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Visual inspection of transmission tower insulators

Inspección visual de aisladores para torres de transmisión

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One of the most important processes in the maintenance of electrical networks is the detection of faults in the insulators of transmission towers. These prevent an unexpected voltage drop at a point on the line. Therefore, it is necessary to maintain and supervise them in time so that they do not act inefficiently. There are systems to facilitate, streamline, and classify the detection of faults without putting anyone at risk, since the maintenance of electrical systems is one of the most risky and thus requires a quick solution. In this article, a methodology was implemented that facilitates the location of faults in the insulator system by means of an image that is captured by a drone and sent to the database to be analyzed by the code, detecting the possible fault. Thus, allowing in a quick and timely manner to maximize the visibility of the electrical system to generate an optimal solution.

Keywords: Artificial intelligence, drone, electricity, isolators, transmission tower

Uno de los procesos más importantes en el mantenimiento de redes eléctricas es la detección de fallas en los aisladores de las torres de transmisión. Estos evitan que exista una caída de tensión no esperada en un punto de la línea. Por ello, es necesario el mantenimiento y supervisión a tiempo para que no actúe de manera ineficiente. Existen sistemas para facilitar, agilizar y clasificar la detección de fallas sin poner en riesgo ninguna persona, ya que el mantenimiento de los sistemas eléctricos son uno de los más riesgosos y así buscando una rápida solución. En este artículo se implementó una metodología que facilita la ubicación de fallas en el sistema de aisladores por medio de una imagen que es capturada por un dron, enviada a la base de datos para ser analizada por el código, detectando la posible falla. Así, permitir de manera rápida y oportuna maximizar la visibilidad del sistema eléctrico para generar una óptima solución.

Palabras clave: Aisladores, dron, electricidad, inteligencia artificial, torre de transmisión

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Introduction

According to (Sampedro et al., 2019) the inspection of the insulators are an important part to have the good functioning of the electrical system and the transmission of energy through these lines. The parameters and standards lead us to give importance to isolating each transmission line to ensure the transport of that energy from one point to another. But it projects to us that each one of them must work according to the regulation, that it does not present cracks, nor dusting of them. Therefore, it is said that any failure of this would lead to low power usage and processing power outages of sectors especially benefited by the power supply of these transmission lines (Guo et al., 2018a).

Based on (Sampedro et al., 2019) the inspection of insulators for power transmission lines is an important process in the supply of electricity to power grids, we can detect faults in the insulators of the transmission lines, presenting economic losses at the time of the supply of energy through one of the lines in failure (Odo et al., 2021). This proceeds to keep the transmission and distribution systems working satisfactorily being necessary to have accurate information on the service performance of the insulators, over time these tend to fail due to various factors such as cracks, vandalism, bird nests, or accumulation of dust (Mohana et al., 2021).

The maintenance of transmission towers can present several challenges and hazards for those involved (Ochoa & Penagos, 2021). One such issue is the risk of accidents during the process of preventive maintenance (Romero et al., 2019). This can occur when personnel is required to change out elements that have accumulated energy, or when deploying the lines of the transmission tower. These difficulties underscore the importance of proper training and safety protocols for those working on transmission tower maintenance.

In addition to the safety risks, some logistical challenges can arise during the maintenance of transmission towers. For example, the equipment and tools needed for the job may be difficult to access, or the location of the tower may be remote and difficult to reach (Khanna, 2021). Furthermore, the size and scale of transmission towers can make it difficult to carry out necessary repairs or upgrades.

Despite these difficulties, it is important to maintain transmission towers in good working condition to ensure the reliability and stability of the power grid. This requires a combination of proper planning, training, and resources to effectively address the various challenges and risks associated with transmission tower maintenance.

According to (Belitsyn et al., 2021; Gao et al., 2019), the use of artificial intelligence to predict or detect faults in the electrical system is a promising and innovative alternative, as it can improve the quality of electric power by reducing the possible failures, these can be implemented in the power transmission system automatic inspection based on aerial platforms with unmanned vehicles such as drones: (Belitsyn et al., 2021), since with its image detection method that could evidence the problem presented by the transmission line, detected the influence of weather, network infrastructure or nearby vegetation, thus maintenance teams are properly prepared and take action as planned by AI's previously (Guo et al., 2018b).

