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Detection of Corrosion in Galvanized Steel of Electrical Transmission Towers with Neural Networks using Roboflow

***Abstract*—Corrosion is a leading factor in the degradation of structural integrity, especially in metallic components, posing a considerable challenge for industrial applications. In the search for effective tools to detect corrosion in electrical distribution towers, the opportunity arises to develop a conventional neural network that automates this process, aiming to optimize and enhance maintenance efforts.**

A sample of approximately 1,500 images were collected with various differences in distance, size and shape of corrosion on electrical towers, with the purpose of gathering enough data to correctly train a Neural Conventional Network.

The research involved the creation, training, and development of a conventional neural network capable of detecting corrosion in electrical distribution towers, using Roboflow as a tool for photo management, labeling, and training.Spiral methodology was implemented to enhance network efficiency.

A dataset of images was obtained for training, the training process was completed, and its functionality was tested using the efficiency parameters demonstrated in the project. A mAP of 91.4%, a Precision of 95.3% and a Recall of 84.4% were achieved. This indicators ensure the CNN is able to recognize corrosion on electrical towers optimally.

***Index Terms*—conventional neural network, corrosion, electrical towers, maintenance, rust**

I. Introduction

Corrosion is a major cause of structural deterioration, particularly in metallic components, and represents a significant challenge for industrial applications. In the United States alone, it generates economic losses of approximately $300 billion annually, with nearly 12% of metallic structures classified as deficient or obsolete.

Electrical transmission towers are especially vulnerable to corrosion due to environmental factors, with humidity being the most impactful. This degradation compromises their structural integrity, increases maintenance costs, and poses safety risks. Proactive maintenance strategies are critical to ensuring the durability and reliability of these structures, which are essential for efficient energy distribution.

This paper proposes a novel approach to corrosion detection using machine learning. By leveraging tools such as Roboflow and YOLO, a neural network is trained to identify corrosion on metallic surfaces. The solution is designed to be adaptable to drones, cranes, and any other video-recording solution, reducing inspection risks and costs while improving detection accuracy.

II. Context

A. Background

In recent years, advances in artificial intelligence (AI) have accelerated, particularly in the field of deep learning, which explores convolutional neural networks (CNNs). This area has become essential for simplifying monitoring tasks that are challenging for humans to perform effectively in real time.

This section highlights relevant research on neural networks with an emphasis on corrosion detection for electrical transmission towers:

- University of Queensland, Australia (2019): **Researchers published "Deep Corrosion Assessment for Electrical Transmission Towers**"[13], focusing on high-quality dataset generation for corrosion detection in transmission towers. Photographs were categorized by distance and component, achieving detection accuracies ranging from 73% to 92%. Unlike their work, which used 80 images per model, this study aims to employ over 2,000 images to improve performance in practical applications.
- Federal University of Pernambuco, Brazil (2019): The paper "**An Electromagnetic Multi-Parameter Strategy to Detect Faults in Anchor Rods Using Neural Networks**"[1] proposed a non-destructive system to detect early corrosion in anchor rods using frequency waves. Their neural network achieved 96% accuracy. This differs from the visual approach of the present study, which focuses on image-based corrosion detection.
- Federal University of Pernambuco, Brazil (2021): Building on previous research, the study "**Artificial Neural Network-Based System for Location of Structural Faults on Anchor Rods Using Input Impedance Response**"[2] proposed measuring metal impedance to detect corrosion. While precision metrics were not disclosed, the results suggest industrial applicability.
- China (2020): Researchers developed a neural network model in the study "**Design of Neural Network Model and Its Application to Coating Performance Prediction**"[12]. The model assessed the resistance of protective coatings, achieving simulation variance below 0.3%, indicating reliable results.
- Brazil (2021): The paper "**Machine Learning-Based System for Fault Detection on Anchor Rods of Cable-Stayed Power Transmission Towers**"[6] detailed a study

comparing 14 anchors over 15 summer days. Their neural network achieved a detection accuracy of 98.18%.

These studies highlight the increasing use of neural networks as essential tools for corrosion detection and maintenance in electrical transmission towers.

B. Problem Stating

Corrosion is a pervasive issue affecting all electrical distribution towers due to their material composition. These towers are critical infrastructure for any society, making their maintenance essential throughout their entire service life.

