

Revolutionizing power line inspection: automated data acquisition through autonomous UAVs in simulated environment

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ABSTRACT

Due to the growing need for electricity, the effective inspection of the power lines is becoming an important matter. In this paper, the author presents the inspection of power or transmission line with autonomous automatic UAVs (Unmanned Aerial Vehicles). For the comprehensive inspection of power lines and its different components, such as (cross arms, cracks in poles, rot damage, and insulator burn), it is needed to inspect from every side of the elements and the masts. So, the angle and speed of the drone are much more important to take images while moving around the poles. The simulator used for the experiments, including deep learning models, acts as a vital source of data analysis. At the same time, pictures are used as the primary data source. Through the Deep learning method, a suggestion of action generated for the movement around the masts. The use of a simulator is a quick, accurate, and inexpensive solution, with less real/world factors affecting the inspection process, such as weather, time, and cost of using many different resources. This study presents experiments with lightweight deep learning models through developing the prototype of vision based unmanned aerial vehicle to inspect the power line in a simulated environment. It focuses on the large demand of power companies to inspect the power line autonomously with the influence of deep learning. Finally, several deep learning models are compared when inspection along the power lines. The model shows satisfactory results in the testing path. The model trained by MobileNetV2 performs best among all other models.

Keywords: power line inspection, vision-based model, deep learning, unmanned aerial vehicle (UAV), drone.

1 INTRODUCTION

Due to the increase of research effort in the field of aerial robotics, the application scenarios of the Unmanned Aerial Vehicles (UAVs) are growing very fast during the last few years (Liew et al., 2017). The UAVs are seen to be interesting for the power companies because it allows the collection of data from different positions, distances, and angles and makes it more suitable for the inspection of power lines and

electric assets like insulators and pylons(Azevedo et al., 2019). UAVs are also used in different inspection applications like building inspection, construction site inspection, bridge condition, and wind turbine monitoring(Shang & Shen, n.d.). In critical situations such as earthquakes, storms, and hurricanes, teams are sent by helicopter or by foot to visually inspect the power lines with different equipment's (Katrasnik et al., 2010). Power line inspection plays a key role in a power transmission system to confirm the safety and the continuous operation of power services(Miao et al., 2019). Due to free movement in every direction, the UAVs are suitable vehicles for inspection of different elements of the power line(Azevedo et al., 2017).

Currently, power line inspection is done by unmanned aerial vehicles (UAVs) instead of the traditional manual patrol to understand more efficient and automatic inspection(Sampedro et al., 2014). In manual inspection, people walk along the path near transmission lines and check each insulator by using different kinds of an instrument such as sensors, infrared images, cameras, and ultraviolet images(Han et al., 2019). To reduce the failure of power/transmission lines and improve the operating efficiency of lines, researchers from the countries with frequent failures like Canada, Russia, Japan, India, Norway, Finland carried out research on the failure mechanism and running status of the transmission conductors(Y. Zhang et al., 2019). The unmanned aerial vehicles (UAVs) inspection technology developed for the power lines with the excessive improvement of computer vision techniques and image sensors(J. Zhang et al., 2012). The researchers are working on different kinds of algorithms for line detection and the extraction of different features from aerial images(Zhao et al., 2017). Some are working on the separation and fault detection algorithm for aerial images(Homma et al., 2017; Qinggang Wu et al., 2012). The vision-based technology is also implemented in the detection of different defects like railheads and metallic conductors(Yuan Li et al., 2010).

A power line inspection can be done by using laser scanning data, images which are obtained by the UAVs(Santos et al., 2017). At the early stage of defect detection in the power lines can save the cost and life of the system, so the continuity in the surveillance of power lines plays an important role in ensuring the constant electric transmission.

Exact identification and localization of the lines can be helpful for autonomous navigation so, the precise detection method is required in this field. Sometimes the power lines are surrounded by leaves and branches, which escalates the difficulty for gradient-based methods. Existing methods rely on different parameter settings, so they are not steady in practical use(H. Zhang et al., 2019). Some of the most used inspection methods are discussed below(Jalil et al., 2019).

