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Transmission Line Isolator Fault Detection Based on Deep Learning and UAV Imageries

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Abstract: ***Transmission line inspection is critical in a power transmission system to guarantee the protection and continuous, dependable operation of the power supply. The role played by the basic components of the electricity transmission system between the substation the and final consumer is crucial. The power line components are exposed to extreme weather conditions, like extreme temperature due to high voltages and they suffer high mechanical tension. They are therefore prone to physical defects and should be visually maintained periodically. The main conventional methods of inspection methods are a manual visual inspection by a trained artisan who visually looks for defects. The goal of this study is to look at the feasibility of merging optical and thermal images in drone inspection of transmission lines. Convolutional neural networks strategy of deep learning was selected after gathering sufficient data encompassing both optical and thermal images of substation isolators under different environments and implementing augmentation methods on the data. The model learns the separation between defective and non-defective substation isolators in experimental analysis using TensorFlow object detection API. A comparison was made between a custom-made convolutional neural model and the pre-trained VGG16 and ResNet50 models. The results reveal that the VGG16 pre-trained model accurately detected images with a maximum accuracy of 100%.***

Keywords: convolutional neural network (CNN), Unmanned Aircraft Vehicle (UAV) (drone), Deep Learning, transmission line inspection

1. Introduction

Currently, unmanned aerial vehicles (UAVs) are used to examine power transmission devices on a regular basis. Deep-learning approaches and machine learning have gotten a lot of interest in the field of intelligent UAV control since they're a great method to boost inspection accuracy. Traditionally, utilities send teams of employees to foot patrol the lines or inspect substations after switching off power for the said equipment. [1]

The CNN has brought about a lot of improvement in the accuracy of many machine learning tasks because it is good at dealing with classification and detection. Using deep learning on aerial images to recognize objects and detect anomalies or deviations has been adopted in many applications. [2] In these types of applications, drones can provide a low-cost platform for the aerial image acquisition.

Drone images provide utilities with an unlimited amount of data for determining where network equipment is located and its physical appearance. Combining this data with scientific and technology advancements such as artificial intelligence allows a large amount of data to be processed. When combined, the CNN and Drone systems can provide more effective power line maintenance with more penetration across regions. This provides increased accessibility as well as a significant reduction in the time it takes to notice problems and restore them. [3]

2. Related Work

Several studies have been conducted in recent times to automate the assessment of power lines These include use of various mapping systems for acquisition of images which are then processed to achieve transmission line inspection. Such techniques include remote sensing, helicopter patrol and foot patrol which are expensive and time consuming. UAVs are primarily inexpensive systems and flexible which makes them a good alternative solution [4].

Existing recognition methodologies use image processing to abstract features from aerial photos in order to identify power line components. To differentiate power line components from complicated backgrounds, colour, shape, and texture are widely used. [5]

In most instances, each research study is centred on one specific component (like insulators or transformers) and its related faults. Research on other components continues to diminish because of dissimilarities of component materials, insufficient data, and unsuitable metrics. Small object detection is a difficult problem for most object detection systems [6]

Ramesh et al added to the study of drone support for transmission line recognition within the electrical industry. They employed pixel intensity-based clustering and morphological techniques to recognize power lines in their article, employing remote sensed images obtained by a camera on board the drone as a strategy for detection. [7] This approach's performance was assessed, and also the characteristics produced from the confusion matrix were near to one, indicating that it absolutely was a decent classification method. It is however challenging to assess more complex linkage structures, or use on complicated data sets.

Zhang et al determined the performance of common object detection algorithms and feature extractors for identifying people, bushes, vehicles and structures. In their study they used current target recognition systems and prototypes on drone imageries [8] In their experiments, they utilized TensorFlow object detection API to get object recognition in drone videos. They made use of existing object detection systems namely SSD together with Faster R-CNN. They also utilized MobileNet, GoogleNet/Inception, plus ResNet50 as extractors of the base features. In their observations, they evaluated the SSD and the Faster R-CNN target recognition techniques in terms of promptness of recognition and accuracy. In the study they discovered that the recognition precision for the respective models for bushes, persons and structures is high, with a lower end of 85% and an upper end of 99%.