Based on (Guo et al., 2018b) the importance of insulators and the different types of failures that these can present, this article will relate how the different types of neural networks can interact according to the detection of failures at the exact time of this event and how they interpret the situation to not incur in over maintenance and its costs when repairing the damage. Thus, visualizing the damage of this insulator material and the prompt repair for the supply of the affected line in the electrical system (Sopelsa et al., 2021).

Based on (López et al., 2021) it is said that the preventive maintenance at the time of the first failure presented in the electrical system using the supply of electrical energy to the industrial sectors and the residential Zones. Based on the corrective maintenance, it is presented a diagnosis that has been visualized in the previous maintenance, detailing what should be fixed at the point of the line and its insulator. Therefore, the maintenances are essential for the supply of the service of electric energy employing the passage of the line and its corresponding insulator in the transmission towers, of transporting that energy until the substation is distributed to the residential and industrial zones of the cities (Odo et al., 2021; Sampedro et al., 2019; Yin et al., 2020).

Therefore, the development of this paper is organized as follows. In section two we will see the formulation of the problem, how the idea and problem arose in which the approach was given, and the solution method that is considered to be the most optimal, Experimental results of various conditions and the corresponding analysis are presented in Section three, Section four concludes the results and also discusses future improvement methods.

Problem statement

The installation of a transmission line requires a series of procedures to verify and ensure proper electrical operation of the transmission towers. One crucial aspect of this is proper maintenance of the system of insulators implemented. Insulators play a vital role in the transmission of electricity by preventing the flow of current from the transmission line to the ground, and it is important to ensure that they are functioning properly.

Proper maintenance of insulators includes regular inspections to detect faults, which can occur due to a variety of factors such as weathering, mechanical damage, or contamination. However, inspecting for faults in the electrical sector is one of the most dangerous tasks in transmission line maintenance, as it requires personnel to work near high-voltage equipment. Therefore, it is crucial to have different methods of analysis and visual monitoring in place to detect faults in the insulators, as undetected faults can lead to leakage currents and an increased risk of fire or loss of continuity in the electrical system. This can result in costly repairs and unexpected expenses.

One of the methods used for visual monitoring of insulators is the use of drones equipped with cameras, which can safely and efficiently inspect hard-to-reach areas of the transmission line. Additionally, the use of infrared thermography technology can detect hot spots on insulators caused by faults, which can be indicative of a problem.

Furthermore, regular cleaning of insulators is also an important aspect of maintenance as insulators that are dirty or contaminated can also cause leakage currents and reduce the insulator's effectiveness. For this reason, it is important to establish a regular cleaning schedule and to use appropriate cleaning methods and materials.

In summary, proper maintenance of the system of insulators in a transmission line is crucial for ensuring proper electrical operation and preventing costly repairs. This includes regular inspections and visual monitoring to detect faults, as well as regular cleaning to prevent contamination. Adequate methods and tools, such as drones and infrared thermography are important to ensure the safety of the personnel involved and the effectiveness of the maintenance process.

Methods

The inspection of insulators on transmission towers can present several difficulties, and as a result, it is important to have a well-planned and organized approach to ensure that all necessary inspections are carried out effectively. Based on this consideration, we have decided to follow up and analyze the towers and the different problems that may occur in the insulators.

To accomplish this, we have taken into account some factors that can affect the inspection process. For example, the number of towers to be inspected, the types of insulator material used, the voltage levels in Colombia, and the types of damage that have been classified into different categories. Based on these considerations, we have developed a staged approach to the inspection process.

The staged approach is designed to ensure that all necessary inspections are carried out efficiently and effectively. This allows us to focus on specific areas of concern, while also ensuring that all necessary inspections are completed promptly. It also enables us to prioritize areas of higher risk and allocate resources accordingly.

Additionally, classifying the types of damage into different categories, makes it easier to identify patterns and areas of concern. This information can be used to develop targeted maintenance and repair plans, which can help to prevent similar issues from arising in the future.

