Automatic Detection Method of Birds Nest on Transmission Line Tower

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Abstract- *In this paper,we advocate that the Bird disruption to transmission line tower is becoming more frequent as the number of high-voltage transmission lines increases. On transmission line tower, some birds build their nests. The birds' nests serve as conductors during rainstorms, causing power lines to trip. In a dry climate, the branches of the bird's nest are also vulnerable to burning, which not only disrupts regular power supply but also poses a major security danger. As a result, the research issue of identifying and finding bird nests on transmission lines and poles is of considerable importance in order to ensure the stable and efficient functioning of transmission line tower, as well as to minimise the negative effects of bird activities on transmission lines and other facilities is of great scientific importance and practical significance. The identification of a bird's nest on a high-voltage transmission line is an issue of image classification and target detection. As a result, our project is built on a CNN convolution neural network-based automatic detection system of a bird's nest on a transmission line tower. Using photographs taken with drones, this approach will automatically detect the bird's nest on the transmission line tower. Unsupervised learning is used to train the algorithm. This approach has a greater applicability and generalisation ability than the conventional nest detection method. It provides scientific assistance in evaluating bird behaviour and implementing appropriate preventative steps.*

Keywords- Bird's nest, Transmission Line Tower, CNN, Neural Network model, Image Classification, Automatic Detection

I. INTRODUCTION

The three major obstacles to overhead transmission lines are bird pests, lightning interference, and external force damage. Bird disruption accounts for 32 percent of overall damage, according to related records, and the amount of line trips caused by bird movements is second only to those caused by lightning and external force damage. Bird breeding has increased in recent years, owing to ongoing improvements in the natural climate, and bird behaviours have become more popular. The bird pest on overhead transmission lines is increasing year after year, posing a significant danger to the transmission line equipment's safety and stability. Furthermore, because of their excellent radiation tolerance, high mechanical efficiency, and environmental friendliness, composite insulators are commonly used in electrical power systems. The major causes of electrical damage are abnormal temperature increase (ATR) of composite insulators and insulation failure, and the actions of birds indirectly influence the insulation efficiency of transmission lines. The experiment proved that using CNN to detect bird's nests takes less time, has less missing and inaccurate detections, and that the current algorithm produces correct results. This approach has a greater applicability and generalisation ability than the conventional nest detection method. It offers scientific assistance in evaluating bird actions and introducing appropriate preventative steps. Deep learning approaches like convolutional neural networks (CNNs) have piqued ecologists' interest. These tools can automate the study of a wide range of data, from species abundance to behaviour, and from a variety of sources, including photographs and videos. CNNs are a form of deep neural network that, unlike other artificial intelligence approaches that involve handcrafted feature extraction, learns the features that are best for solving a given classification problem automatically from the data. This CNN will eliminate the need for time-consuming manual detection in future experiments, resulting in a more effective data processing pipeline.