These common object detectors were then incorporated by other scholars in the field of power line component detection some with minor alterations others combining strategies from different object detection techniques. S. Zhuang, J. Fan and H. Jiang [9]used the SSD (single shot multibox detector) and a fine-tuning strategy to detect isolators aerial images for power transmission line inspection system. In the study they proposed deep detection approach. The SSD-based model can realize automatic multi-level feature extraction proficiently from aerial images instead of manually extracting features in contrast without dated guideless hand-crafted feature extractors. [10] [11]

The pre-classification of the regions of interest (ROI) is the key differentiating factor amongst these researches. However, most of these methodologies use machine learning techniques to classify these ROIs.

After evaluating various studies attempting to decode the techniques that can be used for automatic power grid inspection using deep learning, the following important factors need to be considered when choosing a model to use:

i) Insufficiency of training data
ii) Challenges in detecting defects in small components
iii) Recognition of previously invisible data (components and errors)
iv) Detection of components in a confused environment
v) Lack of metrics for performance evaluation
vi) Gap between data collection and data analysis

A number of ways have been engaged to address these irregularities. Geoffrey et al. offered the analysis of some of these object detection techniques in classifying component faults and categorize their severity in power equipment using different image processing methodologies [12]Shawal et al. also appraised the diverse approaches for categorizing the level of damages in electrical equipment [13]. Even though the CNN has performed well in object detection the detection of small components remains a challenge. Although there have been some improved algorithms to alleviate the problem of small object information loss to a certain extent, it is still an unsolved problem.

3. Problem Definition

Isolators are mechanical switches that are used to isolate a portion of an electrical circuit when it is necessary. They are mainly used to separate the transmission line from the conductor in transmission lines. Electrical isolators have a variety of mechanical issues. Proper maintenance is essential to overcome this. If the flaw on an isolator is minor, it can be cleaned by rubbing it with sandpaper. During maintenance, the proper arrangement of contact rods must be examined. Bolts and their connections, such as electricity and earth, must be tightly attached.

The detection of isolator faults is complex because isolator components are varied. Faults can occur on the connections and contacts. Connections can become loose and galvanized by salty deposits. Contacts can become rusty. Such types of faults are not easily detected from RGB images.

Fig1 below shows a sample of images of isolators with loose connections and parts damaged by corrosion.

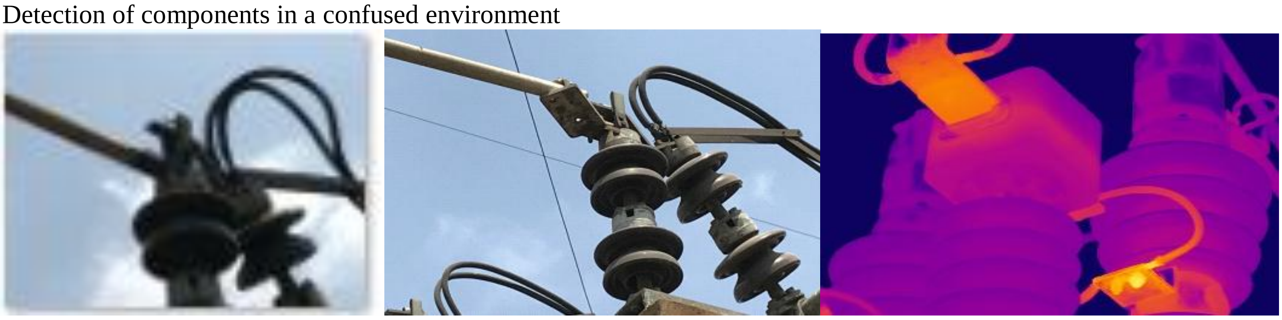

Figure 1: (a), (b), (c)

We investigate a deep learning-based technique for identifying electrical isolator components in aerial photos for a transmission line monitoring system in this study. The system proposed in this study attempts to address challenges of identifying damages occurring on small electrical components by use of multimodal data captured by drones. We need to define a deep learning framework that can directly conduct detection on aerial RGB datasets coupled with information from thermal images. Thermal imaging cameras, unlike infrared and visible imaging, can capture the thermal information of objects in a spectrum of lighting environments, such as at twilight. [14]In order for your thermal imager to measure surface temperature correctly, the reflected temperature (RTC) must be considered in addition to the emissivity (ε) setting. Thermal images settings that were used in this study were Image Temperature Range, Emissivity, Reflected temperature, Ambient temperature and Distance

4. Methodology

In this experiment, a drone with dual cameras collects photos in both the visible and infrared spectrums.

