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A COMPARATIVE STUDY ON OBJECT DETECTION ALGORITHMS TO DETECT DEFECTS IN ELECTRICAL INSULATORS

Ayyaan Faras, Yash Pawar, Kamlesh More, Shantanu Ranaware*

[a]First affiliation, Address, City and Postcode, Country
[b]Second affiliation, Address, City and Postcode, Country

ABSTRACT :

Addressing the imperative of ensuring the integrity of high-voltage transmission lines, this paper presents a comprehensive comparative study on defect detection algorithms, with a particular focus on You Only Look Once (YOLO). Leveraging YOLO algorithms, specifically YOLO versions V3, V5, and V7, our research aims to evaluate their performance in identifying defects in insulators. The study includes the assessment of YOLO's ability to accurately detect and classify defects in diverse aerial images, encompassing both non defective and defective insulators. defective and defective insulators. The outcomes of this comparative analysis contribute to refining defect detection methodologies for insulators. By employing YOLO algorithms, the research seeks to identify the most effective approach for discerning insulator defects. The insights gained from YOLO versions V3, V5, and V7 evaluations will inform future enhancements, ensuring the robustness and efficacy of defect detection in high-voltage transmission lines. This research not only aims to identify the optimal algorithm but also paves the way for advancements in insulator defect detection, enhancing the re liability of critical power systems.

Keywords: Defect detection, insulators, high voltage transmission lines, YOLO V3, YOLO V5, YOLO V7, object detection, algorithm comparison, convolutional neural networks, image processing.

INTRODUCTION :

Amidst the increasing importance of maintaining high-voltage transmission line integrity, this paper presents a comprehensive investigation into defect detection using various algorithms. The study emphasizes the evaluation of You Only Look Once (YOLO) algorithms, specifically versions V3, V5, and V7, to address challenges in identifying insulator defects. Our research centers on leveraging advanced computer vision techniques to enhance defect detection. By employing YOLOV3, YOLOV5, and YOLOV7 algorithms, the project aims to compare their performance in discerning defects in insulators. These algorithms are evaluated based on their ability to accurately identify and classify defects in diverse aerial images, including non-defective and defective insulators. The outcomes of this comparative study will contribute to refining defect detection methodologies for insulators. Additionally, insights gained from YOLOV3, YOLOV5, and YOLOV7 evaluations will guide future enhancements, ensuring the robustness and efficacy of defect detection in high-voltage transmission lines. The research not only seeks to identify the most effective algorithm but also aims to pave the way for progressions in insulator defect detection, fostering the reliability of critical power systems. Our research is about using a set of defective and non- defective insulators to train the models and drawing conclusions from the resulting metrics.

1. LITERATURE SURVEY

Traditional Methods Visual Inspection The most basic method. It in volves a human who visually inspects the insulator [1]. This method has certain drawbacks such as: it is potentially dangerous, human error can lead to bad result; as a human can only inspect a certain number of insulators.

(Advanced) Traditional Methods

1. Ultraviolet Pulse Method:
   The ultraviolet pulse method is a non-destructive testing method that uses ultraviolet (UV) light to detect defects in insulators. The method involves applying a short pulse of UV light to the insulator surface and then measuring the reflected UV light. Defects in the insulator will absorb the UV light, resulting in a decrease in the reflected UV light signal. The magnitude of the decrease in the reflected UV light signal is proportional to the size and severity of the defect.[2]

- Pros: Non-destructive testing method–Very sensitive method–Relatively fast
- Cons: Relatively expensive method–Requires specialized equipment–Can be affected by environmental factors

2. Creeping Wave Method:
   The creeping wave method is a non-destructive testing method that uses high-frequency (HF) volt age to detect defects in insulators. The method involves applying a high-frequency voltage to the insulator surface and then measuring the current that f lows through the insulator. Defects in the insulator will cause an increase in the current flow. The upsurge in the current flow is proportional to the size and severity of the defect.[2]

- Pros: Non-destructive testing method–Relatively inexpensive–Easy-to-use method
- Cons: Less sensitive than the ultraviolet pulse method–Can be affected by environmental factors

3. Distribution Voltage Method The distribution voltage method is a non-destructive testing method that uses the distribution voltage of the power system to detect defects in insulators. The method involves measuring the voltage distribution across the insulator surface. Defects in the insulator will cause a disturbance in the voltage distribution. The magnitude of the disturbance in the voltage distribution is proportional to the size and severity of the defect.