- **Stage 1** Determine the area to be inspected and make a detailed survey of the information obtained by drone (photos, videos).
- **Stage 2** Segmentation and classification of the images and videos obtained taking into account the categories to be studied.

Class definition

Category A: Voltage levels

Some examples are shown in Fig. 1.

Figure 1

Voltage levels

- Level 1: Systems with rated voltage less than 1 kV.
- Level 2: Systems with rated voltage greater than or equal to 1 kV and less than 30 kV.
- Level 3: Systems with rated voltage greater than or equal to 30 kV and less than 57.5 kV.
- Level 4: Systems with rated voltage greater than or equal to 57.5 kV and less than 220 kV.

Category B: Insulator material

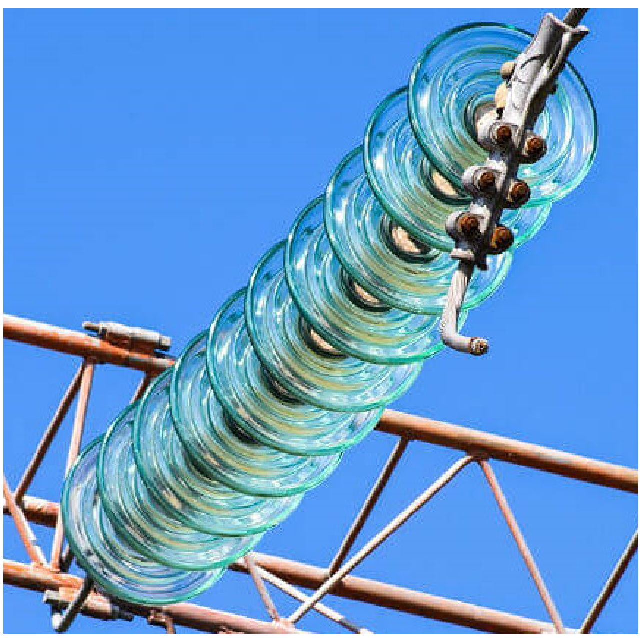
- Porcelain insulators (Fig. 2).
- Glass insulators (Fig. 3)
- Composite insulators (Fig. 4).

Figure 2

Porcelain insulators

Figure 3

Glass insulators



Category C: Types of damage

- Cracks (Fig. 5).
- Bird nests (Fig. 6).
- Corrosion (Fig. 7).
- Dust accumulation (Fig. 8).

The classes defined for this design according to the condition of the insulator were: fair, bad and critical.

Figure 4

Composite insulators

Figure 5

Cracks

Fair class

The images are classified in this category when there are problems that can be quickly solved, narrow and discontinuous leakage lines in the element (Fig. 9).

Bad class

Images are classified in this category when part of their section has been lost (Fig. 10).

Critical class

Images are classified in this category when more than 50% of the element is lost (Fig. 11). In the case of porcelain

Figure 6

Bird nests

Figure 7

Corrosion

insulators, it occurs when breakage or cracking is observed on the insulating surface. In the case of glass insulators, when there is a lack of the insulating part.

- **Stage 3** Once the images have been categorized and the problems detected, the information is sent for the respective maintenance.

The use of drones in the inspection of insulators on transmission towers has proven to be an efficient way to identify and categorize possible faults (Cadena et al., 2016). The high-resolution images taken by the drones allow for a detailed examination of the insulators, which is crucial for identifying and classifying the type of damage (Martınez et al., 2017).

The classification process begins by determining the voltage level of the tower, as different voltage levels may have different requirements and potential issues. This information is used to determine the type of insulator that is being inspected and to identify the type of damage that has occurred.

Figure 8

Dust accumulation

Once the type of damage has been identified, the next step is to subcategorize the dimension of the fault. This information is crucial for providing an appropriate solution for the fault. For example, a small crack in an insulator may be repaired with a simple patch, while a large crack may require a complete replacement of the insulator.