II. REVIEW OF LITERATURE

(1)An Automatic Detection Method of Bird's Nest on Transmission Line Tower Basedon Faster RCNN by Fan Li was born in Zhumadian, Henan, China, in 1989.This paper provides an automated bird's nest detection system for transmission line towers that addresses the limitations of conventional bird's nest detection methods, has improved applicability and generalisation ability, and is beneficial to the transmission line's safe and secure activity. Enlarging the data of a bird's nest image solves the issue of inadequate training samples and overfitting of a neural network classifier. The results of the tests show that this system can efficiently identify bird's nest targets in a complex environment, with the highest recall rate of 95.38 percent, the highest F1 score of 96.87 percent, and the detection period of each picture of 0.154s.The method has the potential to vastly increase inspection performance and consistency, as well as provide a solid basis for intelligent identification on overhead transmission lines. The automated identification of other standard transmission line equipment will be discussed next, using the approach suggested in this article.(2)A Solution for Identification of Bird's Nests on Transmission Lines with UAV PatrolbyQinghuaWang,During their natural activities, birds also disrupt the daily activity of transmission lines. Jobs who search, locate, and extract bird's nests from transmission lines are now normal, but their observation is inefficient and geographically restricted. This paper proposes a solution for identifying bird's nests on transmission lines based on feature recognition, which locates the transmission line's pole tower using LSD line detection, Harris corner detection, and morphological closing operation, and identifies the bird's nests within the range of the pole tower using shape and colour features in order to distinguish.(3)Optimizing the distribution of transmission line tower and foundationby Zhu- heyan,in this research paper The architecture institute would design the towers for the long and short legs, as well as the base of the pole, in mountainous transmission lines in order to meet state and national grid standards for environmental safety. To that end, the paper presents a design scheme for a long and short leg iron tower in the Liaoning region, as well as an analysis of the iron tower's design requirements, base surface calculation, insulation alignment, and optimization design.The aim of this paper is to determine the mutual configuration of long and short leg towers, as well as high and low foundations, that can be used to optimise transmission lines in mountainous projects, and to use finite element software to ensure that the minimum amount of base materials is the same while the tower location is constant. The simple base surface requires the least amount of shovel drilling, which helps to maintain the geographical landscape of the tower's location while also limiting the amount of basic materials used and lowering the project's overall cost.(4)Bird's protection and electricity transmission lines by LiutaurasRaudonikis, Knowing the nature of the issue and its role in protecting local and migrant birds, adequate steps are being taken to resolve it. The current power lines, of course, are not equally harmful to birds. As a result, it is clear that the most dangerous stretches of power lines must be identified, and adequate precautions to protect the birds must be devised. It is therefore possible to determine the causes of bird mortality in particular sections, the reduction of which would result in diminished or no negative consequences. Furthermore, reports of birds hatching on power lines raise concerns over how to ensure their safety. It may also be worthwhile to entice those animals to lay their eggs on electricity transmission poles. This is the subject of this brochure. It is important to note that understanding the threats posed to birds by high-voltage power lines, as well as potential approaches to mitigate them, is precisely what allows for the planning and execution of effective realistic bird safety initiatives.

Deep Learning-Based Bird's Nest Detection on Transmission Lines Using UAV Imagery The use of unmanned aerial vehicle (UAV) images for automated object detection has valuable deployment prospects, such as the detection of bird nests, in order to ensure the safety of transmission lines. The analysis of morphological characteristics of the bird's nest is one of the most popular typical bird's nest identification methods. These techniques have limited applicability and precision. We suggest a deep learning-based architecture for automated identification of birds' nests in this paper—region of interest (ROI) mining faster region-based convolutional neural networks (RCNN). To increase the precision of coordinate box generation, the prior dimensions of anchors are obtained using k-means clustering. Second, the focal loss feature is added in the area proposal network (RPN) classification stage to match the amount of foreground and background samples in the training phase. Finally, the ROI mining module is introduced to the classification stage to solve the class imbalance problem, which is coupled with the characteristics of difficult-to-classify bird's nest samples in UAV images. The deep learning-based bird's nest automatic detection architecture introduced in this paper achieves high detection accuracy after parameter optimization and experimental verification. Furthermore, the suggested method's mean average precision (mAP) and formula 1 (F1) score are better than the original faster RCNN and cascade RCNN. The feasibility of the suggested approach is confirmed by their comparative study.

III. BACKGROUND

The number of line trips caused by bird activities is higher than other damages except lightning damage and external force damage. The bird nest on overhead transmission lines increases year by year, which genuinely undermines the protected and stable activity of transmission line tower.

IV. PROPOSED SYSTEM

A. Architecture Diagram

The given architecture diagram shows the pictorial representation of the working principle of this tool. The system comprises of four different modules namely acquisition module, segmentation module, feature extraction module and classification module.

