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Transmission Line Monitoring Using Computer Vision & AI

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Abstract— Unmanned aerial vehicles (UAVs)with artificial intelligence (AI) can provide a revolutionary solution for the monitoring and inspection of power transmission lines. This study employs the YOLOv5 deep learning model to detect faults from custom datasets for the context of Nepal, where rugged terrains impede the feasibility of inspections. Some major faults we are proposing to inspect are broken insulators, vegetation encroachment, conductor sag, and corona losses. We used 950 bounding boxes in 400 images annotated manually, and augmented data was used for model robustness. The evaluation demonstrated the system was precise and accurate, demonstrating the system has the potential to reliably detect a fault. First, this research advances the state of the art in AI-driven infrastructure monitoring by proposing a scalable, efficient, and context-aware system for enhancing Nepal's energy transmission reliability.

Keywords— UAVs, AI, YOLOv5, CNNs, GPU

Introduction

Transmission lines are the backbone of power grids as they facilitate the transfer of electricity over longer distances. Over 68% of the land in Nepal is challenging hilly terrain and maintenance and inspection of transmission lines are both a critical and arduous task. In the past, therefore, these inspections have been based on relatively infrequent manual patrolling conducted every two to three times per year, an unsuitable regime for proactive fault diagnosis [1]. The reliance on human resources without technological aid increases inefficiencies, and costs, and delay fault mitigation efforts.

Transmission line faults, such as broken insulators, vegetation encroachment, corona losses and sagging conductors severely affect energy transfer efficiency. In addition to resulting in significant energy losses, these issues become safety risks for technicians and the general public alike. Examples of vegetation faults are common in Nepal, where the growth of vegetation close to transmission lines leads to short circuits, decreasing operational efficiency and increasing outage risk [2].

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Artificial intelligence (AI) and unmanned aerial vehicles (UAVs), in particular, have recently shown promise as potentially solving these problems [3]. Computer vision based on AI techniques coupled with drone-based inspections provides a cost effective and scalable solution for monitoring transmission lines. Given high resolution cameras in drones, by integrating drones with high-resolution cameras and a trained AI model (YOLOv5), one can detect visible faults like problems of insulator damage, vegetation encroachment, and sagging wires with a high precision. To detect corona losses traditionally, manual observation is used, but thermal imaging cameras on UAVs is an efficient alternative. This approach reduces dependency on human labor and improves the accuracy of fault detection by enabling frequent and automated inspections.

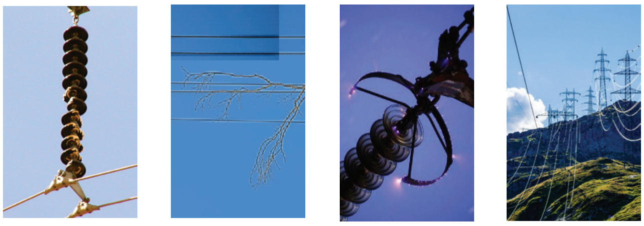
There have been many studies on the use of UAVs and AI for transmission line monitoring [4]. In particular, CNNs have previously been shown to succeed in identifying transmission line faults in aerial images. Advanced architectures like YOLOv5 can outperform traditional CNNs for speed and detection accuracy. Thus, this is ideal for real-time applications [5] [6]. While there are many of these advancements, relevant datasets are still lacking and in areas such as Nepal, customized datasets must be created.

A particular objective of this research is the development of a drone-based transmission line monitoring system suitable for Nepal's unique geographic and operational problems. Using AI in image-based fault detection and UAVs for mobility, the proposed system aims to enhance the reliability and efficiency of Nepal's power transmission network. Detecting some visible faults like vegetation faults, this study uses a custom dataset developed for this project to explore them further. This is a contribution to the emerging field of AI-driven infrastructure monitoring while meeting local needs in Nepal's power sector.

Materials and Methods

To correctly identify the faults in the transmission line's components, many datasets are required. These datasets are basically images of the components in their normal and damaged conditions. These datasets were collected from the internet and labelled manually. A total of around 400 images were collected and around 950 bounding boxes were manually delineated. To create the object detection model, a pre-trained AI model, YOLOv5 [7] is used.