There are thousands of transmission towers across the country, many located in remote or hard-to-reach areas. Additionally, varying weather conditions complicate maintenance efforts. Therefore, it is crucial to explore and develop new technologies to optimize maintenance practices, ensuring that distribution towers function effectively throughout their lifespan.

III. Theoretical Framework

Object detection in images or videos through computer vision requires a structure that allows the analysis of each object within them. For this, image acquisition, digitization, feature extraction, and classification of each object are essential. The classification helps the system recognize and respond more effectively to objects, patterns, or object classes with which it can identify. This includes the task of classifying groups of objects in images.

A. Current Situation of Neural Networks for Corrosion Detection in Electrical Distribution Towers

With the continuous improvement of energy capacity and the ongoing expansion of the electrical grid, accidents caused by corrosion occur frequently [5]. Galvanized steel distribution towers experience corrosion at varying levels depending on the environment and age [13]. Structural failures caused by corrosive processes are among the leading natural causes worldwide for tower collapses. Since these towers serve both as energy transmission structures and as antenna supports, their collapse can lead to unexpected disruptions in telecommunications and electricity distribution services [2]. Globally, electrical towers suffer from corrosion, a problem that could affect thousands of people in the event of a failure. Factors such as humidity, elevation, pollution, and temperature greatly impact these towers, and the research community is working tirelessly to implement better control measures. Many alternatives are being developed around the world to detect corrosion and extend the service life of transmission towers.

B. Deep Learning

Artificial intelligence has progressed substantially, with machine learning enabling data-driven algorithm creation and deep learning enhancing tasks like object detection via neural networks. AI streamlines large-scale detection processes through image analysis.

Notably, NVIDIA's DAVE-2 project (2016) employed a convultional neural network for autonomous vehicles, using camera data and steering inputs for training. The system achieved 9% autonomy, advancing computer vision applications in vehicles and spacecraft.

These findings illustrate that this technology is continuously evolving, enhancing its ability to perform an expanding array of tasks with greater proficiency. [3]

C. Conventional Neural Networks

In the rapidly evolving field of artificial intelligence, computer vision has made significant strides, offering solutions that go beyond just visual recognition.[10]

Convolutional Neural Networks (CNNs) originated from early artificial neural network models inspired by the brain's processing methods. With advancements in computational power and algorithms, CNNs have become essential for tasks such as image recognition and computer vision. [9]

Neural networks are considered the pinnacle of deep learning algorithms, capable of automatically identifying features and building resilience. Deep learning's core strength is in creating conventional layers that learn from data to extract features—essentially granting machines the ability to ”see” and learn from the world around them.

The potential of neural networks is immense, as they can uncover patterns and relationships within complex data, marking a turning point in artificial intelligence. Combined with computer vision, AI enables ongoing progress across various industries, including applications in metallic machinery.

D. Research Variables

The research variables are as follows:

- Independent Variables: These are the inputs used to make predictions. In this research, the independent variables are the factors that affect the images of corrosion on the towers. These are:

  Distance: Two distances were considered when taking the photographs. One characteristic of electrical distribution towers is that they are not always in easily accessible locations, so the photographs could not always be taken from an ideal distance. Because of this, two distances were categorized. The ”close” distance is less than 30 centimeters. Due to the possibility of residual charges on the towers, it was not safe to get any closer. Distances greater than 30 centimeters were considered ”long” distances. To ensure the network's full functionality, the final model will include a mix of both distance categories, but they will be studied separately to verify how distance affects the network's efficiency.

  Database: This refers to the total number of photographs used to train the network. The difference in the final mAP was observed when increasing the number of samples for training.

  Saturation: Three levels of saturation were considered for training: 0, 20%, and -20%. These levels are somewhat high, but they were tested to see if they actually affected the network.

Blur: Two levels of blur were considered for training: 0px and 2.5px. The aim was to observe how blur affects the mAP of the trained network.

- Dependent Variables: These are the output or results of the work the network performs. The dependent variables include the state of corrosion (whether corrosion is present or not), as well as the mAP, accuracy, recall, F1-score, and others.

