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UAV Flight Fuzzy Controller with Deep Learning Network Fault Checker of High-Voltage Lines

Abdullah J. H. Al Gizi[1]

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Abstract: In recent years, more and more power transmission lines have been inspected using unmanned autonomous vehicle UAVs. Intelligent UAV control using deep learning methods and machine learning has received a lot of attention due to its ability to increase inspection accuracy. This paper presents the development of a tele-powered fuzzy-controller vehicle sonar tracking checker developed by using UAV in data power line detection for high-voltage power line preventive maintenance. The Vehicle Sonar Tracking Checker is designed with portability in mind, so cable spacers, suspension clamps, and other obstacles that previously prevented inspection of high-voltage power lines do not impede inspection of the lines. In contrast, deep neural network DNN has improved the accuracy of many machines learning tasks because it can categorize and detect various errors. Deep learning on aerial photographs has been used for several applications. Drones can provide a low-cost aerial imaging platform in such applications. There is no limit to the amount of data that can be collected using drone photos to find network infrastructure. A significant amount of data can be analyzed by combining it with other technologies such as artificial intelligence (AI). This reduces the time it takes to identify and fix issues, making it easier for the team to get started and fix. The combined DNN and drone technologies can enable more effective power line maintenance, reaching areas with higher effectiveness. This reduces the time it takes to identify and fix problems, making it easier for individuals to get in and fix things..

Keywords*: Overhead Power Line, DNN, AI, UAV, fuzzy controller, Tracking Checker*

1. Introduction

The components in a power scheme are the transmission lines in which an enormous amount of power is often transferred through these conducting cables. Generally, the backbone of high voltage electric transmission lines span over thousands of kilometers or more, carrying the electrical power or energy from source to the distribution network through various substations and conversion centers. In short, these transmission lines serve as links between the production and distribution points, eventually connecting the point of sale. Whenever there is a failure, fault or any damage of these lines, the repair, replacement and maintenance process in not only very expensive, unsafe and needs skilled manpower but also too much time consuming [1]. Over the years several strategies have been adopted for easy detection and repair of such faults in the high voltage transmission lines that run very high above the ground [2].

This paper [3] presented a self-tuning PID control technique for a four-engine air vehicle with a changeable payload wherein the traditional PID and PID basis self-tuning were compared using fuzzy logic. the results revealed that both methods can control reasonably well. In addition, the results with identical weights of the payloads showed an outperforming nature of the suggested self-adjusting PID, indicating excellent performance in terms of turbulence reduction and track tracking under varying actual weights. Examined the possibility of improving the stability and control of a micro-UAV to use in path planning or target acquisition [4]. A supervisory PID controller was utilized in order to give the UAV more autonomy and MATLAB code was developed to enable the quadcopter to do the necessary task. All quadcopter movement was monitored and the error from each waypoint was determined accurately using preprogramed PID, MATLAB code, and PD switch cases. Used cascaded PID controllers to designate the inner and outer loops [5]. Then, perpendicular rapidity and yaw percentage were controlled by the inner loops and the height as well as direction was controlled by the outer loop. Neither of these loops differed much from the actual flight controller of quadrotor. In addition, in this control approach the inner loops were substantially quicker than the outside ones called a time-scale separation [6]. In order to identify the electricity transmission lines, a LiDAR was pointed vertically and was used to alter the image acquisition quality such as magnification and focusing of the camera, studied a quadrotor's trajectory tracking problem in which the lively prototypical of the UAV helicopter was controlled by a sliding approach block process. Following an accurate first-order differentiator, the copied of the virtual regulator contributions was calculated. The grades showed an exceptional performance of the wished-for control scheme in terms of asymptotic stability. Used advanced mathematical models to investigate the kinematics and

1 1Thi-Qar Technical Collage , Dept. Of Electromechanical Engineering, Southern Technical University
Thi-qar, Iraq
** Corresponding Author Email: abdullah.algizi@stu.edu.iq*

dynamics of the quadrotor [7]. Using a modular fuzzy logic method, they demonstrated an autonomous control of the quadrotors without requiring any detailed mathematical explanation for the intricate and ill-defined dynamics. Developed the fuzzy inference engines to compare the outcomes of various fuzzy methods. Six fuzzy logic modules of the controller were used to regulate the position. Both control strategies were evaluated in a simulator by incorporating the actual disturbances such as wind and sensor noise in order to generate a more realistic condition. In addition, the fuzzy flying controller was created on a quadrotor test bed. The studies were first conducted on a computer simulator to confirm the achievement of a real test bed. The obtained results (based on the Mamdani inference engine) revealed an effective control performance when compared with more conventional systems. As opposed to the previously introduced technique, the proposed system was more robust to the applied perturbations. This paper [8] investigated a quadrotor UAV specifically designed for the transmission lines inspection. As a precaution against the singularity problem, the quaternion approach was used to calculate the mechanical pressures and torques on the quadrotor. In addition, the effect of electromagnetic field interference caused by high voltage transmission cables on the quadrotor was considered in the calculation. A novel mathematical model was developed by considering the limitations of the quadrotor for the power lines inspection rather than the conventional motorised replicas that only explain a generic flight scenario of a UAV. It was acknowledged that a scientific prototypical considering completely the limitations of the undertaking category is essential. The proposed quadcopter for the transmission line inspection was most cost-effective, easiest, safest, and efficient approach related to the existing state. In order to express mechanical and electromagnetic equations, the model assumed that perfectly conducting nature of the propellers, ground, and root-mean-square line voltage. Evaluated the characteristics of UAVs used in transmission line inspection [5, 9, 10]. It was shown that various types of UAVs can be implemented for different activities of the line's inspection. In other nations, the UAV technology is being used for the transmission lines inspection related to the current situation. Essentially, the UAV technology has progressively been more used for the transmission line inspection wherein its industrial standardization played a significant role in the rapid popularity. The UAVs produced in China are the most popular ones worldwide, with a wealth of expertise and cutting-edge equipment that is unparalleled anywhere else. Other nations can use Chinese UAV line inspection standard as a model to make it easier for them to enter into the transmission lines inspection market based on UAV. The existing UAV inspection criteria allow electric power companies to deploy this technology for routine patrol work. Nevertheless, there is significant potential for the development and extensive use of UAV in the future. developed an automated system for inspecting the power transmission systems and studied its hardware and software configurations [11].