To cover the basic types of faults, we annotated four types of targets, including, broken insulators, corona rings, conductor sag, and vegetation short, as shown in Fig. 1. The datasets are divided into three subsets: training, validation and test sets.



a b c d

Fig. 1 Examples of four types of target classes: (a) broken insulator, (b) vegetation short, (c) corona ring, (d) conductor sag

Creating Datasets

Images collected were labelled manually using makesense.ai, which is a website providing a free annotation facility. Each image was annotated to identify regions of interest with bounding boxes assigned to fault types or components. Since, a single image could contain multiple target areas (bounding box), a total of around 950 bounding boxes were annotated from around 400 images. The annotations followed the YOLO format, where each label file contains class IDs and normalized bounding box coordinates as shown inFig.2.

Fig. 2 Annotation of normal suspension disc

Fig. 2 shows the annotation of the normal suspension disc. The ID for this case is assigned normal suspension disc and the normalized bounding box coordinates are<0, 0.309936, 0.742144, 0.113671, 0.486137>, <0, 0.454776, 0.672828, 0.134450, 0.495379>, <0, 0.603282, 0.532348, 0.096560, 0.454713>.This annotation follows the YOLO format given by <class_id, x_center, y_center, width, height>, where class_id is a unique label for each dataset class, x_center and y_center are the normalized centre of the bounding box and width, height normalized dimensions of the bounding box.

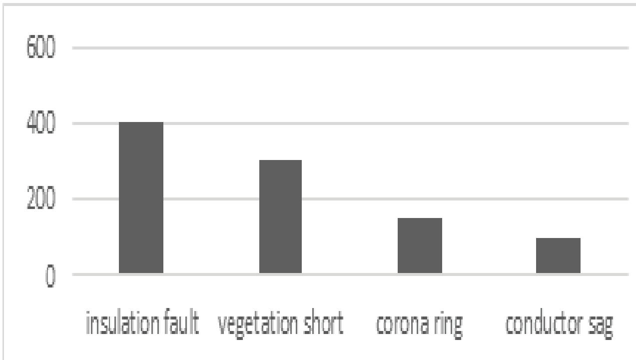


Fig. 3. Number of instances per class

Data Augmentation

The inbuilt data augmentation techniques of YOLOv5 such as scaling, flipping, color jittering, and mosaic augmentation were used to improve the model's generalization capabilities. These augmentation techniques improve the model's reliability and make it capable of localizing the faults in different conditions, such as varying lighting, angles, and background clutter.

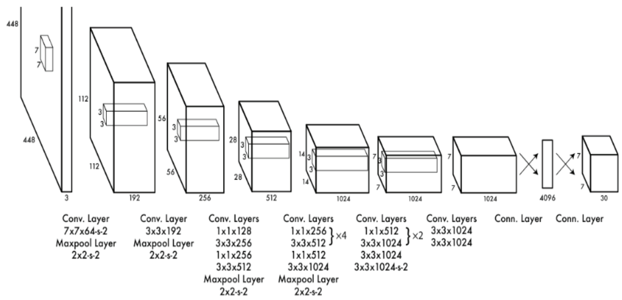


Fig. 4. YOLO architecture [1]

The architecture consists of 24 convolutional layers followed by 2 fully connected layers. Here, alternating 1x1 convolutional layers reduce the feature space from preceding layers. The convolutional layers are pre-trained on the ImageNet classification task at half the resolution (224 X 224 input image) and then double the resolution for detection. The final output of our network is the 7 x 7 x 30 tensor of predictions. The labelled datasets are divided into training (70%), testing (20%), and validation sets (10%). The prepared dataset was used to fine-tune the pre-trained YOLOv5 model through transfer learning [8], a widely used technique to leverage the knowledge of a model trained on a large, generic dataset and adapt it to a specific, smaller dataset. While fine-tuning, the model was trained for 300 epochs, utilizing the a100 GPU of Google Collab.