1.1 MANUAL TRADITIONAL PATROL

Manual traditional patrol is the most extensively used inspection method even if it is tedious, long, and exhausting, a team inspects the transmission lines from the ground with the help of different instruments such as binoculars, infrared cameras.

1.2 HELICOPTER AIDED INSPECTION

It is an expensive but fast method for inspection of transmission lines, the pilot flies the helicopter, and the camera operator takes the recording of the power lines with color, infrared and thermal cameras and its various components like insulators, masts, and conductors. After that, the fetched data are manually inspected by the workers with the help of a machine.

1.3 ROBOTIC INSPECTION

To reduce the cost and the risk of life, another solution is advised, which is climbing robots. It is faster, less expensive, and safer than the foot patrol and travels along the conductors, but having these huge benefits is not a practical solution to inspect the vast network of lines(Ludan Wang et al., 2010).

The drone simulator or simulated environment is used to run the experiments because it takes less time as compared to the real environment to collect the training data and to minimize the costs to establish the experiments. Given the increasing importance of the topic, in this paper the author presents the data acquisition of the power line inspection using UAV's. Our approach is in the use of deep learning in the acquisition of data for the inspection of power lines, providing it with new understandings on the topic.

The remainder of this paper is ordered as follows: In section 2, background and related work. In section 3 the method and result is discussed. Section 4 presents the conclusion.

2 BACKGROUND AND RELATED WORK

Power lines are inspected traditionally by the foot patrol and by helicopter after regular intervals. A team is carried out the inspection on foot or with the help of a helicopter to collect data for further visual inspection for the power lines. Enhance accuracy and speed, a significant amount of research has been carried out to systematize vision-based power line inspection.

2.1 UAVS SUPPORTED METHOD

The advanced and fast way to inspect the power lines from the required distance is the UAV supported method. According to recent development in-flight handling techniques, UAVs now equipped with proper payloads (thermal and visible cameras) (Nguyen et al., 2019). Last few years, the UAVs are used in a wide range of applications, including navigation, inspection, and maintenance activities. UAV

supported inspection has its own edge over traditional manual inspection; it is safer than any other; it is advanced, time, and cost-saving inspection. Still, it has some common problems like gimble and automatic detection (Zaidi & Colomo-Palacio, 2019) of irregularities. Examine the electrical foundation using UAV requires to make the inspection fully programmed.

2.2 TRADITIONAL GRADIENT-BASED METHOD

Previously the focus is on the low-level local features of gradients, texture, and brightness. These works first separate potential pixels of lines from the background by using the Canny and Sobel edge detector and then applied the (W. Zhang et al., 2019).

Hough transformation. To extract the line segments Yan used the Radon Transform through Kalman filter and grouping method while Chen used the improved version of Radon transform to extract the power line feature form images, Li suggested Hough transformation to detect lines and applied k-means clustering to improve the results; Song suggested the sequential local to global detection method for power lines, and Zhang presented hand-designed filter to extract features and used epipolar constraints to improve line segments(W. Zhang et al., 2019). In recent years these types of approaches have improved very fast, but they have some limitations because we can't tune dozens of parameters manually to get the optimal results(H. Zhang et al., 2019).

2.3 DEEP LEARNING-BASED METHODS

A development in the field of deep learning CNN based model(Wei Shen et al., 2015) has proved an astonishing performance. These methods demonstrated the ability to learn multiscale features. R.Madaan suggested the framework using a dilated convolutional network(Madaan et al., 2017) and treated the lines as the semantic segmentation task. Several networks are designed using the dilated convolution with various architectures and evaluated to find the optimal one. The performance improves a lot compared to traditional methods and efficient on NVIDIA Jetson TX2(H. Zhang et al., 2019).

Larrauri applied a fully automatic UAV based system for real-time inspection so, multiple images and data are processed to recognize the other objects, and the Thermal infrared TIR camera is used in this whole process for the bad conductivity detection (Larrauri et al., 2013).