E. Applied Techniques and Tools

- **Roboflow**: Roboflow is an online platform that enables the creation of models to use computer vision and image processing for training a neural network. It provides the ability to label images, create classes for identification, and use trained models to label new images.
- **Google Colab**: Google Colab is a platform that provides a cloud-based development environment for executing Python code. It offers easy access to GPUs to accelerate task execution and integrates with TensorFlow and PyTorch.
- **Image Preprocessing**: A technique used to reduce training time and improve performance on the images in a dataset.

F. Materials

- **Camera**: A smartphone with the following cameras was used: Triple, 12 MP Wide Angle (f/1.6), 12 MP Telephoto (f/2.2), and 12 MP Ultra-Wide (f/2.4)..

G. Study Methodology

The spiral methodology is an iterative approach used in project development, especially in engineering and software development. This methodology combines design and prototyping elements with planning and risk evaluation in each cycle, making it particularly useful in complex projects.

H. Procedure

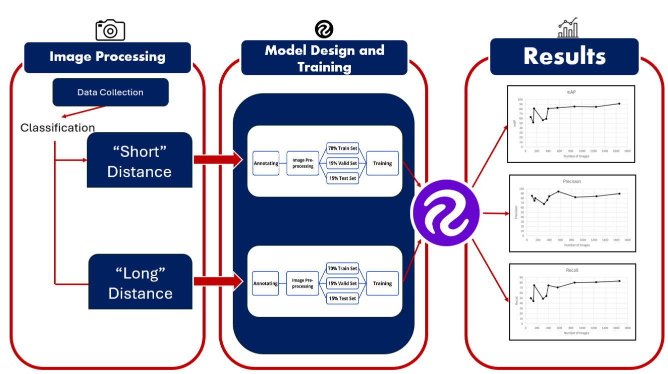

Fig. 1. Integrating Image

Fig. 1 Summarizes the complete process of the training of the network, it basically starts on the image collection. Once the entire sample of corrosion images has been collected, it will undergo proper preprocessing before being imported into Roboflow. Once imported into the software, the next step is to label each image in order to train the network to correctly detect corrosion. Simultaneously, the same network will be trained using different versions of YOLO, and results will be compared to determine which model provides the highest precision for detection, ensuring the network operates optimally. The camera used for data collection captures photos in HEIF format, which is not supported by Roboflow. Therefore, a format conversion was performed to make the images compatible with Roboflow. After conversion, the labeling process was carried out. Once completed, results were verified and necessary information was gathered to ensure the network functions as designed.

I. Objectives of the Spiral Methodology

In the context of this project, which involves creating a neural network for corrosion detection in electrical distribution towers, the spiral methodology serves several key objectives:

- **Iteration and Continuous Improvement**: The spiral methodology allows for the gradual development of the neural network, making adjustments and improvements in each cycle. As we progress in the project, we can fine-tune the model parameters and test new configurations to improve corrosion detection accuracy.
- **Risk Management**: Each cycle of the spiral includes a risk assessment phase, which is essential for projects like this. The early identification of potential issues (such as data quality or the model's ability to generalize) enables informed decision-making and the mitigation of risks before proceeding with development.
- **Flexibility to Adapt to Changes**: The iterative nature of the spiral methodology allows adjustments to be made throughout the project as new needs or discoveries arise. If the quality of images needs improvement or data preprocessing needs adjustment, these changes can be made flexibly without drastically affecting project progress.
- **Progressive Development of the Model**: Thanks to the spiral methodology, it is possible to validate the effectiveness of the neural network with small data sets before conducting larger tests. This ensures the model is robust and accurate before full implementation.
- **Continuous Feedback**: The methodology encourages constant feedback, both from the results obtained and from stakeholders (corrosion experts, tower engineers, etc.). This feedback allows adjustments to be made during the project development and ensures the system effectively meets its objectives.