Finally, the inspection concept was integrated into the proposed quadrotor helicopter-based system. It was acknowledged that one may easily and securely establish an inspection plan employing the newly designed graphical user interface (GUI). This system demonstrated the possibility of accessing the transmission cables and towers in their entirety automatically. Typically, although the flown UAV made an autonomous examination of the transmission lines and also be flown at a adjacent offset to obtain the photos on both sides of the wires. These papers [12] [11] proposed a mechanism for capturing the photographs of the insulators wherein the paddings were identified using the YOLO approach and sequential image dispensation throughout the inspection process. The results indicated the suitability of the proposed technique. However, it must be improved for accurate recognition in complicated backdrops especially when considerable learning is performed and the images with tower components or flora in the background.

Within the 5th section, a contemporary local proposal technique that be contingent on a Discrete Wavelet Change [11, 13, 14].

The problem and research gap are high voltage electric transmission lines span over thousands of kilometres or more, carrying the electrical power or energy from source to the distribution network through various substations and conversion centres, whenever there is a failure, fault or any damage of these lines, the repair, replacement and maintenance process are very difficult.

The propose uses a flying automaton baptized Butterfly to overhaul injured or debilitated conversation or dispersal regulator links, particularly in unreachable areas or in high crags. We used a vehicle as exposed in Fig. 1 to scan a control T.L and differentiate among the outside the insulator and conductor to restoration injured.

2. Technical specifications of rule fuzzy

Stretches short-lived applied conditions for all basics compulsory drone will have a current camera reader. Fig. 1 demonstrates the vital sizes of the rudimentary surround of the quadcopter. The correct value of shove per motor-powered could be envisioned:

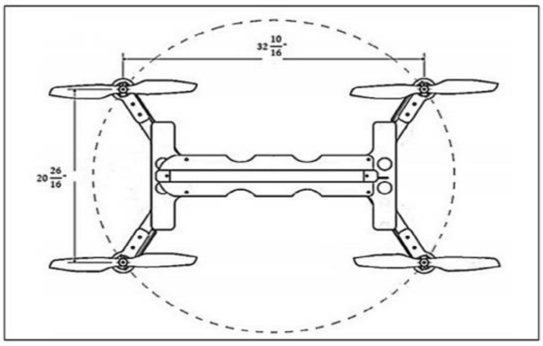

Fig.1.Shows a)A opinion of the vehicle automaton from the front. b)The vital dimensions of the UAV frame

$$\text{Thrust} = \frac{(2*z*W)}{N} \quad (1)$$

Where; N is the number of machines used in the scheme, and a is the safety-factor that reflects the machine's competence, this issue is characteristically advanced as 20% of the total heaviness W.

[13, 15] excited electrical basics are so difficult to amount, even from short disinterests. Rendering to their teaching; the chief motivative for this trouble was since of the large amount scene size likened to the slight defect constituent size, the long-distance range, object likeness, and climate status. Thermography is used in this study. Two emotional electrical rudiments are shown in the Fig. 2. Complement to each pixel the fortes of the eight head-to-head residents about it as clarified in Eq. 2 (i.e., the attentions of all pixels included inside a [4x8] pattern are additional to the attentiveness of the dominant pixel in Table 1. Table 2. Fuzzy PID supervisor rules that are then optional to the PID supervisor. If show the comparative locations of the other basics in the same copy we can expose their edges as it is portrayed in the 3rd row of the two impassioned electrical elements.

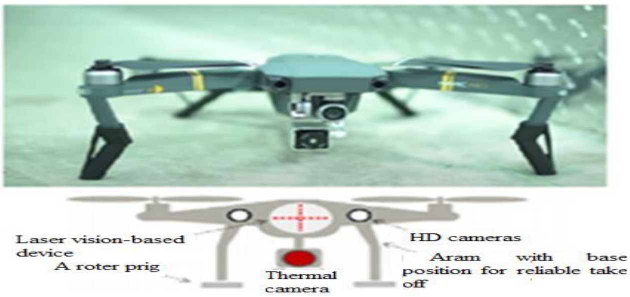

Fig.2 Two impassioned electrical elements

$$O(x,y)=\sum_{i=x-1}^{X+1} \sum_{j=y-1}^{y+1} P(i,j) \quad (2)$$

Where; O is the attentiveness of a pixel after addition the attentions of neighbors. P(x,y) is the attentiveness of each pixel in this home-grown area rendering to its organizes on (x) and (y). So, the rule fuzzy of our regulator reliant on a pixel-enclosed by neighbors.

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3. Methodology of the Proposed System

The *UAV* will feature a thermal imaging camera reader that will capture warm images useful for scrutinizing cables, electrical connections, switches, and circuit-breakers throughout the area. This system examines all portions of the transmission line and takes close-up photos examining the position of the apiece transmission line portion

Table 1. A Pixel Enclosed Neighbour

P (x-1, y-3)	P (x-3, y-1)	P (x-2, y-1)	P (x-1, y-1)	P (x, y-1)	P (x+1, y-1)	P (x+2, y-1)	P (x+3, y-1)
P (x-1, y-2)	P (x-3, y)	P (x-2, y)	P (x-1, y)	P (x, y)	P (x+1, y)	P (x+2, y)	P (x+3, y)
P (x-1, y-1)	P (x-3, y+1)	P (x-2, y+1)	P (x-1, y+1)	P (x, y+1)	P (x+1, y+1)	P (x+2, y+1)	P (x+3, y+1)
P (x-1, y)	P (x-3, y+2)	P (x-2, y+2)	P (x-1, y+2)	P (x, y+2)	P (x+1, y+2)	P (x+2, y+2)	P (x+3, y+2)

Table 2. Fuzzy PID controller rules

$ce_{(t)}$ / $e_{(t)}$	NB P (x-3, y-1)	NM P (x-2, y-1)	NS P (x-1, y-1)	ZE P (x, y-1)	PS P (x+1, y-1)	PM P (x+2, y-1)	PB P (x+3, y-1)
NB P (x-1, y-3)	1 NB	2 NB	3 NB	4 NB	5 NM	6 NS	7 ZE
NM P (x-1, y-2)	8 NB	9 NB	10 NB	11 NM	12 NS	13 ZE	14 PS
NS P (x-1, y-1)	15 NB	16 NB	17 NM	18 NS	19 ZE	20 PS	21 PM
ZE P (x-1, y)	22 NB	23 NM	24 NS	25 ZE	26 PS	27 PM	28 PB

The core goal of using this scheme is to reduce inspection time and charges without sacrificing superiority and increasing employee security throughout checkups. Fig.1 shows a front view of the vehicle robot. This is critical for the safe transmission of energy between a network station and a local delivery station. The suggestion approaches syndicate deep learning approaches and machine learning processing.