The use of drones in the inspection process is a cost-effective and efficient way to identify and classify faults in the insulators. The high-resolution images taken by the drones are used to determine the voltage level of the tower, the type of insulator, and the type and dimension of the damage. This information is used to provide an appropriate solution for the fault, which can help to prevent more serious issues from arising in the future.

Results

To determine the best neural network for detecting faults in electrical insulators, three different networks were trained and their performance was analyzed using our database. These networks were Dataset, ResNet, and Densenet. After a thorough evaluation, we found that the network that best fits

Figure 9

Insulator in fair condition

Figure 10

Insulator in bad condition

our problem is ResNet. This network presents better training and validation results when compared to the other networks.

The implementation of the detection system algorithm using ResNet allows for the location comparison search of possible faults that can be found in the electrical insulators. The network is trained to visualize images that are in the database, which are then compared with the data in its deep environment. This process allows for the analysis of the accuracy, error, quadratic mean, and final categorization of the images.

Figure 11

Insulator in critical condition

One of the main advantages of using ResNet is its ability to handle a large amount of data, which is essential when dealing with a large number of insulators in a transmission line. The multilayer system of ResNet allows it to extract features from images at different levels of abstraction, which makes it more robust to variations in the images. This improves the performance of the neural network when it comes to identifying faults in the insulators.

In contrast, the other two networks, Dataset and Densenet, did not show the same level of efficiency when compared to ResNet (Montiel et al., 2021). The reason for this is that the database used for these networks to work effectively must be much larger than the one presented in the current research. Therefore, ResNet is the best option for our specific problem as it presents better training and validation results, and its ability to handle a large amount of data and extract features from images at different levels of abstraction.

The neural network that was trained for detecting faults in electrical insulators is designed to visualize images that are in the database, and compare them with the data in its deep environment. This process allows for the analysis of the accuracy, error, and quadratic mean of the images. The main goal of this analysis is to identify any discrepancies or faults in the images and categorize them based on their level of severity.

The network begins by analyzing the images in the database and comparing them to the data in its deep environment. The deep environment of the network is composed of multiple layers of artificial neurons, which are designed to extract features from the images. These features are then used to identify patterns and anomalies in the images, which can indicate the presence of a fault.

The accuracy, error, and quadratic mean are important metrics that are used to evaluate the performance of the network (Figs. 12 and 13). The accuracy measures the proportion of correctly classified images, while the error measures the proportion of incorrectly classified images. The quadratic mean, also known as the Root Mean Squared Error (RMSE), is a measure of the average distance between the predicted values and the true values (Rodríguez & Buitrago, 2022). After the analysis is complete, the images are categorized based on their level of severity (Martínez et al., 2020). This process allows for the prioritization of repairs and maintenance, as well as the identification of patterns and trends in the data. This information can be used to improve the overall performance of the network and to develop targeted maintenance and repair plans.