V.N.Nguyen has presented UAV navigation and inspection with vision-based approaches, he reached the conclusion that the inspection of the power line should be conducted by the UAV having different sensors and cameras to detect the faults, and the same method and data can be used for the offline inspections. So, the outcome of the inspection methods suggests different possibilities for the most frequent issues, such as high cost, speed and safety. As compared to the other inspection methods which are mentioned above, UAV inspection cost is relatively low and it can fly close to the power lines to take

the comprehensive views/images of the different components which can improve the accuracy. V.N.Nguyen also mentioned the challenges of power line inspection using automatic and autonomous UAVs, together with the possibilities and disadvantages (Nguyen et al., 2018).

According to (Zhou et al., 2016) there are three approaches regarding the vision-based navigation for power line inspection

- GPS way points-based.
- Pole detection based.
- Power line detection based.

The first approach is commonly used, while the other two have been recently applied by the progress in the field of visual recognition. Nguyen reviewed the methods of the detection of the power line such as (J. Zhang et al., 2012) and (Gerke & Seibold, 2014), He reached the point that they are not suitable for high-speed vision-based navigation and the pole based navigation attracts less attention, and this is due to the lack of information for navigating between the poles.

Towards the vision-based automatic, autonomous inspection, deep learning is the data analysis approach because of the following points (Nguyen et al., 2018).

- In Deep learning algorithms, Convolutional Neural Network improved to a great extent, and the performance of visual recognition systems for many applications such as self-driving cars, image search is remarkable.
- It provides automatic learning features that can reduce the effort in solutions for every subtask in power line inspection.
- The ability of generalization in deep learning opens the possibilities for vision-based inspection, such as the model trained for a specific task that can be used in the related tasks.

2.4 VISUAL SERVOING OF UAVS

VS, also known as the vision-based remote control, is a technique that uses response information coming from the different visual / vision sensors to control the movement of the UAVs. Some line based visual servoing of a UAV is presented in the (Araar & Aouf, 2014). Araar proposed two solutions to the classical IBVS formulation, which is improved by using LQ-Servo control design and the partial pose based visual servoing, which they get from pure visual measurements.

The inspection of power lines can be divided into two modes: tower monitoring and line monitoring. In tower monitoring, we monitor the breakage of all kinds of clips, defects deformation, shock hammer damage, So the task requires the precise positioning of UAVs and the stable flight to gather the high-quality image information. Line monitoring includes the inspections of the trees and the breakage of line, tilted, and collapsed tower(Cui et al., 2017). There is a strong electromagnetic field near the power

line; it may damage the UAV electronic equipment's so the minimum safety distance is required for UAV inspection, and for the safety consideration J.Cui (Cui et al., 2017) proposed the horizontal and vertical range. Based on the regulation and experience, the safe detection distance $s=8$ m and the length= 10 m.

$$R1 = L \tan (\alpha / 2) = 10 * \tan \left(\frac{21.28}{180} \pi / 2 \right) = 1.8787\text{m(Horizontal direction)}$$

$$R2 = L \tan (\alpha / 2) = 10 * \tan \left(\frac{15.92}{180} \pi / 2 \right) = 1.3983\text{m(Vertical direction)}$$

X. Qin proposed a method of detecting inspection objects through LiDAR data, which has four steps. First, the point cloud is divided into a single span as the processing unit. Secondly threshold is created to remove ground points which improves the data extraction efficiency. In third step, surrounding data of the line can be extracted by the position and orientation system, and finally, the partition recognition method is proposed, which improves the recognition effect (Qin et al., 2018).

2.5 CONTROL OF QUADROTOR

It is controlled by varying the speed of four rotors independently, the pitch movement is obtained by changing the ratio of back and front rotor speed and a roll by altering the right and left rotor speed. The yaw movement is achieved by torque resulting from anti-clockwise and clock-wise speed(Cowling, n.d.) as shown in Figure 1.