J. Image of the Process

- **First Cycle**: The selection of images was carried out, categorizing them into "close" and "long" distances.
- **Second Cycle**: The network was trained with all available images until achieving a mAP of 90%.
- **Third Cycle**: Certain augmentations were applied to the images to determine their effects on the network. It was identified which augmentations positively impacted the

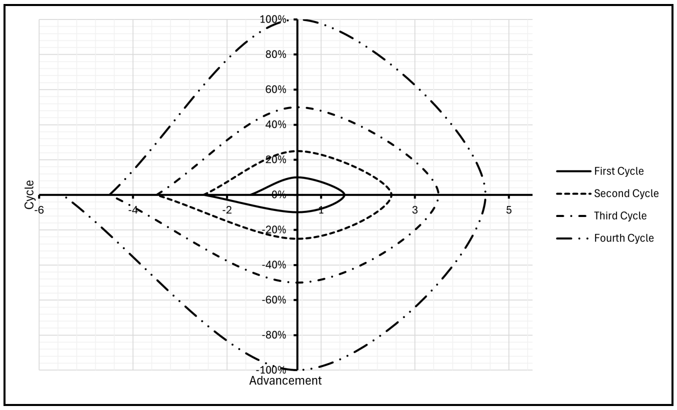

Fig. 2. Spiral Methodology

network, which ones were detrimental, and which had negligible effects on the network's performance.

- **Fourth Cycle**: It was determined which augmentations had a positive effect on the training, and the decision was made to continue training with those specific augmentations.

K. Evaluation Metrics

The evaluation metrics for the project are as follows:

- **%mAP**: Mean Average Precision across all classes.
- **Precision**: The percentage indicating how often the predictions made by the neural network are correct.
- **Recall**: Indicates the percentage of labels that were correctly identified.

By ensuring that these evaluation metrics are as high as possible, we can guarantee that our network functions properly and that it can be a useful tool in the industry.

IV. Results

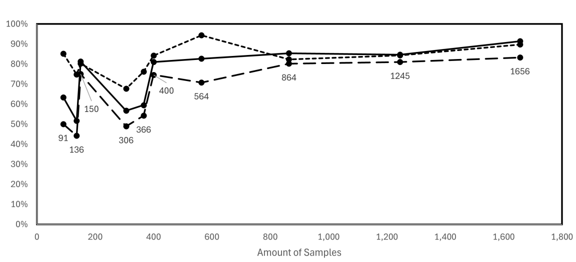

Fig. 3. mAP, Precision and Recall Through Roboflow Trainings

A. mAP

As stated in Fig. 3, The initial training started on 64% mAP, then it lowered to 52%, when it reached 400 images, it was at 80% and it only kept improving with each training after 400 samples.

B. Precision

As stated in Fig. 3, precision was at 85% at the first training, then it improved and lowered on a few trainings until the training with 864 samples, then it only kept improving

C. Recall

As stated in Fig. 3, recall followed a similar pattern as mAP. It improved and declined in the inital stages but around 800 images it started a continous, but not as drastic, improvement.

D. Comparison Between With or Without Augmentations

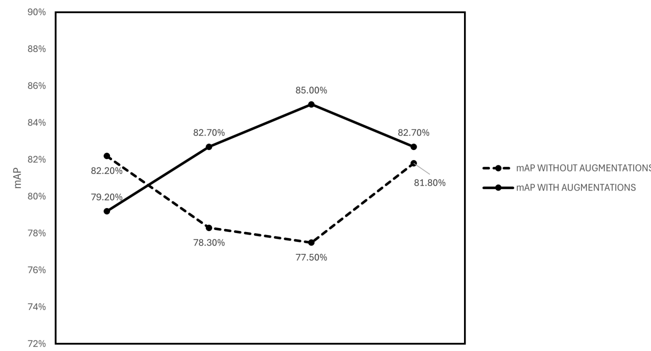

Fig. 4. Comparison With or Without Augmentations

Initially, the mAP of the training without augmentations was higher than that of the training with augmentations, as seen in Fig. 4. Then, as the trainings were being developed it concluded that the training with certain augmentations could lead to a higher mAP compared to a training without augmentations, based on the fact that the network actually improved from that point forward, meanwhile the non-augmentated network only gave the same or in most cases lower results on mAP as trainings were created.