Temperature differences show faults (often referred to as hot spots) or damaged components of the electrical infrastructure (in this case, defective isolators). The identification of problematic isolators in the substation was aided by infrared imaging, which is unaffected by huge scale and lighting fluctuations in the real operating context, while a CNN was developed and trained to recognize and categorize isolators from an optical video stream. The challenge of insufficient data shall be addressed by employing transfer learning and data augmentation techniques such as flipping, zooming and rotation.

A model founded on a convolutional neural network (CNN) has been developed, which uses optical and thermal pictures of isolators as input. The model detects whether an image that has been input is an isolator connection or an isolator contact after training. It also uses temperature deviation data from thermal imaging to classify damaged and non-damaged components.

In addition, pre-trained neural network models based on VGG and RESnet were employed to achieve superior results for the job. The outcomes of various models are then contrasted and compared. The proposed work has been compared to previously published work to see if it is economical and practicable.

Figure 2 shows a schematic diagram of the suggested component detection approach for transmission line isolator detection in aerial photographs. Aerial picture acquisition, model training, and component and failure detection are the three aspects of the system design. The aerial photographs from the UAVs are first collected for transmission line inspection. There are two distinct datasets defined. After pre-processing such as scaling, cropping, and tagging, the original aerial photos are converted to the standard data format for model training. Once the specialized isolator model has been properly trained, it can be used to recognize isolators from aerial photos captured by UAVs for transmission and classifying whether or not they are damaged,

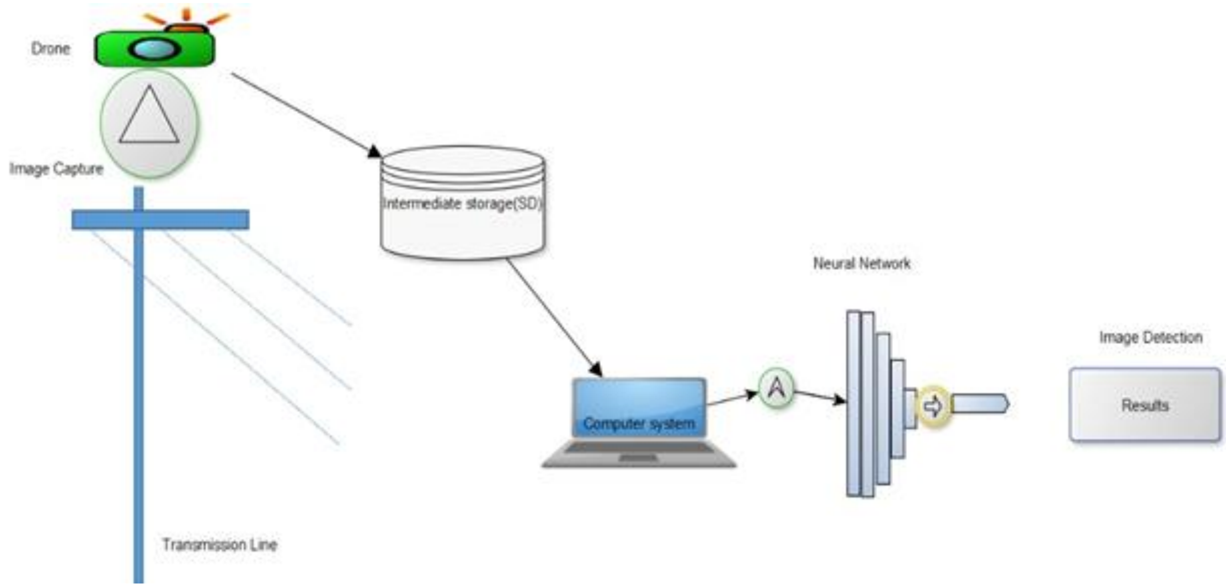

Figure 2: Overview of proposed system

A. Image acquisition and pre-processing

The initial phase in the overall inspection procedure is image acquisition, which entails employing a camera mounted on a drone to capture photographs of transmission line components. Electrical isolators are power line components that need to be checked on a regular basis. Because they are located on components of high-voltage power lines, photographing them can be difficult and time-consuming. The images used in this article were acquired from ZETDC transmission substations scattered around the country. [15]

The device utilized to record the video data of a substation is an unmanned aerial vehicle (UAV). This information is recorded to an SD memory card that can be removed from the device. The DJI Mavic 2 enterprise UAV was used to conduct this experiment. It was fitted with a dual camera, a visual camera Nikon 340 and a thermal camera Flir E95 and Testo 895. The DJI Mavic used can shoot in 4K at 60 frames per second. Additionally, the camera can capture 1080p video in slow motion at 120 and 240 frames per second. The included battery has a runtime of about 34 minutes, with the option of removing the batteries to extend the flight duration per day.