Figure 12

Training vs. validation performance graph

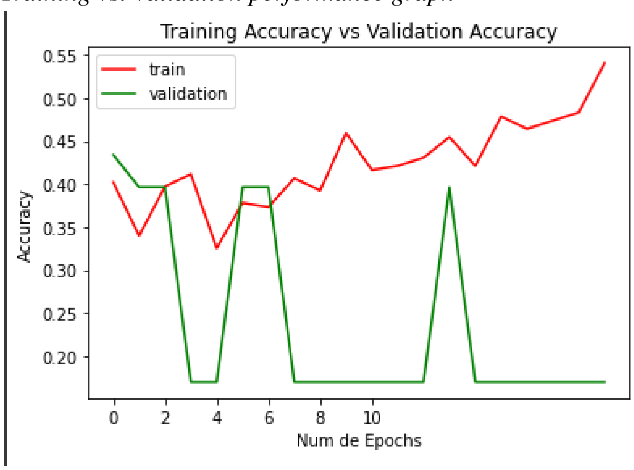


Figure 13

Training error vs. validation error graph

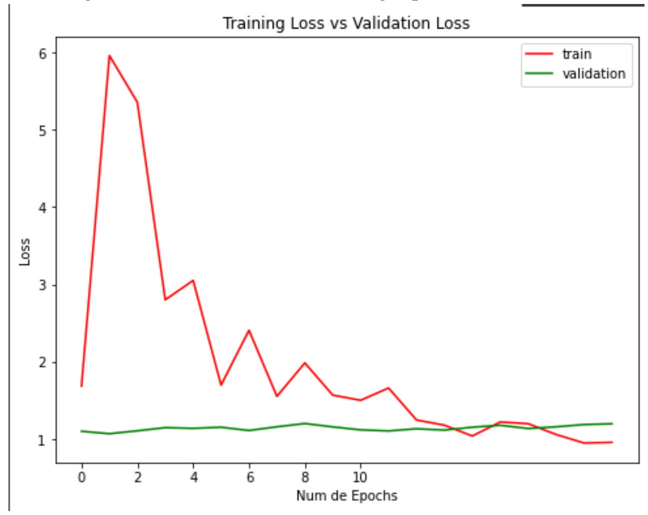
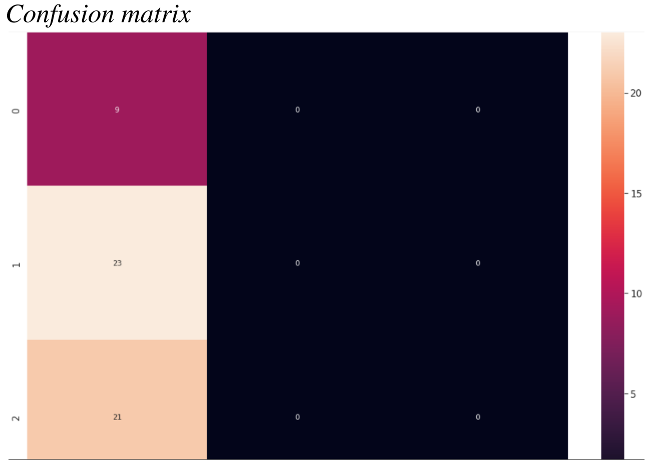


Figure 14

Confusion matrix



Our confusion matrix, which is used to evaluate the performance of our models in classifying the images, is not showing adequate categorization (Fig. 14). The main issue is the coupling of the database and the codification of the Resnet, DenseNet, and NasNet models. The performance of these models is only 35 percent, indicating that there is a problem when comparing the database with the new images presented by our database.

This issue in the categorization of the images can be attributed to several factors. One potential cause is the lack of diversity in the images in the database. This means that the models are not exposed to a wide range of images, which can result in poor performance when dealing with new images. Additionally, the codification of the models may not be optimal for the specific problem at hand, which can also contribute to the poor performance of the models.

Another possible cause is that the data in the database is not properly labeled, which can lead to errors in the classification of the images. This can be due to human error in the labeling process or a lack of consistency in the labeling criteria. This can result in the models being unable to accurately identify and classify the images, which can contribute to the poor performance of the models.

To improve the performance of the models, it is necessary to address these issues. This can include increasing the diversity of the images in the database, improving the codification of the models, and ensuring that the data in the database is properly labeled. Additionally, it is important to consider other models.

We have compiled a table of metrics that compares the performance of the model we have focused on the most, to the performance of the other two models (Fig. 15). However, we have found that the categorization is not accurate in all three models. The first model presents acceptable results, while the other two models have issues with their coding and comparison within the database.

Figure 15

Performance metrics by category

	precision	recall	f1-score	support
0	0.17	1.00	0.29	9
1	0.00	0.00	0.00	23
2	0.00	0.00	0.00	21
accuracy			0.17	53
macro avg	0.06	0.33	0.10	53
weighted avg	0.03	0.17	0.05	53

This lack of accuracy in the categorization can be attributed to several factors. One possible cause is the lack of diversity in the images in the database. This can result in poor performance when dealing with new images as the models have not been exposed to a wide range of images. Additionally, the codification of the models may not be optimal for the specific problem at hand, which can also contribute to the poor performance of the models.

Another possible cause is that the data in the database is not properly labeled. This can lead to errors in the classification of the images, which can be due to human error in the labeling process or a lack of consistency in the labeling criteria. This can result in the models being unable to accurately identify and classify the images, which can contribute to the poor performance of the models. To improve the performance of the models, it is necessary to address these issues.

