RESEARCH PAPER

Enhancing Fault Detection in Power Transmission Line Components Using YOLO V5: Integrating CBAM and CoT Transformer

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***Abstract*—** Transmission line condition monitoring keeps the electricity system healthy, avoids unplanned outages, and lowers maintenance and repair costs. Mechanical loss and power line corrosion have been effectively identified using remote sensing methods. These methods require very high-resolution photographs, from aerial imagery and UAV photos, in order to examine the transmission system, especially in remote areas. Nowadays, the most sophisticated technique for examining electrical wires for defects and damage is unmanned aerial vehicle (UAV) monitoring.For that we process the images taken by drones using any kind of deep learning techniques.in this work we use YOLO v5 as the deep learning tool which has advantages like high accuracy ,precision and speed .In this work we are enhancing the capabilities of YOLO v5 by adding CBAM module and CoT ,Contextual transformer block, which increase its detection accuracy. By adding these features mean average precision increased to 92.1%.

Keywords— "UAV images", "Deep Learning Techniques", "YOLO v5", "CBAM" "CoT."

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I. INTRODUCTION

The most crucial factor is a strong and dependable power transmission line because any malfunction or breakdown could result in significant financial losses. Power transmission lines, both overhead and cable, are the most prevalent part of electrical power networks. The reliability guarantee of power transmission line operation is therefore one of the most urgent issues in this area of electric power engineering.[1][2] The most frequent reasons for technical interruptions on power transmission lines are flashover and insulation failure. And insulation failure is often the cause. Typically, we monitor transmission lines using manual inspection techniques. However, these techniques are expensive and time-consuming. Because of industrialization, the need for electricity transmission systems is also growing daily, and safety is becoming more crucial. Due to faults in transmission line accidents are happening. And its number is also increasing. So, we need to find out new methods for inspection [3].

Since the onset of the fourth industrial revolution, there has been a surge of interest in the intelligent inspection of power plants. And the corresponding technological breakthroughs in mobility and cutting-edge sensors. The advances of this revolution are especially useful for condition-based and proactive operation and maintenance of power transmission systems.

Power inspection can help guarantee the steady operation of transmission lines, but the current method mostly uses manual inspection, which is not only inefficient but also highly costly. Additionally, there is a very high danger associated with using human inspection techniques. To overcome the disadvantage of manual patrolling, we can employ robots that can scale pylons and take pictures as an improved approach. Compared to manual patrolling, this method is less costly, time-consuming, and tiring and doesn't require experienced technicians [4]. However, there are disadvantages to this strategy as well, such as the requirement to protect electrical components and robot sensors from intense electric fields produced by transmission lines. Because of a number of factors, including the ease with which sunlight can interfere with the actual detection scene, the difficulty of capturing wavelengths, and the ease with which equipment can interact with power equipment, it is often difficult to apply the electrical optical characteristics measurement detection approach to the actual task of power inspection.

Helicopter aerial photography is one of the main techniques for inspecting electricity lines and identifying insulators and defects. This method offers a wide field of vision. This approach is quite costly because it requires a pilot, additional technical staff, and a helicopter, which may be hired. This system can be extended to incorporate the usage of UAV photos for transmission line monitoring and problem identification so as to get around the aforementioned restrictions [5].

Fig 1: Power transmission line components

2.LITERATURE REVIEW

M. Zhao employs the Firefly algorithm to oversee the operational monitoring of system. The Firefly algorithm's average accuracy in parameter measurement has been found to improve to 93.13% and 93.66%, respectively, because of continuous testing with the conventional particle swarm optimization algorithm, surpassing that of the traditional algorithm.[5]

Q.Liu suggests that methods based on deep learning is becoming the predominant strategy for identifying safety risks power system, and are essential to monitoring this system components. Above all existing methodologies are frequently too complex and have difficulty in identifying small or obscured components, which restricts its utility in edge-device deployment situations. To address this issue, model was enhanced by adding ConvNeXt module,.[6] Z.Cao provides a detailed examination of the problems occurred with lightweight technologies pertaining to sensors, edge computing, and algorithms in the context of real time target detection. This addresses the potential effects of forthcoming advancements in autonomous drones and communication regarding real-time object monitoring with UAVs.[7]

Q.Yu et.al intends to investigate how various enhanced YOLOv5 based methods improve performance in small target corrosion identification using YOLOv5 model. The study begins by using corrosion testing data with 1266 labelled images. Subsequently, five YOLOv5 models were built using the enhanced IoU loss functions [8]Y. Han et al. developed an approach for detecting rodent presence across high-altitude regions. The newly refined YOLOv8-based segmentation framework was improved to precisely map areas affected by rodent activity in such terrains [9].