The roll and pitch movement are obtained due to the difference between front and back rotors. The equation is written below:

The \tilde{u}_2 is the second actuator output and \tilde{u}_3 is the third actuator where τ_i is the thrust from the i th rotor and l is the distance from the centre of mass. The quadrotor schematic is shown in figure 1.

$$\tilde{u}_2 = l (\tau_4 - \tau_3) \text{ (Nm)}$$

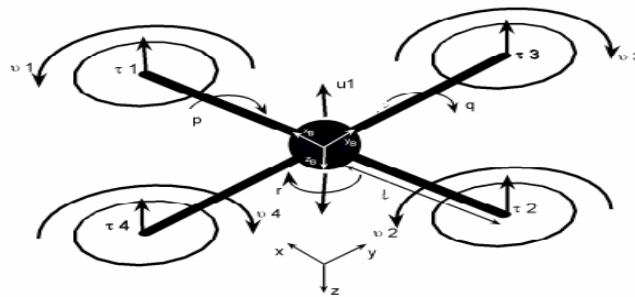
$$\tilde{u}_3 = l (\tau_1 - \tau_2) \text{ (Nm)}$$

The first and the final actuator can be defined by the equations below:

$$\tilde{u}_1 = \tau_1 + \tau_2 + \tau_3 + \tau_4 / m \text{ (m/s}^2\text{)}$$

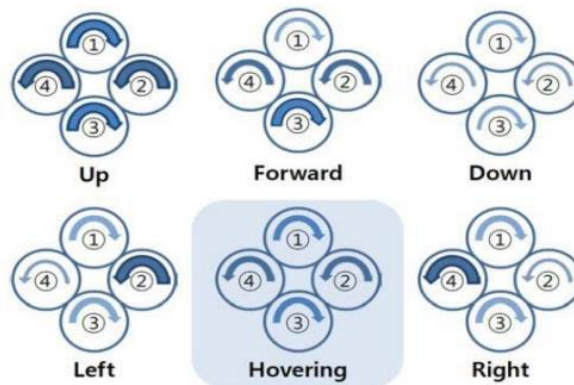
$$\tilde{u}_4 = v_3 + v_4 - v_1 - v_2 \text{ (Nm)}$$

Figure 1 Quadrotor Schematic



Every rotor in the UAV produces a force to lift the UAV and its moment, the (1,3) rotor and (2,4) rotor rotate in the opposite position to cancel the effects generate by the other pair. To make a roll angle (ϕ), increase the angular velocity of rotor 2 and decrease the 4 while keep the thrust constant, in the same way one can get the pitch angle (θ) by increasing the 3 and decreasing the 1 rotor and yawing angle is produced by increasing the speed of (1,3) and decrease the speed of (2,4) the mechanism is shown below(Jithu & Jayasree, 2016) in Figure 2.

Figure 2 Mechanism of Quadrotor movements



3 VISION BASED INSPECTION

Deep learning attracts the attention of the power line companies because of vision-based power line inspection. It also covers an extensive range of faults on a single inspection, vision-based inspection systems explain in (Matikainen et al., 2016), and (Nguyen et al., 2018). The authors proposed the images as the potential data source for vision-based inspection because it provides sufficient information for detecting the wide range of common faults on the components of power lines, it's easy to collect and easy to analyze(Nguyen et al., 2019).

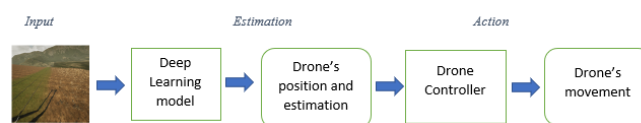
3.1 OUR POWER LINE INSPECTION CONCEPT

With the current advances in deep learning, UAV technology is accurate, reliable, fast, and safe for power line inspection. Our system uses a vision-based power line inspection method with the UAV as the leading method and images as primary data sources and deep learning for the data analysis.