4. Deep Neural Networks

As a category of ANN used in image processing, convolutional neural networks (CNNs) are the feed-forward (non-recurrent), deep learning, and feed-forward neural networks. Here the dot product of a neuron's output is determined instead of using the discrete layers. DNN uses many convolutional layers, each following an activation function. CNN's pooling layers will also be added. It is possible to gradually reduce the structure scope and the numeral of parameters in the net. These variable-size descending filters are modified throughout the exercise phase to incorporate translation and gage invariance qualities, creation them a good optimal for image meting out. At the very end, some DNN variants use layers that are fully interconnected. When the network has finished generating the convolution features, they are combined and used to make the final classification [16-19].

4.1 Deep Network Designer

In this study, a DNN model was built from scratch. A sequential model was built on the MATLAB platform, where the layers were linked in a specific order. The input was processed using a series of two-dimensional convolution-layers with 3 (3 kernel and ReLU-activations, which were responsible for extracting certain feature maps.

You specify the image size, which is 277, in the image input layer * 277 pixels in three channels (RGB) The structure of DNN models can be described as follows (Fig.3):

1.Image input layer: Here you specify the image dimensions, which in this case is 277 * 277 pixels in three RGB channels. These values relate to the width, height, and size of the channel. Since the unit data is in grayscale, the channel dimensions is RGB since a color image has three channels, one for each of the RGB values.

2.Convolutional2DLayer: The primary parameter in the convolution layer is the filter dimensions, which stipulate the width and height of the sieves used by the exercise function when perusing the image. The number 3 designates that the sieve is 3x3 in this case. You can stipulate different dimensions for the width and height of the sieve. The second option, nonfilter, specifies the number of sieves equal to the number of neurons connected to the same range of input. This option specifies the numeral of feature maps to create. Add stuffing to the involvement feature map using the name-value mixture Padding. 'same' stuffing assurances that the output spatial dimensions of a convolution layer with a default step size of 1 is equal to the involvement size. Additionally, you can set the step and learn charges for this layer by means of the convolution2dLayer name-value couple parameters.

3.Batch Normalization Layer: The batch normalization layer normalizes the activations and gradients propagating through a net, making network exercise a simpler optimization problematic.

4.ReLU Layer: Layer of ReLU After the batch-normalization-layer, a non-linear activation function is used. The corrected linear-unit is the greatest commonly used start function (ReLU).

5.Max Pooling Layer: A down-sampling process that reduces the spatial extent of the feature map and eliminates unnecessary spatial information often follows Max Pooling Layer: Convolution layers (with activation functions). Down-sampling allows filters to be added to deeper layers of convolution without increasing the amount of processing required per layer.

6. Fully Connected Layer: we add One or more fully connected layers after the convolution and down-sampling layers. A fully connected layer, as the name suggests, is a layer in which we connect the neurons to all the neurons in the previous layer. This layer integrates all the features learned from the previous layers to find broader patterns in the image.

7.Softmax Layer: Normalizes the completely linked layer output using the SoftMax permit function. The SoftMax layer outputs positive values that add up to one, which the classification layer can use as organization probabilities. After the last completely mated plane, use the SoftMax plane tool to create a SoftMax plane.

8. Classification Layer: The classifying layer is the last layer. It computes the Classification layer: Use the Classification Layer to create a classification layer. It calculates the loss by assigning apiece input to a single of the equally selected lessons by the probabilities provided by the SoftMax activation function. Finally, the production of the classification layer feeds into the dense layer with a neuron that used sigmoid activation to identify the input as 0 or 1..

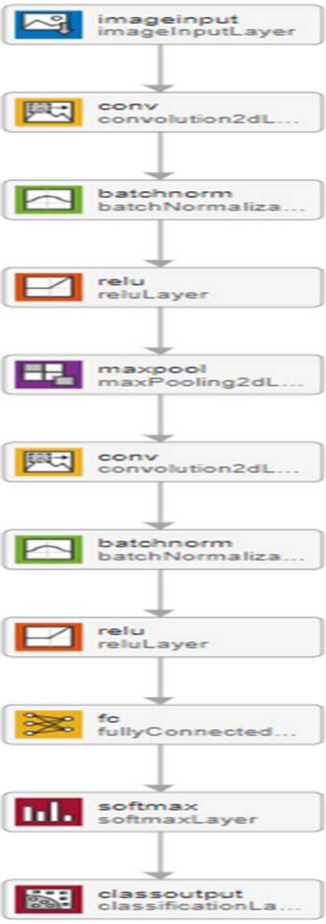


Fig. 3. Convolutional neural network architecture.

4.2 Dataset Used for Training

There is currently no publicly available data-set for the transmission-line checkup task. The experimentation usages a dataset of isolators classified as transmitting power from substations. Shutter speediness, focus, and image contact have all been managed to limit grading and frame rate [20-24].The following thermal imaging settings were adopted:

1. Temperature range of the image
2. Emittance
3. Temperature reflected
4. Temperature in the surrounding area
5. Distinction

4.3 Training the Deep Network Model

The deep learning network from MATLAB code was used to train the CNN scheme . Model development, training and testing were performed quickly over the application network. Table 3. shows the test parameters. Fig.4, Fig.5&Fig.6 show the data set of high-voltage-transmission lines based on the faulty and normal power line components. In short, a huge image data set for HVTL images (normal and defective samples) of components must be used to rate the viability of the results highly.

