos in real-time as static images of insulators. This allows analysis to be carried out remotely on distribution lines, contributing to a faster and more efficient detection rate.
- To validate the results, a confusion matrix will be used, a tool that allows the validation of the precision and sensitivity of the algorithm in various environments, backgrounds, and environments to which the distribution lines are subjected.

2. MATERIALS AND METHODS

The approach proposed in this study uses a drone to capture and transmit video and images of the porcelain insulators used in the 13.8 kV distribution lines. Using this method takes advantage of the advantages of drones for aerial inspection in an agile and precise way, allowing information on the status of the insulators to be obtained. When the data is collected, it is sent to a computer through a Wi-Fi communication network [12], where the fault detection model (YOLOV5) is executed, and the results are displayed. In addition, the model includes an offline mode that allows you to analyze videos and images stored on physical media. It is important to note that remote inspection provides immediate information on the status of the insulator. It is worth mentioning that using the offline model can improve the effectiveness of stopping the fault (Fig. 1).

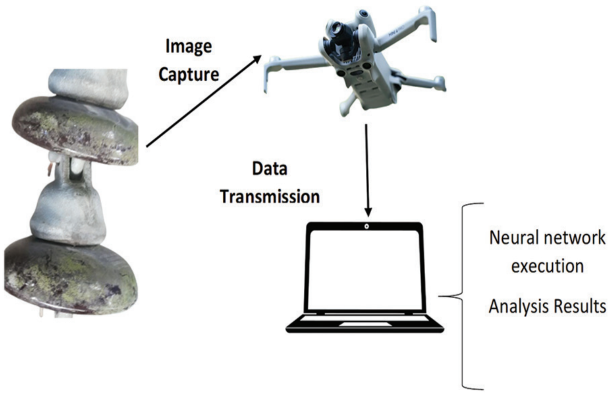

Fig. 1. Insulator Failure Detection System

The insulators analyzed using the proposed algorithm will be classified into three states: good, dirty, and broken. An insulator is considered good when it does not present any damage and, therefore, does not require any maintenance. On the other hand, an insulator will be considered dirty when it has a layer of plant and industrial matter, suggesting the need to carry out preventive and corrective maintenance. As for a broken and cracked insulator, it is an element that must be replaced immediately due to the decrease in its resistance, which compromises its integrity and considerably increases the risk of catastrophic failure.

2.1. DATASET COMPILATION

The experimental data for creating the dataset was collected in the province of Cotopaxi. The electrical distribution infrastructure covers an area of 6172.32 km [28] and is managed by Empresa Eléctrica Cotopaxi SA. The study focused specifically on the cities of Salcedo and Latacunga. The data set contains various types of porcelain insulators and chains of two or a maximum of three links at different angles. The images also present different backgrounds due to factors external to the insulators, such as conductors, poles, structures, vegetation, etc. The sample of the insulators analyzed can be seen in Fig. 2. The data comprises a total of 3000 images described in Table I. The resolution of the images is 1280x720 pixels to improve the fps rate.

Fig. 2. Insulator Samples

Table 2. Condition of the Insulators

State	Characteristics	Label	Number of samples
Good Insulator	Insulator in optimal conditions	Well	1000
Dirty insulator	Insulators with the presence of organic and inorganic dirt	Dirty	1000
Broken Insulator	Insulator with breaks and cracks	Broken	1000

2.2. ARCHITECTURE OF THE PROPOSED MODEL

YOLOv5 comprises 24 convolutional layers organized into three sections: extraction layer, fusion layer, and prediction layer. Added to these are two fully connected two layers, which allows for a latency of less than 25 ms [29]. The structure of the model is illustrated in Fig. 3; the input image enters the extraction layer through the "focus" module, which is responsible for dividing the original image and reconstructing it with a resolution of 418x418. Within the fusion layer, information from different levels of the network is combined through the "upsampling" process, increasing the resolution of the characteristics of the higher levels of the network so that it is coupled to the lower levels. In contrast, concatenation combines features to obtain a richer representation of information. The prediction layer uses the data from the fusion layer to generate object detections. Finally, the two fully connected layers are responsible for classifying the detected objects and determining their coordinates, along with the class of the detected object.