3.2 MOVEMENT OF DRONE AUTONOMOUSLY AROUND THE POLES USING DEEP LEARNING

Micro aerial vehicles are mostly used GPS for their navigation in recent years, and they have very little ability to avoid the obstacles. Bachrach et al. (Bachrach et al., 2012) using an RGBD camera to build a map for planning and localization. Bry et al. (Bry et al., 2012) used the Inertial Measurement Unit (IMU) with laser a finder in an enclosed environment for a reliable flight. For state estimation and map building, Fraundorfer et al. (Fraundorfer et al., 2012) used a downward-facing camera with forward-facing stereo pair cameras. Scaramuzza et al. (Scaramuzza et al., 2014) used three cameras with Inertial Measurement Unit (IMU) The primary responsibility of the drone is to follow the power lines; the auto-drone developed in a way to handle each image input at a time and calculate the waypoint to move the drone in a particular position (Smolyanskiy et al., 2017). Our research is conducted in a drone simulator, which has a power line environment in it. Our system handles the images input continuously and then produces the commands to move the drone. As we are mentioned, the images are the primary source/input, and the steering commands are the output of the system. In all these scenarios, the deep learning models have significant importance as we need it for good accuracy for these types of estimation, and this estimation passed to a simple controller to fly the drone in the right way. Figure 3 demonstrates the mechanism.

Figure 3 Mechanism



3.3 MODEL FOR THE DATA ACQUISITION ON THE MASTS

In our system, we used UAVs as the primary method for the data acquisition of the masts(pole) in a simulated environment. The general idea is to take the images of every mast (pole) from a single camera.

The drone is used to collect data. It moves above the pole and waits to hover and move forward. The collected data was not good enough because it needs data from every side and by using drone hovering. Still, it only get the data/information that is only in the direction of the camera, as shown in Figure 4. Our drone camera permanently faces only one direction; it is not a revolving camera. The data

collected was not useful for us because it is necessary to take the images from every side of the masts. So, the author moved forward to another implementation.

Figure 4. Hovering of UAV



After the first scenario hovering, the author took another step to move the drone in a triangular manner, as shown in Figure 5. It shows some good results. It was not enough for us because some sides of the masts are still missing, and it has the high risk of losing some portions of the masts. If some of the sites are still missing, it will affect our results and requirements, but we tried our best to decrease the errors. After gathering this information, the author changes the approach toward data gathering, while putting these approaches behind and moving to the new way to collect the data. The primary source of input is images, and now we want to move the drone on all sides of the masts and take images from every side. So, considering the requirements, we move to the next step.

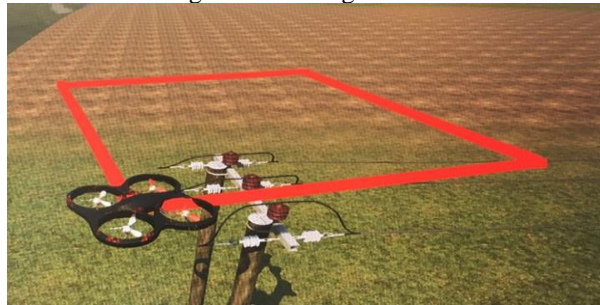
Figure 4. Triangular Path



After investigating hovering and the triangular path, rectangular path is considered to take next step. Figure 4 demonstrates the rectangular movement of the drone to collect the data. Drones move from one corner to another to collect data. This strategy is adequate than the previous two, but it has still some limitations in it. The thing is that the drone moves from one corner to another and then adjusts its position in front of the masts and takes pictures. The reason is that the camera, which is mounted on the drone, only facing the front side is not movable camera like most drones. So, on every corner it must face directly to masts to take images. While moving it only looks on the front side and the masts are not in the frame to take the pictures for data collection. It takes too much time to move from one position to

another and then adjust the camera to take pictures. After examining the pictures, the author comes on the conclusion that it is better than the other two approaches. But still miss some angles to take the pictures.

Figure 6. Rectangular Path



After that, the drone moves all around the masts to collect the images. These images are the combination of different locations/angles of the camera and a drone. After experimenting with the several executions of the drone controller, author reached the implementation, which is quite stable. The maximum velocity of the drone is determined at 1 m/s. The drone is used to collect training data, which is automatically controlled by the script with the AirSim APIs. The drone is designed to keep a constant distance to the masts. Data collection is conducted on every mast (pole), the angle of the camera is 45 degrees, and the height of the camera is fixed, which is 5 points above the mast (pole). At every 5 degrees movement/change, the drone takes the image of it moving all around the masts (pole), as shown in Figure 7.