Table 3. Training options parameters

Training options	***Parameters***
Solver	sgdm
Sequence length	longest
Sequence padding direction	right
Gradient threshold method	12 norm

Fig.4.Normal and defect dataset Insulators

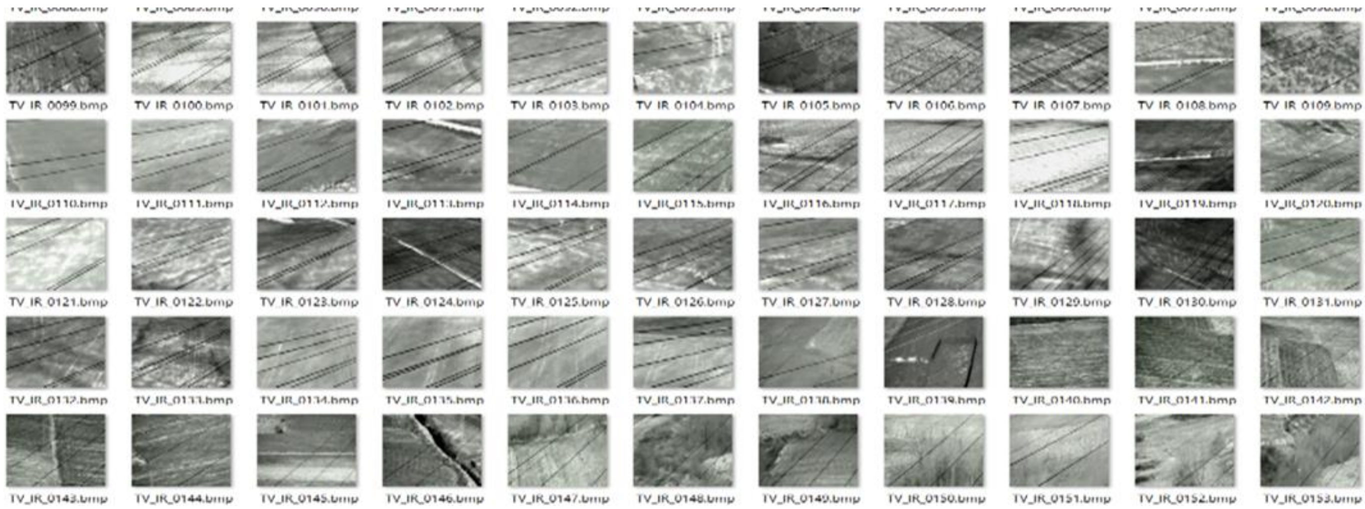
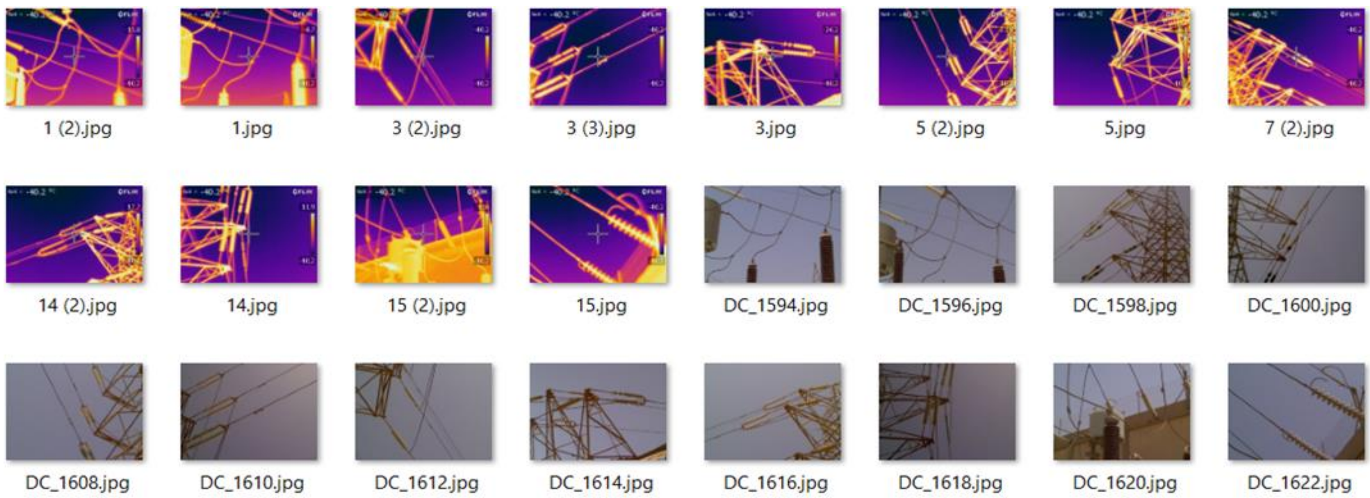


Fig.5.Normal and defect dataset power line



4.4 Results of training and testing deep learning network

For the experiments, the dataset was collected from the Samawa Electricity Transmission and Distribution Company, which contained 600 images. These imagery positions were carroty groves (Beatrice substations and Chertsey in Zimbabwe). The images of the isolators were taken under changed lighting settings. The chief objectives of this work were to accurately detect the faults in the components of the transmission line electrical insulators and to classify the faulty components. The transmission lines and insulators were detected by a deep neural network, capturing a total of 594 images from the internet. The General Directorate of Electricity data set was used for the learning and training process.

The remaining 594 images were used as a proof data-set. In order to accommodate the image dimensions to the input count of the CNN scheme, the pictures were scaled to 227 pixels by 227 pixels 3 channels. Due to the learning process, it was essential to stipulate the knowledge class and the organizes of the leaping boxes within the image where the display indication was set physically. A bunch size of 54 with a higher limit of 432 iterations was used during the training process. The following experiments were conducted [25-27].