2. Deep Learning Techniques

As Artificial intelligence progresses it is frequently employed for detection purpose. Through layer-by-layer training, convolutional neural networks are able to automatically recognize certain aspects of an image with greater accuracy than machine learning techniques.[10].A CNN comprises of many layers including hidden layers. The layer that accepts the image that has to be categorized is called input layer. Pixels from the image are received and arrayed in the input layer. Features are extracted from this by the hidden layers. Convolution, pooling, rectified linear units, and completely connected layers are a few types of hidden layers [11].

3. YOLO Architecture

The YOLO approach is extensively used in real-time item identification applications due of its quick reaction time and accuracy in identifying insulators from aerial photographs. Yolov5 originally uses cross-stage partial network and Darknet to develop CSPDarknet. CSPNet reduces both the YOLO v5s parameters and FLOPS to maintain speed and accuracy. It decreases the its size by incorporating gradient changes into the feature map. The architecture is shown in Fig 2.

3.1 Yolo V5

It is an open algorithm for object detection by Ultra lytics.it has got four stages.

1) Input stage

It is a preprocessing stage in this YOLO V5 processes the images to enhance its features.

2) Backbone stage

This is a feature extraction stage. It is composed of a focus module, convolution batch-normalization (CBS) module, C3 module, and spatial pyramid pooling (SPP) module.

3) Neck stage

At this phase, final predictions are indicated on the image. Also, this phase removes incorrect prediction outputs by non- maximum suppression.

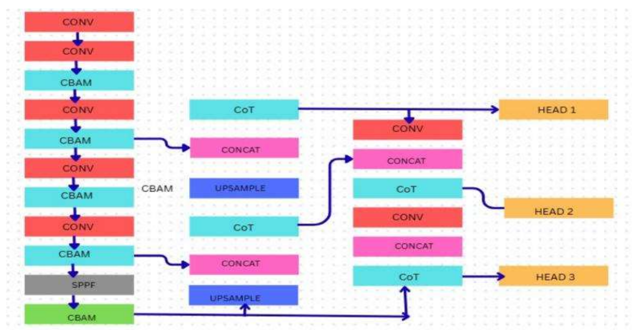
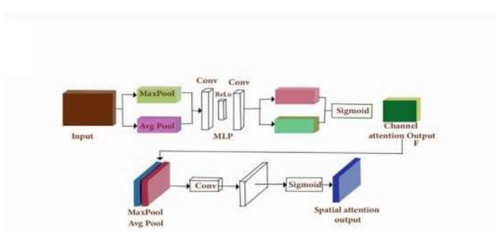


Fig 2: YOLOv5 Architecture

CBAM composes of both a channel and spatial attention (CA & SA) mechanism. The first one assesses the significance of each channel and allocates weights accordingly, whereas the latter pinpoints the locations of important areas in the spatial domain [25].To begin with, the architecture executes average and maximum pooling to feature sets for compressing their spatial dimensions, transforming feature maps F of shape (B, C, H, W) into two feature maps of shape (B, C, 1, 1), Then, the outputs obtained by the above process are send to a MLP to examine the traits of each of them and their corresponding significance patterns. At last, each channel is assigned corresponding weight coefficients using the Sigmoid function. The CBAM architecture is given in Fig 3.



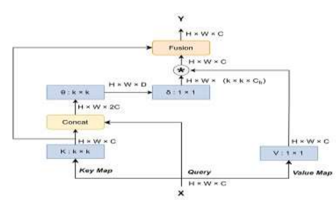


Fig 3: CBAM Architecture [12]

Fig 4: CoT transformer

The outcomes of average and max pooling are combined using a convolutional filter in SA module. This design enhances visual representation by fully utilizing contextual information. The conventional self-attentive mechanism under-expresses the 2D feature graph since it ignores the surrounding contextual information while learning the query and key independently. Therefore, in order to effectively support self-attentive learning, improve feature presentation, CoT module, as seen in Figure 4 is used.The input feature graph is depicted in Figure 4, and the keys, queries, and values are represented by the letters K, Q, and V, where K = X, Q = K, and V = XWυ. To obtain K, a static variable that reflects contextual information between adjacent keys, the CoT block first captures context through a k×k group convolution.The CoT architecture is shown in Fig 4

4. RESULTS AND DISCUSSION

4.1. Proposed Method

Figure above illustrates the basic architecture of the UAV-based real-time insulator and other power line component identification system. We can either collect images directly or convert the UAV footage we obtained into images. These images are then subjected to preprocessing. Data augmentation techniques are employed to prevent overfitting that can occur during training with a small sample size. Methods for data augmentation encompass averaging, rotation, Gaussian noise, blurring, and scaling. These different types of augmentation techniques simulate the real monitoring. For example, brightness adjustment shows the various light intensities, gaussian noise gives the foggy conditions and scaling gives different monitoring distances. The Roboflow annotation tool should be used to annotate these images. In order to train the network, entire data available is divided into training and testing.