Deep learning models need a large amount of data to train well, so; there are about 44,286 images collected from the drone and then split in training and validation set.

Figure 5. Mast in simulator



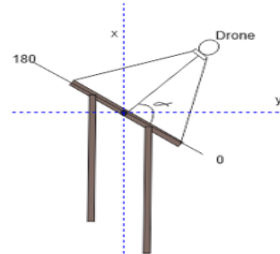
3.4 STEPS TAKING USING DEEP LEARNING MODELS WHILE FLYING AROUND THE POLES

In the data acquisition model, the drone is at some position n and moves all around the poles.

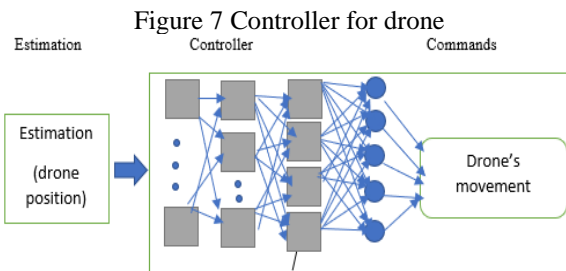
- The first step is to know the exact position of the drone and then move one step in a clockwise or counterclockwise direction with a constant radius.

- The next point is y, in figure 8, and it moves from n (if the drone is on n) to y, then the angle between (n, y) represented as $\Delta \alpha$. And at point 'y,' the drone repeats its function with the new coordinates and completes the circle around the masts(pole) to collect the images.

Figure 6 Pole dimension



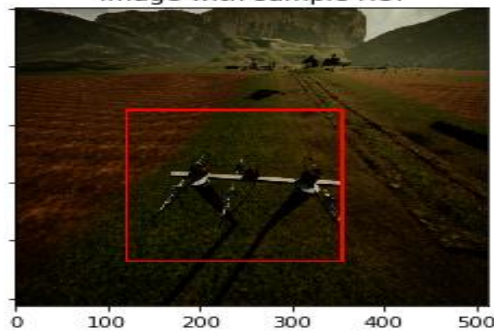
- The flow of the controller is represented in the figure 9. After the inspection model it produces some output and these outputs are handled by the controller to move the drone in a specific direction. Based on the Estimation position and angle the goal of the controller to maintain the drone in a right position.



3.5 DEEP LEARNING MODEL WORKS ON THE INSPECTION OF THE POWER LINES

We have a lot of image data, which is expensive to load directly into the memory, so in Keras have a DataGenerator. We used this concept of DataGenerator; it's like an iterator, which reads data in chunks from the disk. We used the idea of a small portion of the image of interest, and when generating the batches, remove the image piece, which is not essential for us. The model adds or removes the brightness from the images and randomly flip the images, so the model has some new information to learn. Here you can see them in the figure 10 with the rectangle in which we are interested in.

Figure 8. Image with simple ROI
Image with sample ROI



After training the models, the sanity check is performed and load some of the images to compare the Actual and predicted angle and we got some values, as shown in the following figure 11.