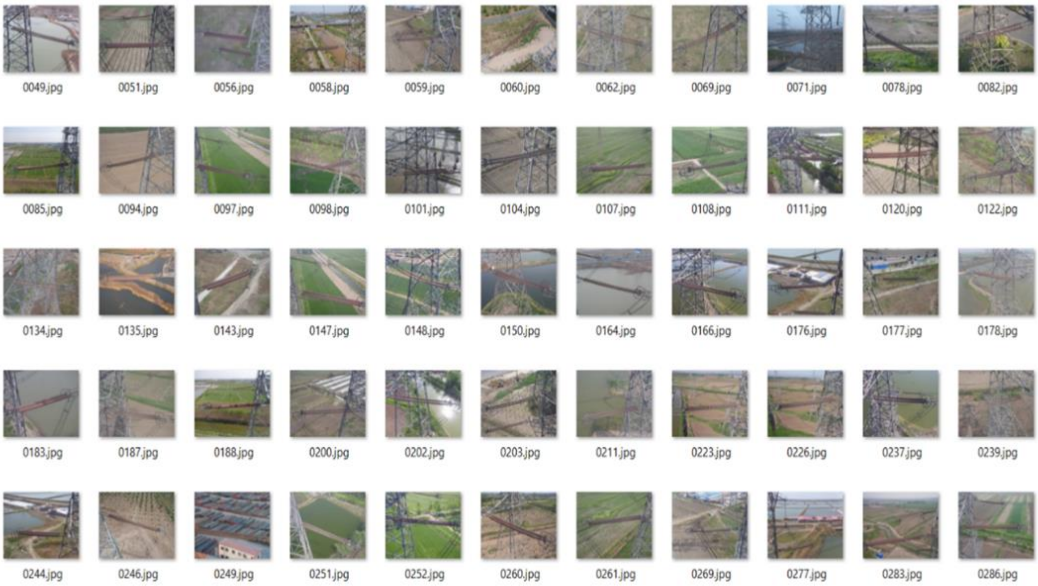


Fig.6. Visual and thermal dataset HVPL

4.5 Experiment 1: Applying AlexNet CNN model

The detection rate of defects on insulators and power lines was evaluated. As explained earlier, 594 images got throughout Google-search were used for cable and insulator recognition. These images were not involved in the training data set. Additional images counting related landscapes from the Google Open Images dataset were used to measure the recognition error rate. Fig.7 shows the design layer of a simple deep learning DNN model. Fig.8, Fig.9, Fig.10& Fig.11 show the successful training and detection results of the isolators. The inputs are: number of layers = 25, training accuracy = 100%, validation accuracy = 95.67%, and final test accuracy = 100%.

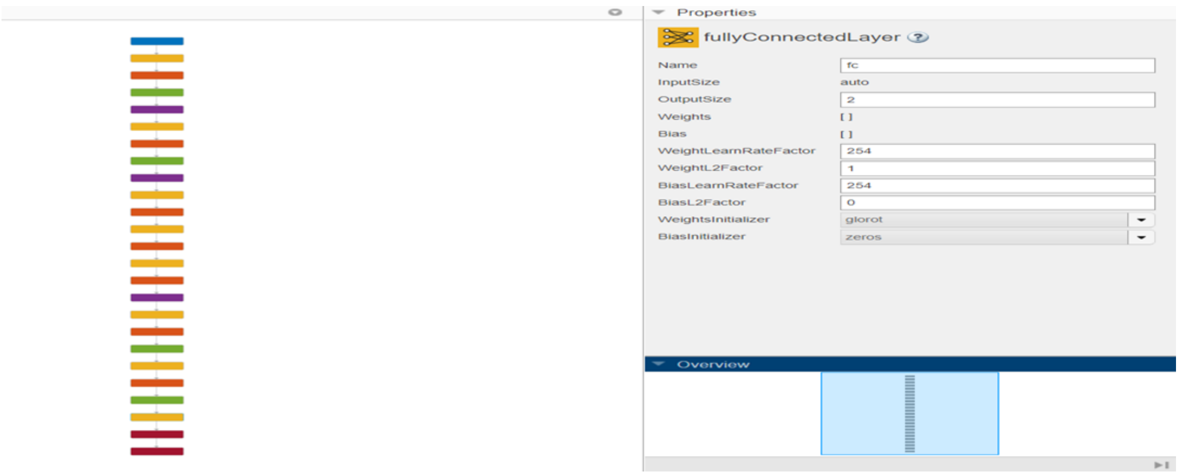


Fig.7. Design AlexNet CNN mode

4.6 Experiment 2: Applying Squeeze-Net CNN model

Fig. 12 through the design and analyzes for training the Squeeze-Net CNN model, respectively. The following inputs were used for the simulation: number of layers = 68, number of links = 75, draw accuracy = 100.0%, validation accuracy = 98.82% and final test accuracy = 96.8%, Fig.13 shows the network structure graph and Fig.14 Experimental results for Squeeze-Net CNN Model. Fig. 14 to 16 show the successful test and detection results of isolators for various test samples collected by Squeeze-Net.