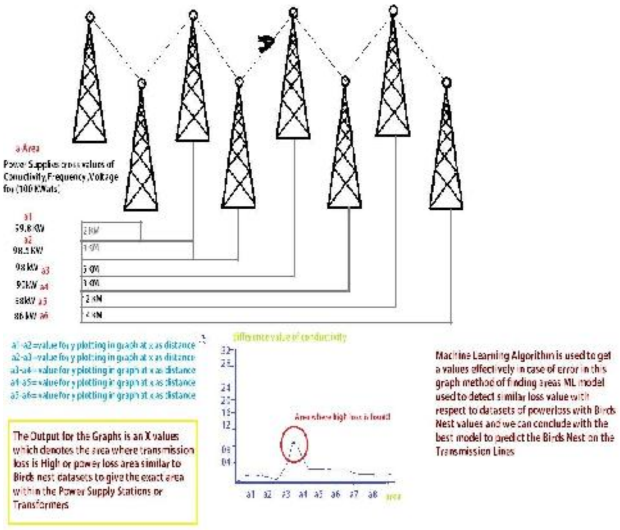

Fig 1: System Architecture of proposed

B. Flow Chart

The flowchart shows the graphical representation of the sequence of functions involved in the proposed system. Firstly the fundus images are given as input to the system which will go through pre-processing stages and then detect the morphological features present in images. Finally based on the extracted features, the birds nest can be detected.

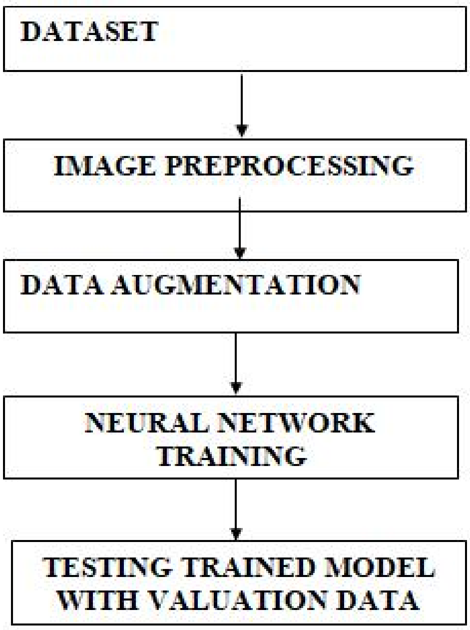

Fig 2: Flow Chart

Dataset Collection:

Reasonable datasets are needed at all stages of object recognition research, from the training phase to evaluating the success of recognition algorithms. Many of the images in the dataset were found on the Website, where they were searched for by name through a number of sites in multiple languages.

Image Processing and Labelling:

Images downloaded from the Internet came in a variety of sizes, resolutions, and content levels. Final images intended to be used as a dataset for a deep neural network classifier were preprocessed to achieve accuracy in order to improve feature extraction. Furthermore, the image preprocessing technique included manually cropping all of the photographs in order to highlight the area of interest.

Augmentation Process:

The key goal of augmentation is to expand the dataset and add minor distortion to the images, which helps to reduce overfitting during the training period. Image data augmentation is a technique for increasing the size of a training dataset artificially by making changed copies of the images in the dataset.

Neural Network Training:

The key aim of network training is for the neural network to acquire the characteristics that differentiate one class from the others. As a result, when using more augmented images, the network's chances of understanding the required features have improved.

Testing Trained Model with Valuation Data:

Finally, after analysing the input images in the valuation dataset, the qualified network is used to diagnose the disease, and the findings are analysed.

REQUIREMENTSPECIFICATION

The requirements can be categorized as hardware requirements and software requirements. Some of the requirements are listed below:

Hardware Requirements

- Hardware - I3 Processor
- Speed - 2.1 GHz
- RAM - 8 GB
- Hard Disk - 160 GB

Software Requirements

- Operating System - Windows 10
- Deep Learning Framework - Tensorflow
- Coding Language - Python

DATAETS

At all stages of object recognition study, from the training process to testing the efficiency of recognition algorithms, adequate datasets are needed. All of the photos for the dataset were found on the website, where they were scanned as birds nest on numerous sources in various languages. There is specific particular dataset source for this, so we developed this model through image.