Figure 9 Angle Prediction

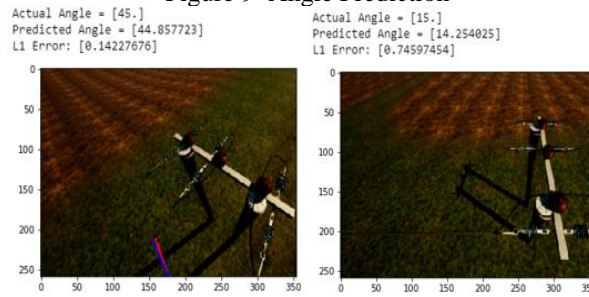
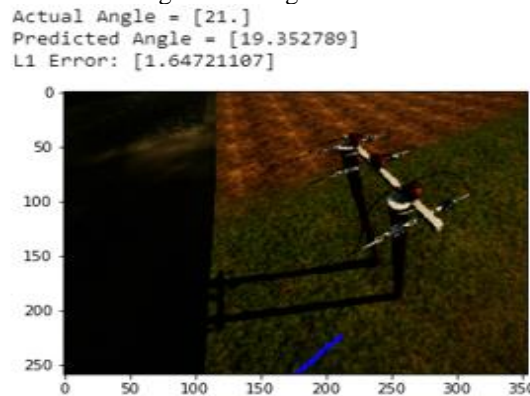
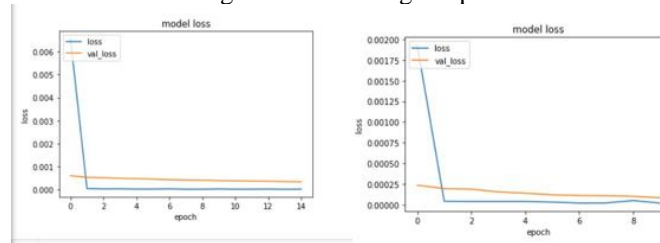


Figure 10. Angle Prediction



The actual angle in fig 9 is 45 degrees, but the predicted angle after training is 44.85 degrees, and the error is 0.142, and in fig 8, the actual angle is 15 degrees. Still, the expected angle is 14.25, and the error is 0.74, and the third figure 10 shows some more error rate, which is 1.64, and the actual angle is 21 degrees, and the predicted angle is 19.35. We applied some different deep learning models on the dataset like MobilenetV2, ResNet50, DenseNet121, NASNetMobile to compare the inspection of the power lines, so some of the training graphs of the model are shown below in figure 13:

Figure 11. Training Graphs



There is a decrease in the plot of loss function of MobilenetV2 graph which is shown in figure 10 and the plot of validation loss decreases and has a gap with loss, and it looks quite stable from start to end, but on the other hand, the graph of DenseNet121 is little change at the epoch 8, the loss rise at this point.

The tests are conducted for the automatic data acquisition of the power line inspection model. There are four inspection model are involved in the test MobilenetV2, ResNet50, DenseNet121, NASNetMobile are shown in table 1.

Table 1

Models	MobilenetV2	ResNet50	DenseNet121	NASNetMobile
Interventions	3	5	4	7

Table 1 shows the number of interventions required to move a drone in a track for the inspection. The minimum 3 times and the maximum 7 times interventions to keep the drone in specific route, the table shows the performance of different models on the inspection of the power line.

4 CONCLUSION

Data acquisition using UAVs for power line inspection is gaining great importance for the companies. The research effort is increasing in the field of aerial robotics. But power line companies are interested in multirotor UAVs. Our modern-day societies are dependent on electricity so; the inspection and monitoring of the power lines are extremely important. The main motivation behind this work was to automatic acquisition of data using autonomous UAVs on the powerline inspection and through all these things in mind author selects simulated environment for this purpose. This paper presents the power line inspection system that uses UAVs for inspection, deep leaning as the data analysis, and images as the primary data source. There is not much difference in the training result of the different models. But the results of the tests show the difference in the performance of the inspection model. It's found that MobileNetV2 stands first in the test, with three times interventions among four inspection models tests. It is a lightweight model between other inspection models and performs good in all four other models. It needs the least amount of intervention in autonomy tests. The grading of the other inspection model as this order: DenseNet121, ResNet50 and NasNetMobile. It seems that the performance of the models for the

inspection is satisfactory. The research shows that our inspection model assists the tests of the power lines and provides some better results without any more adjustment methods such as sensors and camera adjustment.

FUTURE WORK

To enhance the power line inspection by the autonomous UAVs, first need the object detection model, then it can make progress in developing the automatic capturing function. The primary task of the function is to capture and detect the faults and do it automatically. After doing all this research, the next step is to apply this autonomous UAV power line approach in a real power line environment. The data collection method in a real environment could be a challenge due to the gap between the actual and simulated environment. The inspection model trained on the synthetic training images used in the real environment. However, it is in the simulated environment; we want to extend this work in the real environment for the powerline inspection method.

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