Fig.8. Training result of AlexNet CNN

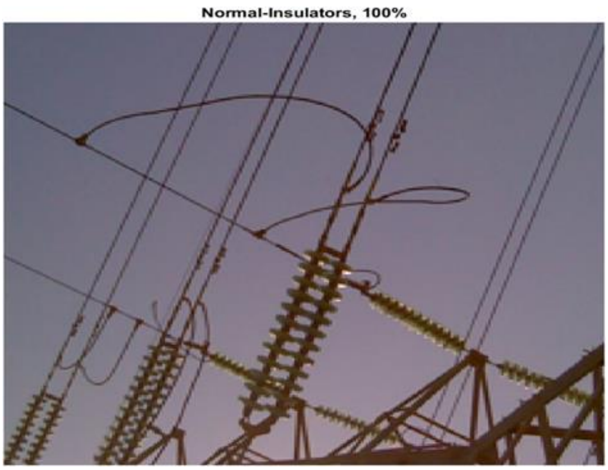


Fig.9. Detection result sample 1 of AlexNet CNN

Fig10. Detection result sample 2 of AlexNet CNN

Fig.11. Detection result sample 3 of AlexNet CNN

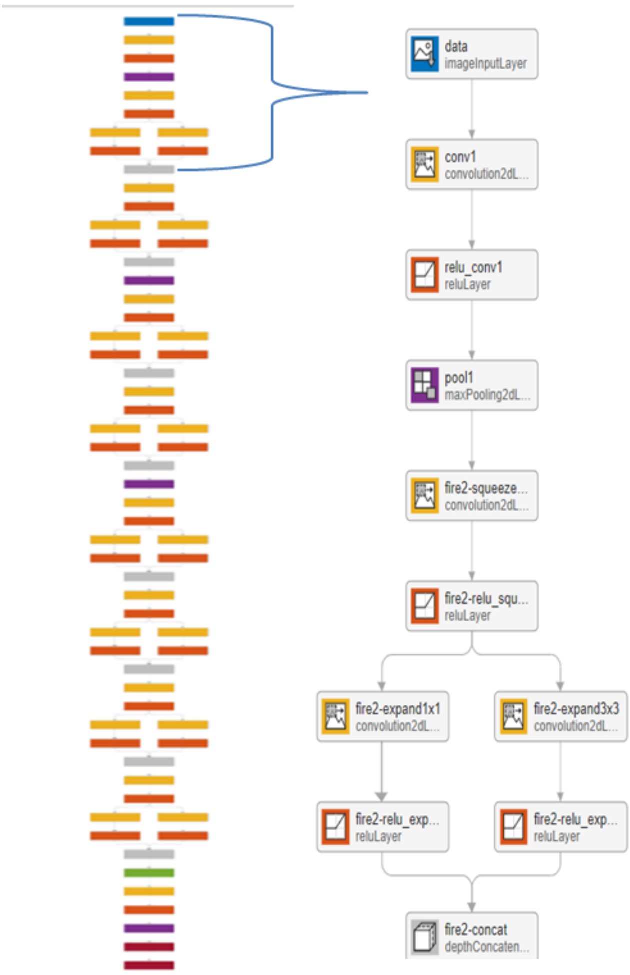


Fig.12. Design Squeeze-Net DNN model

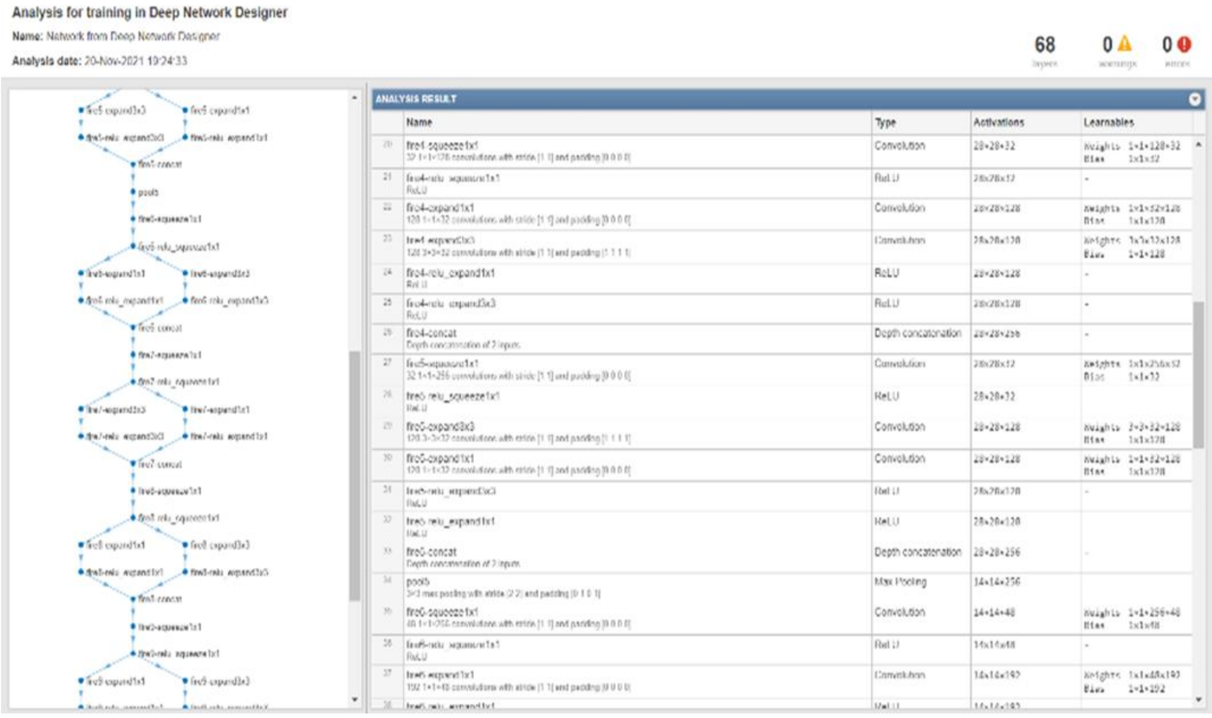


Fig.13. Analysis for training Squeeze-Net CNN

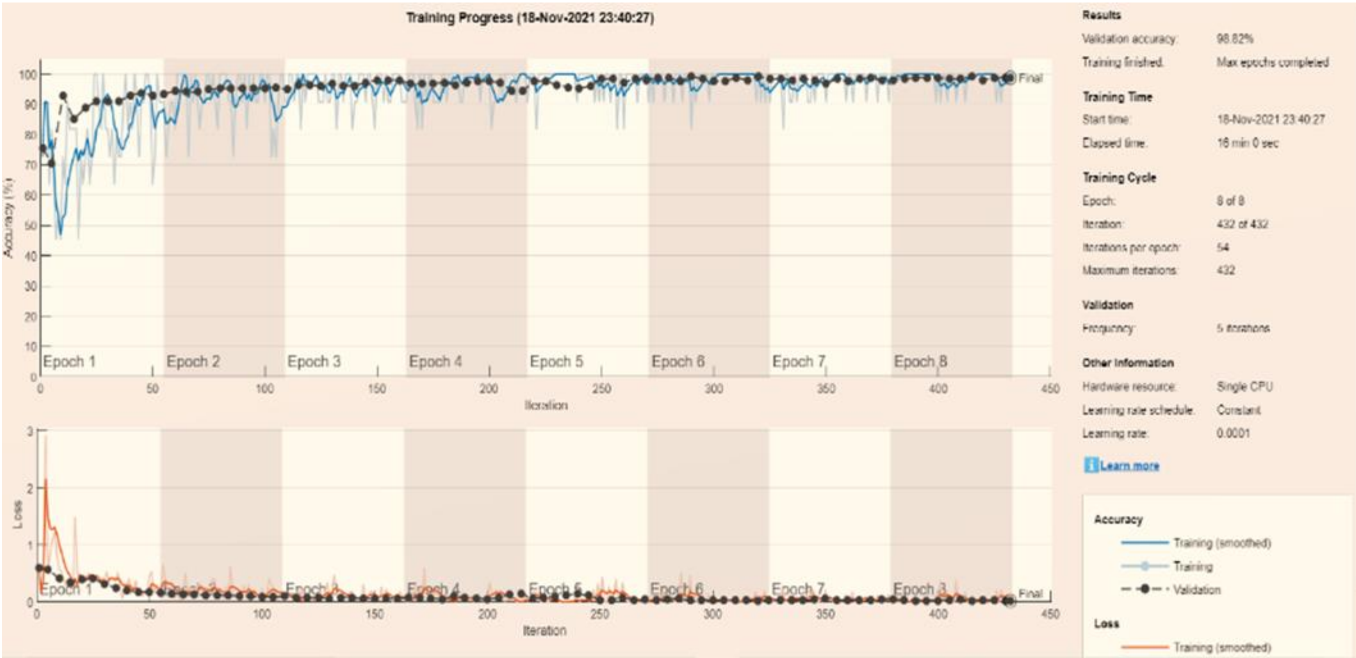


Fig.14. Training result of Squeeze-Net CNN

4.7 Experiment 3: Applying GOOGLE-NET CNN model

Fig.17 to 21 show the successful test and detection results of isolators for various test samples collected by Google-net.

Fig.19 shows the experimental results obtained using the Google Net data set in training processes. The experiment was performed with draw accuracy = 100.0%, validation accuracy = 100.00%, and final test accuracy = 100% **.**