E. Comparison Between Roboflow, YOLO v8 and YOLO v11

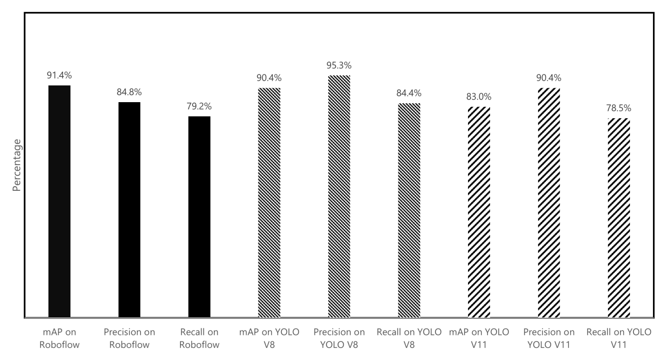

Fig. 5. Comparison Between Models

The best values given by each training model tested are displayed on Fig. 5. YOLO v8 gave the best group of values per model, since it was the most balanced. Unfortunately, Roboflow and YOLO v11 gave less than ideal results, since the difference between values was more than ideal.

V. Discussion

A. Interpretation of Results

The results obtained in the research indicate that the study was successful. We were able to achieve a mAP above 90%, which demonstrates that the network functions properly and effectively performs the task for which it was designed: detecting corrosion in electrical distribution towers. In the early stages of training the network, the results were not as expected. However, as more samples, augmentations, and different training strategies were added, the desired outcome was achieved, meeting the objectives set for the project.

B. Results Comparison

Training was conducted in Roboflow and in YOLO v8 and YOLO v11. Specifically, using YOLO v8, the best results were obtained. Although the mAP dropped by 1%, precision increased by 5.5%, and recall improved by 1.1%. This resulted in a fully functional network capable of detecting corrosion.

Additionally, research was conducted to investigate how augmentations affect the neural network. A brief study concluded that among all the possible augmentation options available in Roboflow, variations in saturation, brightness, and rotation were beneficial during training. Despite a slight initial decrease in mAP, the network improved further with these augmentations, significantly aiding in the completion of the training process.

The outcome of this research aligns with the trend of similar networks designed for the same purpose, which are typically useful and achieve mAPs above 90%. The network is innovative as it is trained entirely with samples from the national territory, providing higher precision when used in the country. It offers a new perspective on the use of emerging technologies for national development, as well as providing a new tool to improve a critical area in the country, such as maintenance.

13

C. Neural Networks in Honduras

Conventional neural networks has been a research topic that has been signifcicantly studied on recent years, nationally a few outstanding neural networks have been developed.

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- On 2020, researchers of Universidad Tecnologica Centroamericana (UNITEC) published the paper **”Coffee Fruit Recognition Using Artificial Vision and neural NETWORKS”** [7], explaining the implementation of a CNN to determine if a coffe fruit is ready or not.

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- UNITEC (2020): **”Work Safety Assessment through Contextual Analysis with Computer Vision”**[11], researchers developed a CNN that was capable of determining if a worker was wearing their personal protective equipment.

20

- UNITEC (2020): **”Implementation of Artificial Neural Networks Using NVIDIA Digits and OpenCV for Coffee Rust Detection”**[4], researchers continued the development of a CNN that was capable of determining certain sickness that affected coffee bean’s leaves.

Currently, no records have been found of a neural network specifically designed for corrosion detection in transmission towers in Honduras. That being said, there is a need to develop a tool to assist with the monitoring and maintenance of electrical transmission networks, as they are of vital importance to the country’s economy.

VI. Summary and Conclusions

A. Summary

The research achieved a mAP above 90%, confirming the neural network’s effectiveness in detecting corrosion on electrical distribution towers. While initial results were lower, improvements in samples, augmentations, and training strategies met the objectives.

Analyzing augmentations showed that changes in saturation, brightness, and rotation improved training despite an initial mAP drop. Using data exclusively from the national territory enhances local accuracy and supports technological development in maintaining the country’s electrical infrastructure.

B. Conclusions

- A neural network capable of identifying corrosion in the steel of electrical distribution towers, using machine learning techniques through the Roboflow platform, facilitating early detection and optimization of maintenance processes was developed.
- Photographic samples of corrosion cases for training the network were obtained.
- A neural network capable of identifying corrosion in different metal structures within a 2-month period was designed.
- The efficiency of the network was verified.

Final Results: mAP 90.4%, Precision: 95.3% & Recall: 84.4%

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