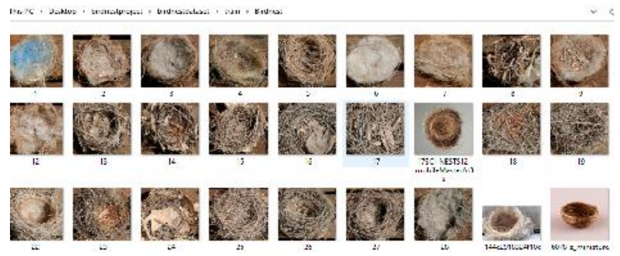

Fig 3:Birds nest training datasets

Fig 4: Birds nest validation datasets

V. RESULTS

By using 200 images as training dataset we get the results on classification. Here we get results satisfactorily according to our analysis. The test process took around 5-6 hours to run over the images with the processor Intel(R) Core (TM) i5-6200U CPU @ 2.30GHz2.40GHz,installedmemory(RAM)8.00GB(3.90usable)andsystemtype64- bit Operating System, x64-based processor . Here the whole data set is also run for validation.Asaresult,oursystemcanabletofetchtheimagesfromth edatabaseand predict the result.

```
In [5]: model.summary()

Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 222, 222, 32)      896
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 220, 220, 64)      18496
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 110, 110, 64)      0
_________________________________________________________________
dropout (Dropout)            (None, 110, 110, 64)      0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 108, 108, 64)      36928
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 54, 54, 64)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 54, 54, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 52, 52, 128)       73856
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 26, 26, 128)       0
_________________________________________________________________
dropout 2 (Dropout)          (None, 26, 26, 128)       0
_________________________________________________________________
```

Fig 5: Convolutional Neural Network Output

In the above Figure, it shows the result as the fetched image is true for the label birds nest. The upcoming screenshots will elaborate the process of model training and testing process with CNN algorithm.

```
train_generator = train_datagen.flow_from_directory(
    'C:/Users/Welcome/Desktop/birdnestproject/train',
    target_size = (224,224),
    batch_size = 32,
     class_mode = 'binary')

Found 606 images belonging to 2 classes.
```

FIG. 6:Training with dataset model output

The number of images fetched is seen in the above figure, and the CNN algorithm is used to train the model with the dataset.

```
validation_generator = test_dataset.flow_from_directory(
    'C:/Users/Welcome/Desktop/birdnestproject/val',
    target_size = (224,224),
    batch_size = 32,
    class_mode = 'binary')

Found 68 images belonging to 2 classes.
```

FIG 7.Validation with the dataset model output

FIG 8: Loss and Accuracy Output(Epoch begins)

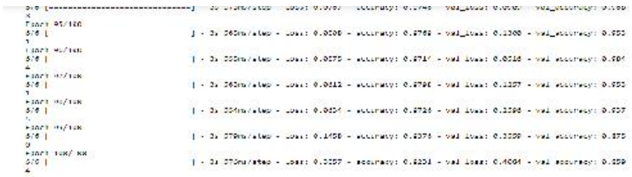

FIG 9: Loss and Accuracy (Epochs Ends)

The number of epochs is a hyper parameter that defines the number times that the learning algorithm will work through the entire training dataset.

VI. CONCLUSIONS

Our system for automatically detecting a bird's nest on a transmission line tower overcomes the limitations of conventional bird's nest detection methods, has greater applicability and generalisation ability, and contributes to the transmission line's secure and stable service. The findings of the experiments demonstrate that this system is capable of detecting bird nest targets in a complex environment. Enlarging the data of a bird's nest image solves the issue of inadequate training samples and over-fitting of a neural network classifier. The algorithm is easy to use, with a limited measurement volume, making it perfect for transmission line tracking and early warning. As a test object, aerial transmission line photographs were paired with image recognition and neural network information. These approaches offer the best approach to the issue of model overfitting. The system should be more robust to handle large amounts of data in real time, allowing us to forecast the performance as quickly as possible.

VII. FUTURE WORKS

In future we would like to boost the precision of the machine in detecting birds nest, so that the findings are more reliable and consistent. Our thesis introduced a concept of detecting birds nest in transmission lines using a robust algorithm. In the future, we can discover the drone that is more powerful to detect and clear the nest on transmission lines by processing a server-based programme that reads and updates the value of datasets to improve the accuracy and predict the nest on transmission lines to overcome power failures using this optimal Algorithm. In addition, we will include processors and motors to monitor the birds and clear their nest.We can also improve the model by including standard optimizers that detect the model's looser bounds and aid the machine in avoiding overfitting for even small datasets. As a result, we will get better results when it comes to finding nests on transmission lines.

VIII. ACKNOWLEDGEMENT

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