- Pros: Non-destructive testing method–Relatively inexpensive–Easy-to-use method
- Cons: Less sensitive than the ultraviolet pulse method and creeping wave method–Can be affected by environmental factors

2. METHODOLGY

YOLO Models:

1. YOLOV3:
   YOLO V3, introduced in 2018, marked a significant improvement over its predecessors by incorporating several innovations to enhance detection accuracy and speed [4].
   The key features of YOLOV3 include:
   - Backbone Network: YOLO V3 uses Darknet-53 as its backbone network, which is a 53-layer convolutional neural network.
   - Feature Pyramid Network (FPN): It utilizes feature maps from three different scales, enabling it to detect objects of various sizes.
   - Bounding Box Predictions: YOLO V3 predicts bounding boxes at three different scales, each re sponsible for detecting objects of different sizes.
   - Loss Function: It uses a multi-part loss function that accounts for classification loss, localization loss, and confidence score loss.

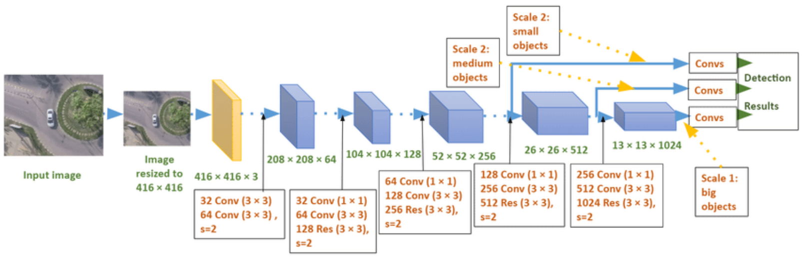

Fig 1. YOLOV3 architecture

2. YOLOV5:
   YOLO V5, introduced by the Ultralytics team in 2020, brought several optimizations making it faster and more efficient [7][6].
   Its architecture improvements include:
   - Backbone Network: It employs CSPDarknet53, which integrates Cross Stage Partial (CSP) connections to reduce computational bottlenecks. Neck: Incorporates a Path Aggregation Network (PANet) for better feature fusion across different scales.
   - Head: Utilizes three different detection heads, each responsible for detecting objects at varying scales.
   - Optimizations: YOLOV5 includes numerous optimizations such as mosaic data augmentation, auto-learning bounding box anchors, and hyperparameter evolution.

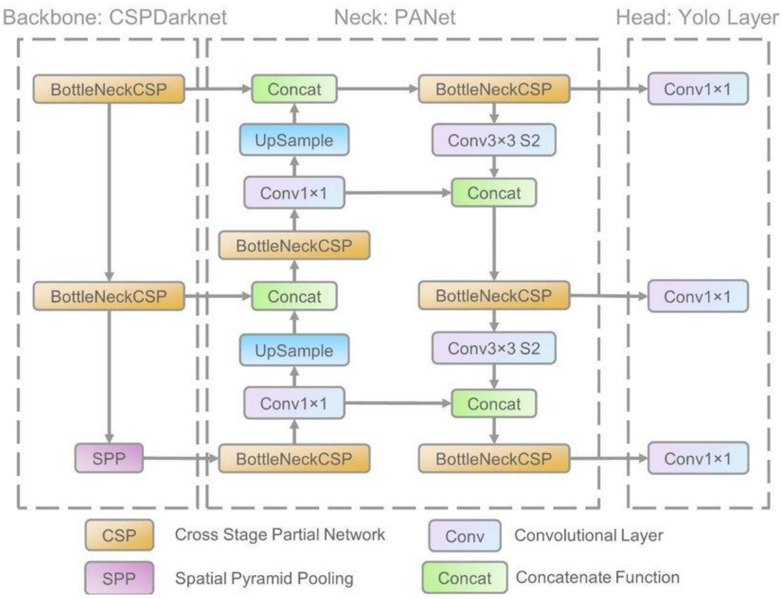

Fig 2. YOLOV5 architecture

3. YOLOV7:

   YOLOV7, one of the latest versions in the YOLO series, introduces several advanced features to further improve accuracy and efficiency [1][8]. It is said to be the state-of-the-art.

   Key characteristics of YOLO V7 include:

   - Improved Backbone: It employs an advanced version of CSPDarknet with additional modifications to enhance feature extraction.
   - Dynamic Head: Incorporates a more flexible head architecture that can dynamically adjust to different detection tasks.
   - Anchor-free Mechanism: YOLO V7 integrates anchor-free mechanisms to simplify the bounding box prediction process.
   - Enhanced Training Techniques: Utilizes advanced training techniques such as knowledge distillation and model pruning for better performance