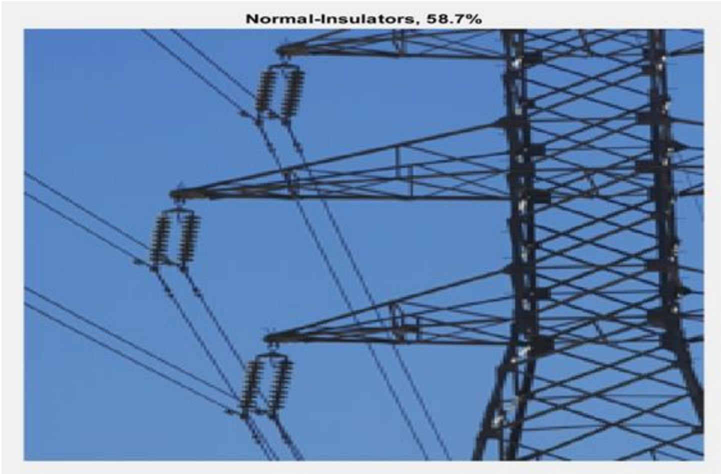


Fig.15. Detection result of test sample 1 for Squeeze-Net

Fig.16. Detection result of test sample 2 for squeeze-net

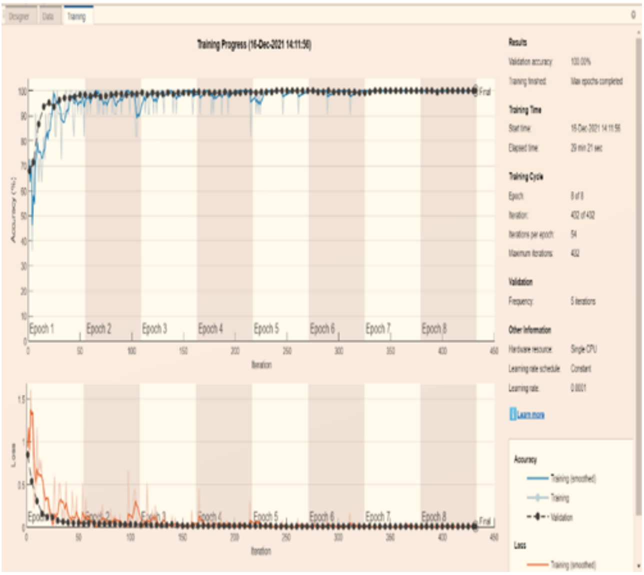


Fig.17. Training result of Google-net dataset

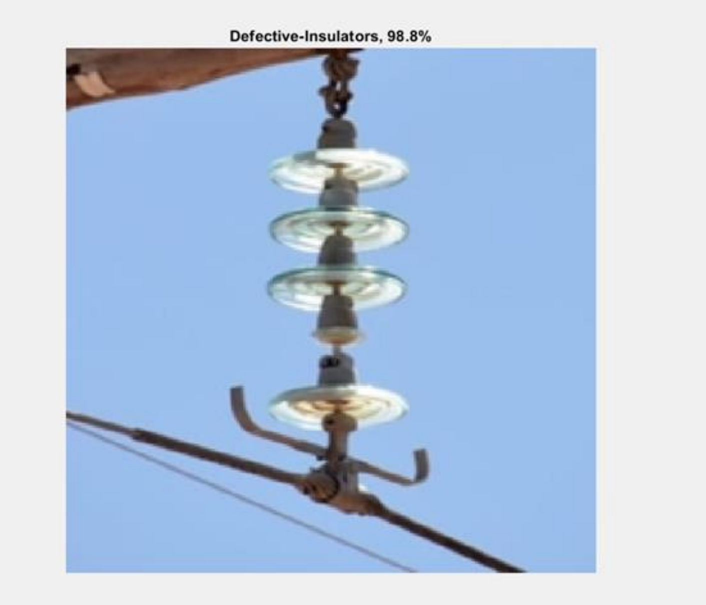


Fig.18. Detection result of test sample 1 for Google-net

Fig.19. Detection result of test sample 2 for Google-net

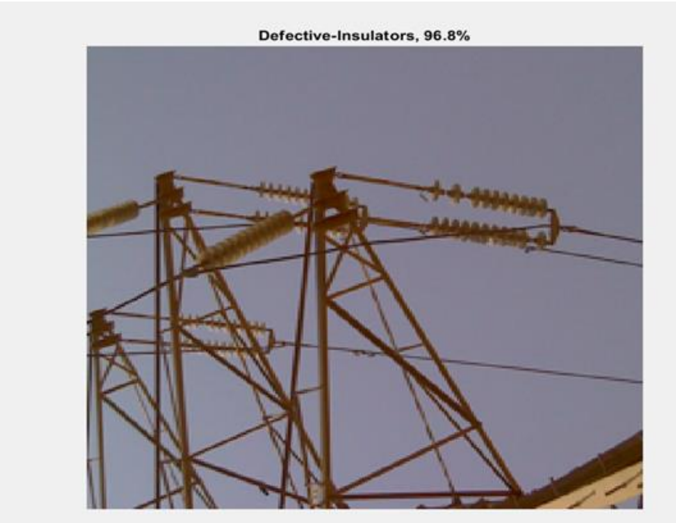


Fig.20.Detection result of test sample 3 for Google-net

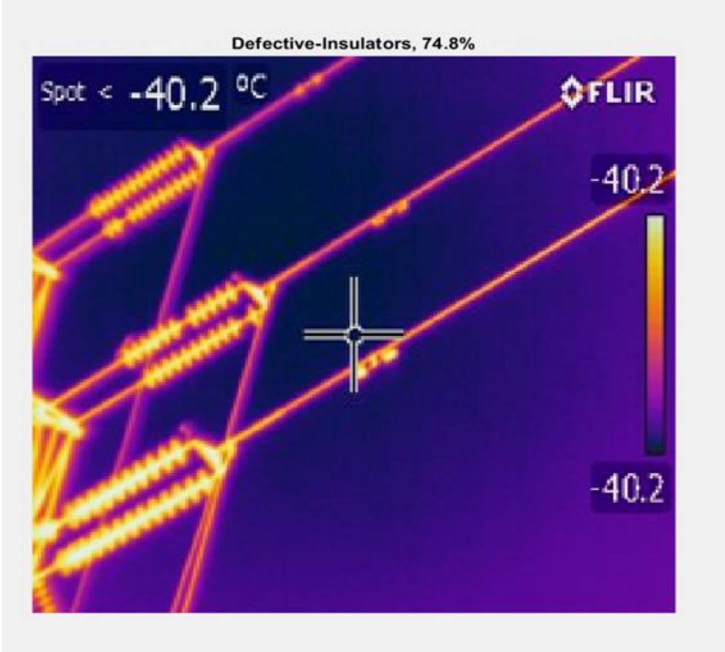


Fig.21.Detection result of test sample 4 for Google-net

5. Result Discussion

This paper emphasized different ways to detect and inspect various defects and damage in the power transmission lines using visible and infrared imagery when a drone takes the required trajectory and captures multiple images. The images are input into the MATLAB image processing algorithm and the correct and quick actions are taken to send the maintenance team before the system crash. Methods such as deep and machine learning are receiving a lot-of attention due to their ability to increase inspection accuracy. The wished-for methods can sense different categories of transmission-line components. Quadcopter flight controls were simulated using the PIDC, controlling position, speed, and altitude with fuzzy-assisted parameter tuning. Compared to the base model, the CNN technology outperformed the traditional methods of error detection. On the data set provided, the proposed power line method performed well in terms of accuracy and rapidity. Once it was determined that the apparatuses of the power line were defective, activated the defect inspection system. We evaluated the proposed fault inspection set of rules using a large data set of transmission line component maps free from bias and limitations. The newly developed inspection system can provide a viable alternative to address the key issues related to faults in electrical transmission lines. A low-cost drone based on a PSO-CNN algorithm can replace expensive patrolling-helicopters to check transmission-line apparatuses, reducing the risk associated with the work of electrical personnel who often climb transmission towers, to fix the errors. The application of the suggested fault detection system has shown that it is easier to detect and repair faulty components in the high-voltage transmission lines. The error detection obtained in Google net Deep CNN was 100% accurate, but in basic CNN it was only 20% accurate to detect the errors with false