Figure 3: DJI MaviC 2 enterprise advanced

Description of Dataset

There is no public data set in the transmission line inspection task at present. The experiment uses the transmission power classification data set of isolators taken from substations scattered across Zimbabwe. Approximately 500 images of isolators were collected

Figure 4: Sample images from Dataset

Visual image photos were extracted from the optical camera using Adobe Lightroom, a video editing program. Thermal pictures were analyzed with Flirtools and Cronista. Shutter speed, focusing, and image exposure were all regulated to control scaling and restrict the amount of frames-per-second (FPS).

i) Thermal image settings were
ii) Image temperature range
iii) Emissivity
iv) Reflected temperature
v) Ambient temperature
vi) Distance

We established separate spreadsheets for recording the dataset information from each of the two cameras during data gathering. One spreadsheet contained the attributes fault type, fault rating and temperature range. The attributes of the other spreadsheet were as follows optical image id, thermal image id and reflected temperature

The table below shows the classification of faults from the temperature information obtained from the thermal images.

Fault Extent	Temperature Deviation
No Fault	Temperature Deviation 0-10
Minor Fault	Temperature Deviation 10-25
Low	Temperature Deviation 25-40
Medium	Temperature Deviation 40-75
Serious	Temperature Deviation 75-100
Severe	Temperature Deviation <100

B. Data augmentation

Data augmentation techniques are used to enlarge a data set. They lessen the effect of overfitting of a model and improve detection accuracy. [14] Illumination adjustment, arbitrary rotation, zoom, contrast tuning, and horizontal flip are some of the data augmentation techniques used in this article. The number of sample pictures increased to 600 after data augmentation, with an 8: 2 ratio between the train and validation datasets.

C. Preprocessing

The image dataset is divided into two folders, one with images for training and the other with images for testing. These images were then divided into 2 classes, Faulty Isolator connection/contact and Isolator Ok. All images in the training dataset share equal dimensions. In creating the defective isolator dataset. The PASCAL VOC dataset standard was utilized as a benchmark. The image details (imagefilename, path, image width, image height, image depth and image id) and bounding box coordinate coordinates (xmin, ymin, xmax, ymax) are stored in an xml file generated by the LabelImg software. Figure 5 shows an example of a labelled data sample

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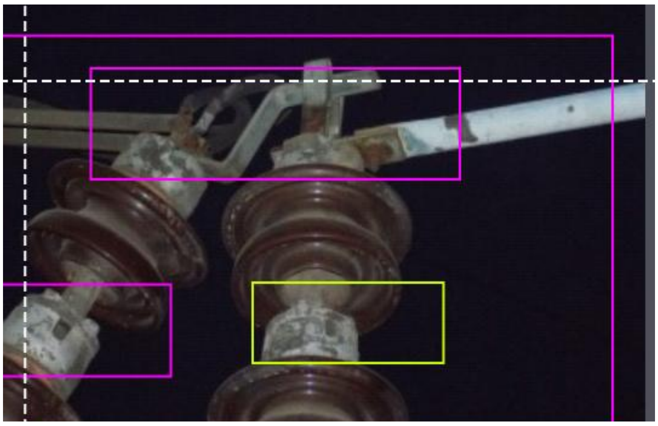

Figure 5: Example of a labelled dataset

D. Proposed model

To apply CNN to the dataset there were two options, one of constructing a specific custom made model and/or utilizing a pre-trained model. As a result, we ran a number of tests on the dataset using CNN in various methods. The following were the three broad experiments that were carried out:

i) Using CNN models that have been custom-made
ii) Using CNN based on VGG16 models
iii) Using CNN based on RESnet models

Applying Custom-made CNN model

We started by developing a convolutional neural network model from beginning. The architecture of the CNN model that was custom-built is described below. We created a sequential model in Keras in which the layers are linked in a specific order.