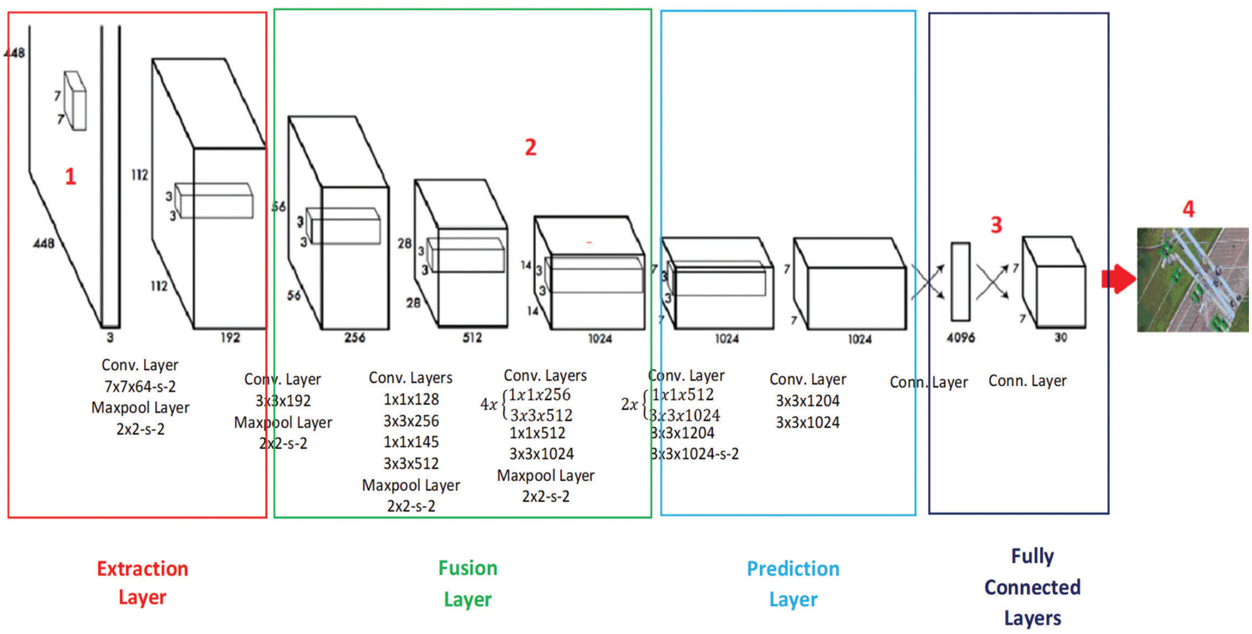

Fig. 3. Yolo architecture

Detection is based on probabilities, where the input image is divided into an SxS grid, generating bounding boxes with different sizes depending on the number of pixels in the input image. YOLO analyzes each bounding box to obtain the probability that they contain an object, predicting the possible classes. The object delimitation process is made up of five elements:

$$(x, y, w, h, k) \tag{1}$$

- (x, y) = Coordinates on the x, y axes.
- (w, h) = Size of the object.
- k = Value of perdition.

When generating the predictions by the neural network, the non-maximum suppression (NMS) algorithm is applied to eliminate overlapping and redundant boxes.

The bounding boxes are sorted according to their confidence score; the box with the highest score will be selected as the final box, along with the insertion over join (IoU) ratio [21], that exceeds the defined threshold. Finally, the final bounding boxes are obtained for each object detected in the image, along with its class. The probability of the class is given by the following:

$$Pc = Pr(Class) \cdot Pr(Obj) \cdot IoU \quad (2)$$

- Pr (Class) = Class Probability
- Pr (Obj) = Object Probability
- IoU = IoU value
- Pc = confidence scores

The class to which the object belongs can be predicted by obtaining a high Pc value. Subsequently, convolutional layers are applied to increase the resolution of the grids and improve the attributes through the use of the Local Binary Pattern (LBP). LBP is a texture descriptor used for attribute refinement, calculating the difference between the pixel and the values of neighboring pixels. The result is binarized to create a pixel texture with the best possible resolution. The refining is based on the following equation:

$$LBP(bx, by) = \left(\sum_{N=0}^{N-1} 2^{p} \; s\left(i_p - i_c\right) \right) \quad (3)$$

- (bx, by) = Location of the central pixel
- Ic = Gray Intensity Value
- Ip = Gray intensity value of the adjacent pixel
- N = Number of pixels in the image
- S = Activation function

With this approach, the aim is to improve detection accuracy, reduce possible false positives, and increase detection speed. To complement YOLO, neural networks present an architecture with intermediate layers that process information to extract specific features, from basic details such as edges and colors to the most complex textures between the input and output layers. These middle layers allow the neural network to learn increasingly complex representations of the input data as you go deeper into the network. Information flows through multiple layers, and each layer processes the information to extract specific features. The neural network becomes deeper as more intermediate layers are added, allowing it to learn increasingly abstract and complex features from the input data. By combining it with a CNN classifier, YOLO increases its prediction efficiency. Structures based on Residual Neural Network ([20]ResNet) are considered.