UAV

After the model is fine-tuned, a processor and a camera can be attached to a drone. The camera captures the real-time images and sends them to the processor. The processor then analyses the image, predicts the state of the transmission line, and sends the report to the nearby substation. Hence, the overall block diagram of the methodology can be realized as shown in Fig.5

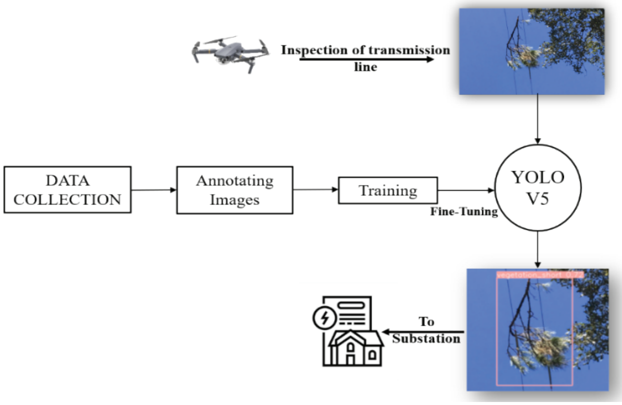


Fig. 5. Block diagram of the overall model.

Results

Inference

The test datasets, which remained untouched during the fine-tuning process, were fed into the fine-tuned YOLOv5 model. The model was able to detect faulty and normal conditions as shown in Fig. 6. The inference results demonstrated the model's ability to accurately detect and localize faults such as vegetation short, and suspension disc rupture under diverse conditions. The results were visualized with bounding boxes and corresponding fault names and labels overlaid on the images.

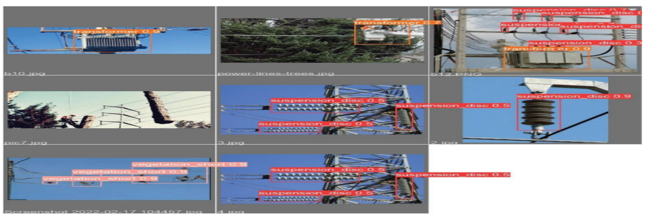


Fig. 6. Correct detection of vegetation fault and normal insulator condition

Losses

The training and validation loss is illustrated in the Fig. 7.

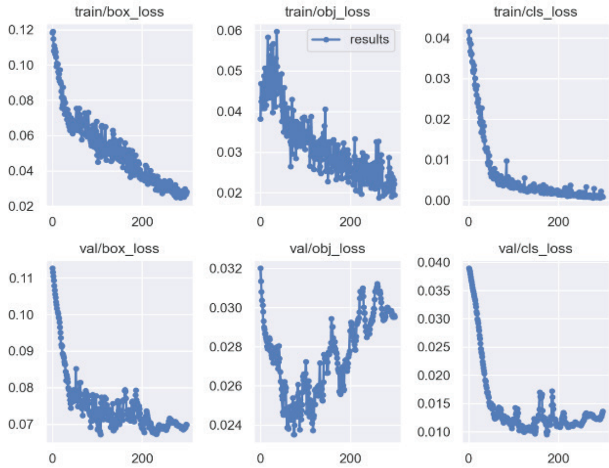


Fig. 7. Training and validation losses

Box loss

It represents the quality of bounding box predictions. In other words, it evaluates the difference between the predicted bounding box coordinates and ground truth bounding box coordinates for an object. The coordinates are given in the form of (x, y, width, height), where x and y are the coordinates of the central pixel of the section bounded by the bounding box. It can be seen that, as the number of epochs increased, the training and validation loss decreased, indicating good model accuracy.

Object loss

It shows to what extent the model has correctly identified the existence of an object in any of the grid cells. It is an important part of the YOLO loss function which concerns the model's ability to detect objects in an image. This loss uses binary cross-entropy loss [9] to compare the predicted score with the ground truth.

$$BCE = -[y \cdot \log(y') + (1-y) \cdot \log(1-y')] \quad (1)$$

Where,

BCE = Binary Cross-entropy Loss

y = ground truth

y' = predicted objectness score.