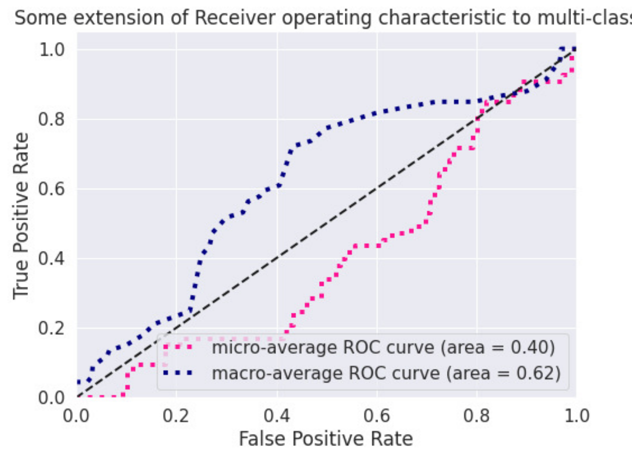
The ROC curve is a powerful tool that allows us to evaluate the performance of a model by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR). This gives us a clear picture of the positive and negative aspects of the model's performance, as well as its accuracy within the database. By analyzing the ROC curve, we can gain insight into how well the model can distinguish between positive and negative examples.

In our analysis, we have used the ROC curve to compare the performance of three different models simultaneously. The models that we have compared include ResNet, DenseNet, and NasNet. The results of this comparison show that the ResNet model is one of the best models when it comes to accuracy and performance (Fig. 16). However, its performance would depend on the database that we manage.

The ROC curve also allows us to determine the optimal threshold for the model, which is the point at which the trade-off between TPR and FPR is most favorable. This is particularly useful when working with imbalanced datasets,

Figure 16

ROC curve



where one class is significantly more prevalent than the other. By adjusting the threshold, we can improve the performance of the model and achieve better results.

Conclusion

In this paper, we present an analysis of the performance of three convolutional models for the task of classifying electrical insulator damage from images captured by a drone. The three models that we have trained and compared include ResNet, DenseNet, and NasNet. Our objective is to evaluate the performance of these models in identifying and classifying different types of damage in electrical insulators. The process of training these models involves feeding them a large dataset of images of electrical insulators, along with their corresponding labels indicating the type of damage present in the image. The models are then trained to learn to recognize and classify the different types of damage based on the patterns and features present in the images. Once the models have been trained, we evaluate their performance using a variety of metrics, such as accuracy, precision, recall, and F1-score. We also use the ROC curve to evaluate the trade-off between the true positive rate and the false positive rate of the models. The results of our analysis show that the ResNet model performs the best among the three models, with the highest accuracy, precision, and F1-score. However, the performance of the models also depends on the database that is used.

In conclusion, it was determined that the best neural network to implement for our database is ResNet. The reason for this is due to its complex algorithm, which is capable of determining the type of damage and categorizing it effectively. The ResNet architecture is designed with a multilayer system, which makes it easier to identify faults in the insulators. This is particularly useful when it comes to tracking and identifying issues in the electrical transmission system.

One of the key advantages of using ResNet is its ability to handle large amounts of data, which is essential when dealing with a large number of insulators in a transmission line. The multilayer system of ResNet allows it to extract features from images at different levels of abstraction, which makes it more robust to variations in the images. This improves the performance of the neural network when it comes to identifying faults in the insulators.

Another important aspect of ResNet is its ability to prevent overfitting. Overfitting is a common problem in neural networks, which occurs when a model is trained too well on the training data but performs poorly on the test data. ResNet uses a technique called residual learning, which helps to prevent overfitting by allowing the network to learn the residuals between the input and the desired output.

In comparison to other neural networks, ResNet has been shown to have the best performance when it comes to the follow-up and search for failure in the insulators. This is due to its ability to handle large amounts of data, its multilayer system, and its ability to prevent overfitting. In light of these advantages, ResNet is the optimal choice for implementing in our database to monitor and identify faults in the insulators of the transmission lines.

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