2.3. TRAINING OF THE PROPOSED MODEL

For the analysis and detection of failures, the total dataset images were taken and divided into a training set of 2100 images (70%) and a validation set of 900 images (30%) [23]. The selection of images was developed randomly to guarantee the diversity of both sets. Additionally, 1000 images of the training techniques were used for model validation. The evaluation algorithm was developed in Python. Google Colab was used for the training process. Google Colab is a free platform that allows you to run Python code and other programming languages directly from your web browser. Colab is based on Google Cloud and provides free access to hardware resources such as CPU, GPU, and TPU. These resources allow us to accelerate code execution and reduce training time, which had 2500 iterations, to minimize the error as much as possible. Four indices of the potential results obtained in the classification will be presented to evaluate the efficiency and precision of the algorithm. To validate the image classification methods using computer vision, a confusion matrix is used [22], [23], [25] as shown in Table 3.

Table 3. Confusion Matrix

Real value	Prediction	
	Positive	Negative
Positive	True Positive (TP)	False Negative (FN)
Negative	False Positive (FP)	True Negative (TN)

This matrix presents a synthesis of the results obtained through the algorithm, classifying the results into four categories that describe the agreement between the prediction and the actual state of the analyzed object. It is defined as true positive (TP) when the algorithm's prediction and the actual state of the object are positive, and false positive (FP) when the prediction is true. Still, the exact value of the object is negative, true negative (VN) when the prediction and the actual value of the object are also false, and false negative (FN) when the algorithm predicts negative. Still, the actual value of the object is positive.

By analyzing these confusion matrix values, the algorithm's performance in classifying different classes of images is evaluated, and possible classification errors are identified. These states are fundamental aspects of calculating model metrics, such as Precision (P), Sensitivity (R), and average sensitivity (mAP). These metrics provide a quantitative evaluation of the algorithm's classification performance, contributing to a deep understanding of the reliability and effectiveness in application environments.

$$P = \left(\frac{TP}{TP + FP} \right) \cdot 100\% \quad (4)$$

$$R = \left(\frac{TP}{TP + FN} \right) \cdot 100\% \quad (5)$$

$$AP = \int_{0}^{1} P(r)\, \mathrm{d}r \quad (6)$$

$$mAP = \sum_{n=1}^{N} \frac{AP(n)}{n} \quad (7)$$

For the calculation and subsequent results of the variables, a validation set of 900 images containing different states of insulators, utterly different from the training dataset, will be used. The set of images was analyzed image by image, filling the confusion matrix based on the algorithm's classification results. When studying each one, it is filled according to the classification described above within the confusion matrix, which allows us to validate the precision and sensitivity of the algorithm. If the validation is unsatisfactory, retraining can be performed to improve performance.

Fig. 4 and Fig. 5 present the results of training the model using YOLOV5 to validate the insulator states. It was divided into two spaces for each evaluation according to the number of epochs within the training. Since the model converges in 1480 epochs, the results are presented up to that point. Regarding precision, it is verified that, for the validation data, the model achieves results above 92% from the one hundred and fortieth epoch of training, reaching a maximum of 93%, which validates the model's speed to obtain an adequate result. Regarding sensitivity, the total number of correct detections in percentage is validated, which reached a maximum value of 92% during training.

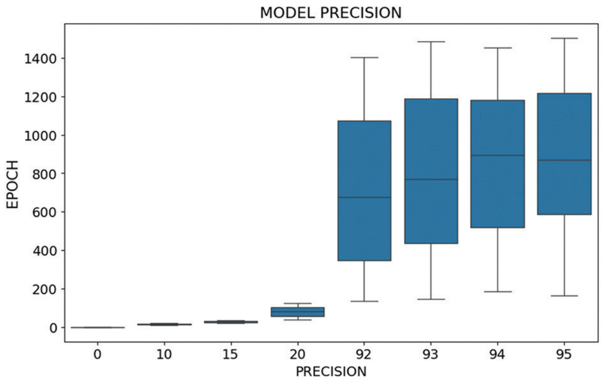

Fig. 4. Comparison of metrics during training (Model precision)

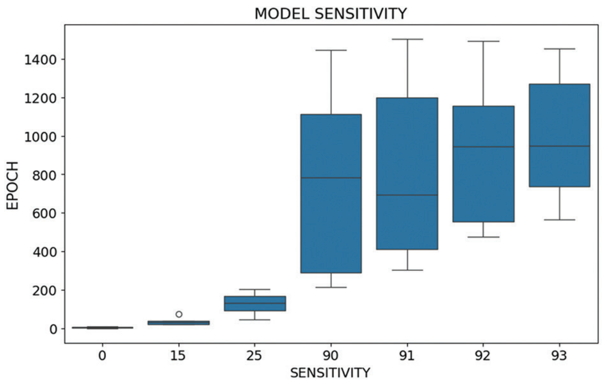

Fig. 5. Comparison of metrics during training (Model sensitivity)

3. EXPERIMENTAL RESULTS AND DISCUSSION

To validate the proposed algorithm, an evaluation was conducted on a 13.8 kV distribution network, different from the original sample, to verify its efficiency and sensitivity in detecting insulators in various environments and backgrounds. In Fig. 6, several results obtained in other posts of the test line are presented, where insulators in good condition can be observed, while, to a lesser extent, insulators that need maintenance.