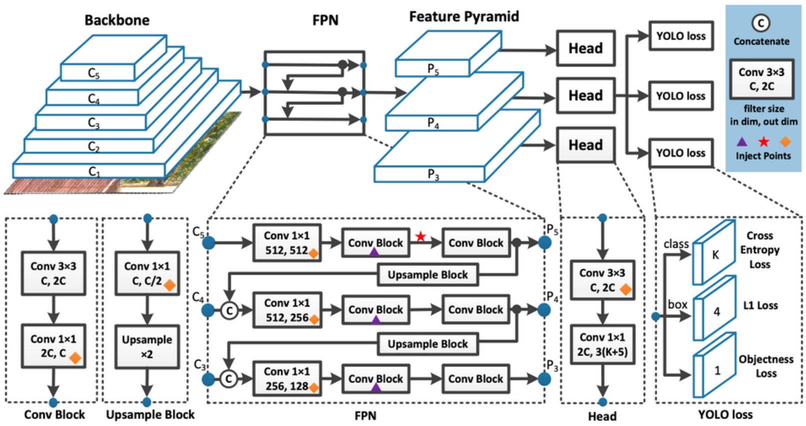

Fig 3. YOLOV7 architecture

3.1 Data Collection & Feature Extraction

Identified and sourced aerial images capturing various scenarios of insulators, ensuring a mix of both non-defective and defective instances. Ensured diversity in the dataset to realistically represent different conditions and challenges faced in real-world scenarios. Severe validation of the dataset to maintain quality and accuracy, considering factors like resolution and environmental variations [3]. In the preprocessing phase of Object Detection using various models, several essential steps are involved to enhance the quality and extract meaningful features from the input images. Initially, the raw input image undergoes image processing techniques to improve its clarity and remove any potential noise. This may involve operations such as noise reduction, contrast adjustment, and normalization to ensure consistent and optimal input for subsequent processing. Usage of high-quality images is recommended.

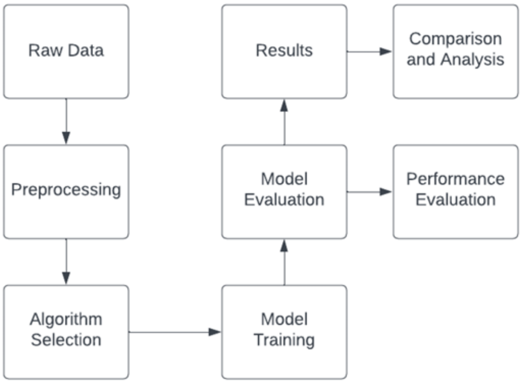

Fig 4. Flow of the project

3.2 Post Processing

Post processing: post processing contains the following processes:

1. 1.Training each of the models using the previously pre-processed data. Before the training, parameters to be passed should be carefully chosen. They should be adjusted according to each of the models' requirements. Computational needs should be taken care of. A secure and reliable platform for this step is will provide convenience and ease of use. Choosing the correct iteration of the model is important as it decides the computational requirements and time needed for completion of this step.

2. Next step is evaluation of the models. The YOLO models provide their own evaluations at the end of the training process. This includes metrics such as Precision, Recall and Mean average precision. The loss functions used here are Intersection-over-Union (IOU). Graphs regarding the evaluation are also provided. This helps understand the ups and downs encountered in training and cases like overfitting are easy to spot when data is visually presented. Numeric metrics are provided as well which help in deciding the peak results as well as average and last results. The peak results define the best achieved results by the model while the last results define the results achieved after the model has passed many epochs and has been refined. This could ultimately lead to better results and can also help to continue the training process as a breakpoint.

3. Comparison of results: After obtaining results from the trained models and evaluating them, the next step is the comparison of these results. This process can include visualization of these metrics to get a better understanding of the performance of each model. Direct comparison of numeric metrics can also give useful insights about the performance of the models. An example of this type of comparison can be comparison of accuracy or precision or the time taken by the model for training given that all the models perform the same number of epochs. This comparison can give a better evaluation of where the models stand according to their performances based on the metrics and can help to decide which model to use under certain conditions. This step gives a good understanding of each model and its pros as well as cons.

4. Ensemble Learning: Ensemble learning is a machine learning method by which results of multiple algorithms can be combined. The method used for this research is know as bagging or bootstrap aggregation. This method helps combine the results of all the three models. The result is an ensemble function which can be used to test the algorithms on images. This method provides better results as compared to the models alone. Additionally, a weight can be assigned to each of the models' predictions to favour the model which generally gives better predictions as compared to others or just to set priority of the models.

3. Conclusion

This project on comparison of object detection algorithms to detect defects in insulators represents a significant advancement in the process of electrical insulator maintenance. It also sets a benchmark for the performance of various YOLO models used in this project. By training multiple models on images of defective and non-defective insulators, comparison of model performance is obtained as well as these models can also be used in a practical environment. The obtained results give a summary of the model's performance on a difficult application of insulator defect detection. The graphs also give a comprehensive understanding of the models working while being easier to understand because of being in a visual format. This system not only provides the comparison of the models but also a robust ensembled model which utilizes the power of all the models in certain amount to provide accurate results about the defects on an insulator. By making this project more accessible, it can revolutionize the way how insulators are maintained and will reduce the risk related to their inspection and fixing. Using more computational power and good hardware, the obtained results can easily be surpassed leading to more accessibility and coverage to this method resulting in digitalizing of another such task which previously required physical work and had risks.

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