Validation loss fluctuates slightly but shows an overall decreasing trend, reflecting stable generalization to unseen data.

Classification loss

It measures how well the model predicts the correct class for each detected object. It plays a crucial role in multi-class object detection tasks where the model not only identifies object locations but also classifies the object into one of the predefined categories. It uses a binary cross-entropy (BCE) loss function for each class. The validation classification loss decreases significantly, indicating improved classification performance on unseen samples.

Evaluation metrics

1) *Precision*

The precision is given by equation (2)

$$Precision = \frac{True\ Positive\,(TP)}{True\ Positive\ (TP) + False\ Positive\,(FP)} \quad (2)$$

Precision is the ratio of the number of correctly predicted positive cases to the number of all predicted positive cases. This is also known as positive predictive value.

The model's overall precision was 85%, indicating the model's accurate detections without only a few false positives.

2) *Recall*

The recall is given by equation (3)

$$Precision = \frac{True\ Positive\,(TP)}{True\ Positive\ (TP) + False\ Negative\,(FN)} \quad (3)$$

Recall is the ratio of the number of correctly predicted positive cases to the number of all actual positive cases. This is also known as the true positive rate.

The model's overall recall value was 80%.

3) *Accuracy*

Accuracy is given by

$$Accuracy = True\ Positive + True\ Negative \quad (4)$$

With low classification loss and good generalization, the model's accuracy was 92%

Discussion

Integration of Artificial Intelligence (AI) and Unmanned Aerial Vehicles (UAVs) in power transmission line monitoring in Nepal through Nepal's rugged terrain addresses the challenges in a revolutionary way. This work used the YOLOv5 deep learning model to demonstrate the successful application of the YOLOv5 deep learning model to detect faults concerning broken insulators, vegetation encroachment, conductor sag, and corona losses. Finally, the results show that the system can attain such a high degree of accuracy with an overall precision of 85% and an accuracy of 92%. These figures illustrate how AI could help power up operational efficiency and safety in Nepal's energy sector.

Nevertheless, we identify several limitations and must consider them to further improve the effectiveness of the system. Of particular significance is the visibility of some faults such as corona rings, which may not always be visible to the naked eye. To handle this problem, thermal imagers should be attached to the UAVs. This technology increases the capability to detect faults, but with a high initial investment that may be a cost barrier to adoption. The study also argues for the need for extensive and relevant datasets dedicated to specific fault types. For now, the model is limited to only detecting a subset of faults because there is no comprehensive dataset. Future research should expand these datasets to include additional fault categories, including line breakage or other structural failure. For instance, this expansion would not only help the model become more robust, but also more useful in other geographic areas and operational settings.

In addition to technical enhancements, there are operational challenges related to implementing UAV-based inspections on a larger scale. They include regulatory hurdles to drone usage over Nepalese airspace or the requirement for trained operators on UAVs. This need to address these regulatory and training issues will be critical to the integration of drone technologies in routine maintenance practices. These findings have major implications to the nascent field of AI driven infrastructure monitoring. This research shows a scalable efficient solution that is proven to be suitable to local needs for future development in the inspection of power transmission line. In addition to enhancing reliability, the proposed system seeks to decrease the operational cost by limiting manual inspections.

Conclusions

To monitor power transmission lines in Nepal, a UAV-based system using the power of AI was successfully implemented in this study. The model was tested using YOLOv5 to detect critical faults with good accuracy and reliability, therefore improving safety and operational efficiency. By integrating drones with advanced imaging technologies, drone operators can safely and automatically inspect more frequently, freeing themselves from the inefficiencies of manual labor. However, multiple challenges exist, for example (i) the high initial cost of thermal cameras required to detect corona losses and (ii) the requirement for additional datasets to include more fault cases for enhanced fault detection. Limitations presented in this work can be addressed in future work to realize the full promise of AI and UAVs for transmission line monitoring.

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