The advantage of the proposed algorithm lies in its ability to automatically identify various states of the insulators, for which a color code has been assigned that facilitates its recognition, in addition to its identification label using VOC-Pascal.

Fig. 6. Detection Result

The proposed algorithm's efficiency was analyzed using the anchor box configuration and the loss function selection for the proposed states. The results obtained in the distribution line are presented in Table 4. Within the test, 1000 insulators were found.

Table 4. Confusion Matrix

True class \ Predicted class	Well	Dirty	Broken
Well	**325**	fifteen	4
Dirty	eleven	**315**	4
Broken	4	4	**318**

When analyzing the confusion matrix, it is observed that % of the one thousand insulators identified in the distribution line sample, 32.5%, are insulators in good condition. In contrast, 31.5% were dirty insulators, for which it is necessary to perform preventive maintenance due to the high probability of failure. In comparison, 31.8% were classified as broken and cracked insulators, indicating the need for immediate corrective maintenance. Additionally, the algorithm presented several discrepancies in its predictions, with 4.2% of the test data classified incorrectly. This can be seen in Fig. 7, which shows the distribution of the insulators found in each kilometer of the test line.

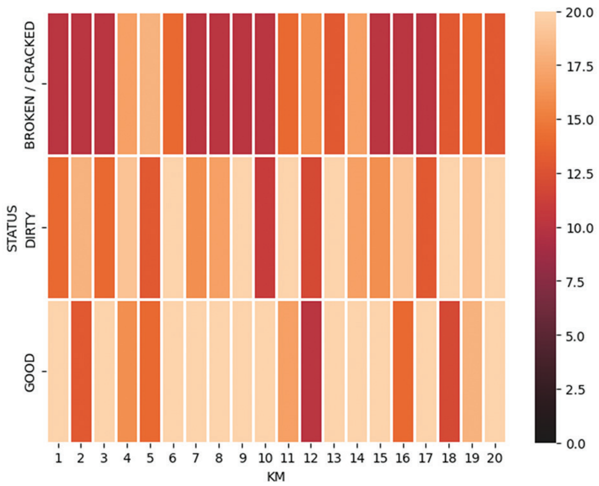

Fig. 7. Distribution of the insulators found

Finally, the precision and sensitivity of the detection of the distribution line insulators are calculated, as shown in Table 5. In it, an accuracy of 93% and an approximate sensitivity of 90% is observed. It is important to note that these parameters may vary depending on the drone's positioning angle and the isolator environment's lighting conditions.

Table 5. Algorithm Evaluation

State	Precision	Sensitivity	mAP
Well	0.94	0.91	0.90
Dirty	0.93	0.90	0.92
Broken	0.95	0.92	0.91

4. CONCLUSIONS

This article presents an improved method for detecting the state of insulators in 13.8 kV distribution lines using the YOLOv5 architecture. This approach can accurately and reliably measure insulators in various background contexts and viewing angles. An exhaustive experimental analysis shows that adding additional convolutional layers to YOLOv5 to generate the anchor boxes significantly improves the algorithm's accuracy and reliability in fault detection, reaching an accuracy rate of around 92%.

The average detection time per image for onboard processing is approximately two seconds, while for offline processing, it is one second. These processing times are considered in the context of an efficient flight route, considering both the drone's flight time and the number of distribution lines that must be analyzed.

This study highlights the importance of performing a detailed analysis of the different components of the electrical distribution system, especially porcelain insulators, which can be susceptible to various types of failures. The tests were carried out over three months, and the following results were obtained: 63.3% of the insulators had failures; the presence of tiny layers of contamination, plant matter, and small breaks and cracks in these insulators underlined the need for regular monitoring and maintenance.

Using the algorithm to detect the states of the distribution line insulators reduces the time necessary to identify possible problems and reduces the resources required for this task, which leads to significant savings for the company in charge of the management and maintenance of said distribution lines. With direction for future research, it is suggested that the algorithm be improved by integrating obstacle detection and avoidance capabilities and expanding the database to include polymer insulators to obtain a more robust and versatile model.

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