i) A number of 2-dimensional convolution layers with 3x3 kernel and ReLU activations are used to process the input. These perform the extraction of specific feature maps.
ii) A max pooling layer follows each convolution layer and its purpose is to reduce the dimension of input further.
iii) The output is processed via a global average pooling which minimizes the size of the output by averaging a region.
iv) The output is normalized using the batch normalization layer and transferred towards the next block after max pooling.
v) Lastly the output of the preceding layer is fed into the dense layer, which has one neuron that uses sigmoid activation to classify the input as 0 or 1.
vi) The loss function in the model is binary cross-entropy, which is a logarithmic loss function.
vii) The RMsProp optimizer was utilized to optimize learning rate

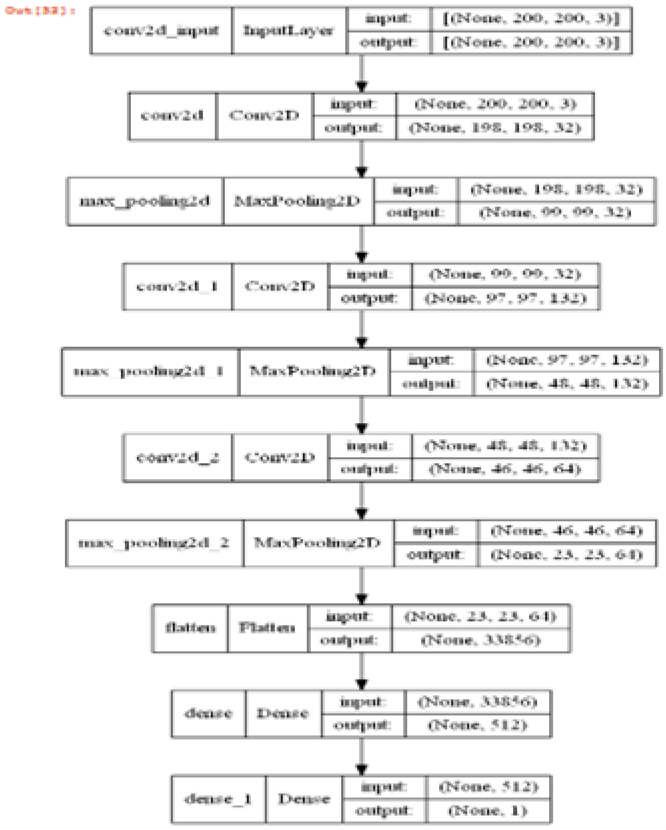

Figure 6: Model Architecture

The CNN model is trained in Anaconda's Jupiter environs. The Keras API offers the capability for fast experimentation to develop, train, and test models from standard layers. The parameters used for the experiment are given below.

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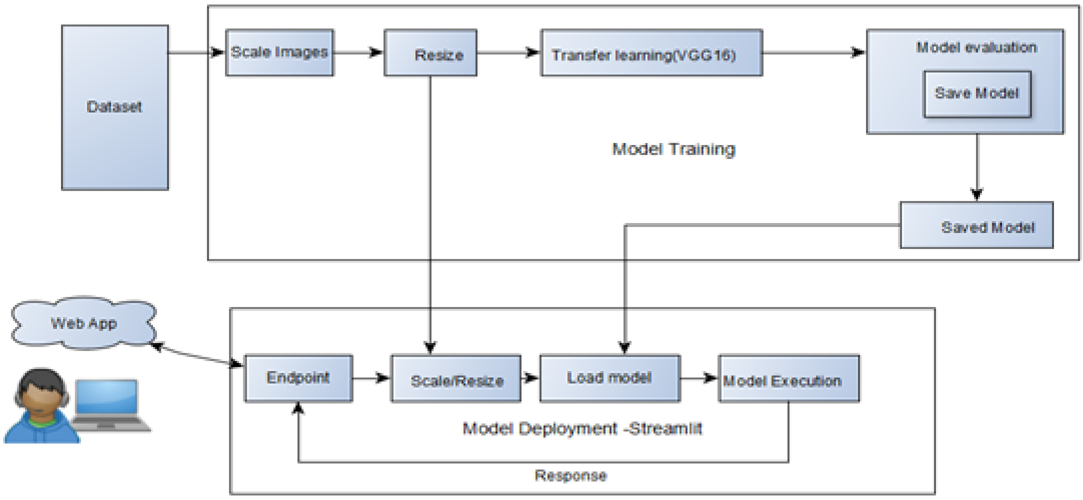