positives due to the 70% accuracy rate. This clearly indicated that Google net Deep CNN did not miss any defective components. Accordingly, the suggested examination method could save up to 76% of human inspection effort. In summary, the suggested checking system was more cost effective than the current manual approach due to its simplicity, scalability, and ease of use. It has been found that IR imaging technique can be successfully used to monitor faults and damage in high voltage power lines [24-29]. In addition, the developed algorithms, based on computer vision, can efficiently detect the hot spots in the power lines. The thermal images of failed insulators in the power lines can be located using the image processing techniques applied to the RGB photos. This is very efficient for diagnosing problems due to the temperature differences at the joints. Proper data registration and data fusion are essential for accurate identification.

6. Conclusion

This paper emphasizes surface topographies that can discern the outside construction of the image. Though the ordinary isolator and the detection isolator have dissimilar surface specification values. In this study, an intelligent controller was developed as a vehicle sonar tracker for fault recognition and repair H.V T.L. The chief goal of this work was to mature a controller for a quadcopter to capture images of HVPL during inspection. This was created to detect various faults to save the power system from a severe breakdown. It has been shown that computer vision techniques combined with DNN can be very useful for detecting and classifying drone images collected from the high voltage transmission lines. This work solved various existing problems and achieved the set goals. First, the quadcopter flight controller was simulated using the PIDC, controlling position, speed, and altitude with fuzzy-assisted parameter tuning. Second, the quadcopter's altitude control was simulated with model flight controls as roll, pitch and yaw controllers in relation to UAV state responses to demonstrate the fulfillment of flight behavior design requirements. Third, the faults in the transmission line insulators were identified using image processing and computer vision techniques such as DNN. In short, the proposed Deep CNN algorithms have been confirmed to be extremely reliable and robust for the overall assessment of the quality of HVPL and electrical infrastructure maintenance, saving costs, time and human lives from hazards.

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