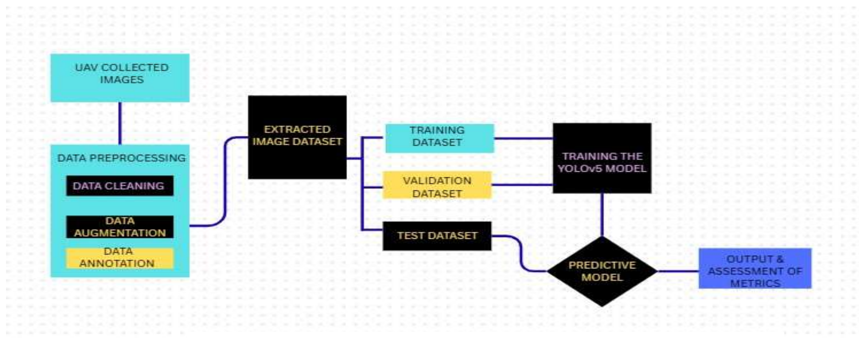


Fig 5: Proposed Model

Fig 5:Precision Model

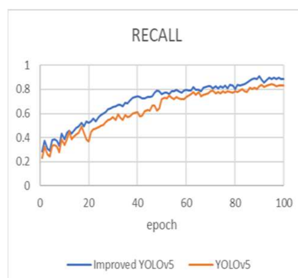


Fig 6 : Recall of the Model

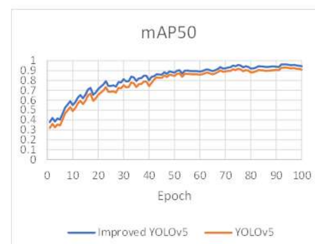
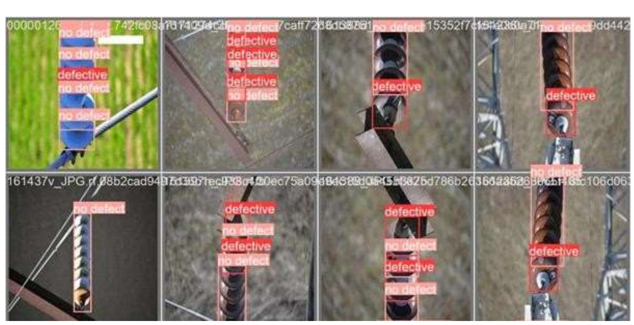


Fig 7: mAP performance of the Model

TABLE I: Result of comparison experiments

Model	Precision	Recall	mAP 50	mAP 50:95
SSD	76.512	76.314	77.298	59.245
YOLO V2	79.845	74.645	78.163	61.325
YOLO V4	81.964	79.236	822.358	66.723
YOLO V5	86.523	82.387	87.824	68.825
Proposed YOLO V5	90.624	87.736	92.174	72.414



The results are shown in terms of True Positive (TP) , False Positive (FP) , and False Negative (FN) samples. Performance Metrics of the

Fig 8: Output of Experiment

mean average precision (mAP) and F1-Score. They calculate how much the system can recognize components and differentiate between various classes.

$$\mathrm{PRECISION} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \qquad (1)$$

$$\mathrm{RECALL} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \qquad (2)$$

$$\text{Mean average Precision, mAP} = \sum_{i=1}^{k} [\int_0^1 P(R)dR \qquad (3)$$

5. CONCLUSION

TABLE II shows the difference in various parameters of our new model with the conventional models like SSD and earlier versions of YOLO .From Table II we can see that our model mAP 50 has been increased by14.876%,Recall increased by 10.4% and precision increased by 14.11%.similarly our newmodel shows significant improvement in precision, recall and mAP 50 values when comparing with models like YOLO v2 ,YOLO v4 and YOLO v5.It shows an increase of 4.1% in precision,5.349% increase in Recall and 4.35% increase in mAP.

This research provides a thorough analysis of the power line component detection mainly insulator fault detection using UAV images. First, the primary methods for evaluating power lines—including manual inspection, climbing robots, and man-made aircraft—as well as their limitations, are covered. The advantages of the UAV inspection method and several image processing techniques are then covered. The importance of adopting deep learning techniques is discussed along with the main limitations of using machine learning and conventional image processing algorithms. Also proposed a method for inspection of powerline components using improved YOLO V5. The outcome is that current approaches face restrictions when it comes to the precise identification of small targets. This research puts forward a detection technique in an innovative way which combines CoT transformer the attention mechanism to tackle this issue. The experimental findings show that using the enhanced methodology, the experimental results shows a substantial increase in the mAP metrics.

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