Figure 7: System architecture

5. Results

The experiments were conducted on Google's Tensor Flow with a computer havingan Intel (R) Core (TM) i7-8550U CPU[at]1.80GHz 1.99 GHz and 16 GB memory. A dataset from Zimbabwe Electricity Transmission and Distribution Company (ZETDC) was used in experiments that contained 400 images. The image data locations were Orange groove, Chertsey and Beatrice substations in Zimbabwe. The isolator images were collected under different lighting conditions. The main goals in this study were precise detection of power line electrical isolator components, and classification of faulty components

Experiment 1: *Applying Custom-built CNN model*
Parameters:
i) No. of epochs =30
ii) loss = binary_crossentropy, optimizer=RMSprop, learning rate = 0.0001,
iii) metrics = 'accuracy'

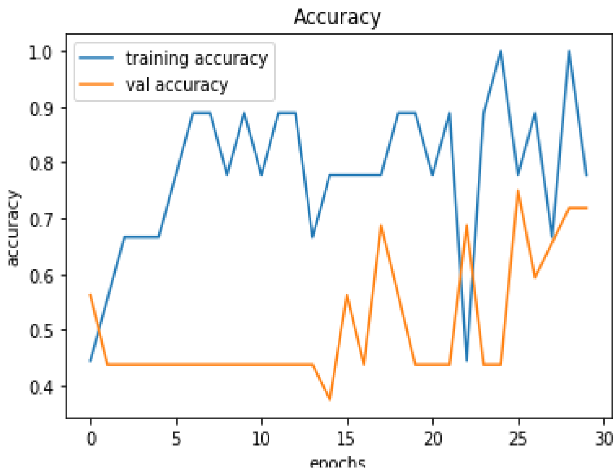

Figure 8: Experiment Observation for custom built CNN model

The findings of this experiment are visually represented in Fig.11. The neural network recognized isolators with an accuracy of 83 percent in this experiment. We also scaled the image data from size 4032 x 3024 to 200x200 for this experiment. Validation testing was done to avoid overfitting. The accuracy of validation was assessed after each period. During neural network testing for this purpose, two epochs were proven to be sufficient for obtaining 70% or above.

Experiment 2: *Applying VGG16 based CNN model*

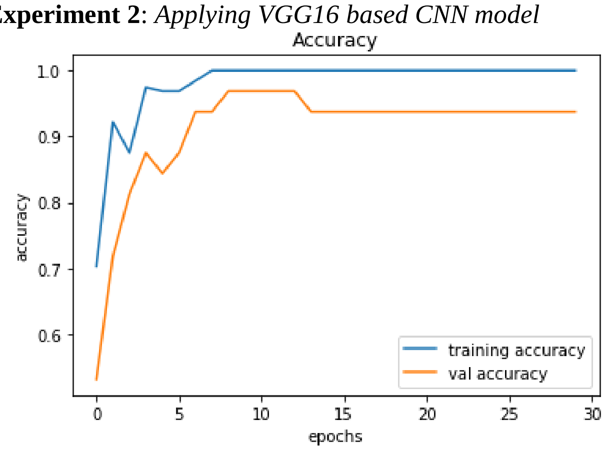

Figure 9: Experiment Observation of VGG16 based model

The findings of this experiment are visually represented in Fig.12. The neural network recognized isolators with an accuracy of 100 percent in this experiment.1e-3 is the learning rate that regulates the magnitude of the weights. We also scaled the data from 4032 x 3024 to 229x229 for this experiment. Validation testing was done to avoid overfitting. The accuracy of validation was assessed after each period. During neural network testing for this purpose, two epochs were proven to be sufficient for obtaining 90% or above. The model can differentiate isolator components with precision

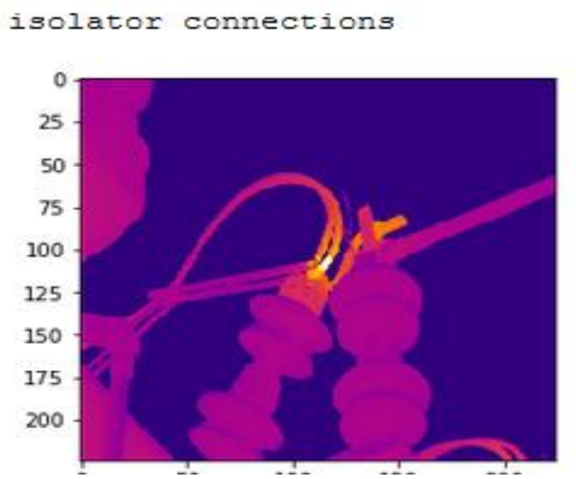

Figure 10: Predicted isolator connections

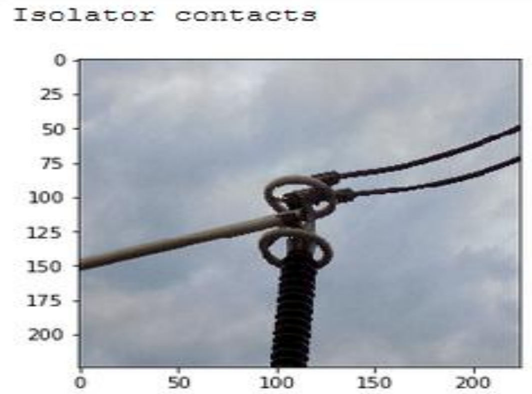

Figure 11: Predicted isolator contacts

Experiment 3: *Applying ResNet50 based CNN model*
The findings of this experiment are visually represented in Fig.15. The neural network recognized isolators with an accuracy of 85 percent in this experiment.1e-3 is the learning rate that regulates the magnitude of the weights. We also scaled the data from 4032 x 3024 to 229x229 for this experiment. Validation testing was done to avoid overfitting. The accuracy of validation was assessed after each period. During neural network testing for this purpose, two epochs were proven to be sufficient for obtaining 70% or above.

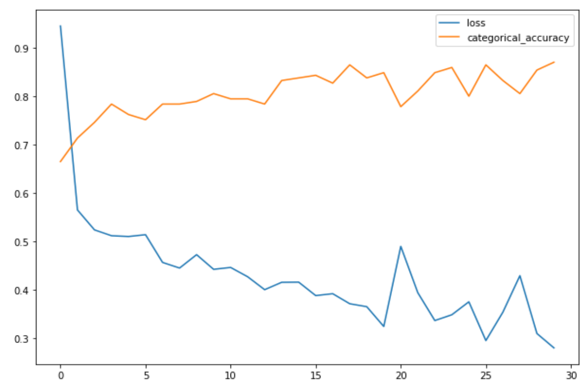

Figure 12: RESNet50 experiment result

6. Discussion of Findings

Most of the variables that influenced the outcome of the study were uncovered by experimentation. Application of CNN to two forms of data for Isolator detection is still an undiscovered discipline with numerous theories and methodologies that could be applied to further this research. To discern every trait and facet of an object, I quickly learned that classifying photographs with software required testing with multiple training models. Individual models should be configured to best suit the input data. We also discovered that as the amount of data grew, so did the accuracy.

This study used a convolutional neural network to recognize objects in video taken by the drone. In this study, we propose that CNNs be used in combination with drones fitted with dual cameras to distinguish certain object types such as isolator connections and contacts. These parts are prone to defects. If there is enough data, this information-driven deep learning technology can address the limitations of conventional defect detection algorithms.

Despite the fact that CNNs are computationally costly, we train our networks with smaller image datasets through the use of transfer learning. We used Tensor Flow's sophisticated object detection API in our project, this allowed us to quickly build a new model and deploy it. We discovered that the two models' detection accuracy for isolator connections is high, with an average of more than 83% and a maximum of 100%. We examined the memory and runtime requirements of VGG16, ResNet50, and our own custom built model in our experiment. VGG16 has the smallest memory requirements of1.7 GB, ResNet50 has approximately 2.5 GB of RAM, and our Custom Model had a memory requirement of less than 2 GB. The results of the aforementioned trials show that VGG16 models based on CNN outperform both the custom-built CNN model and the ResNet50 model.

7. Future Improvements

For this study, the ideal dataset would include visible and thermal infrared images taken at identical times and in the one location for feature merging, raw thermal infrared data (TIFF file) instead of shaped and extracted thermal infrared images (jpg file) for retrieving surface temp mask relevant information, and weather variables such as light, temperature, humidity, atmospheric pressure, and so on for acquiring the temperature mask by construct. . [15]

Future study in this field could lead to collaborations with drone's research. Having entrenched handling proficiency on the drone provides immediate results and increases the timeliness of this inspection service.

In the case of drones with embedded learning algorithms to achieve autonomous vision, wireless transmission of images and videos introduces a latency to the system which may add costs. Image and video processing requires high computational resources which creates a problem in representing deep learning-based algorithms on less expensive and low-power computing platforms.

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