Distribution System Insulator Inspection By UAV And Machine Learning

B.Sc. ELECTRICAL ENGINEERING

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A thesis submitted in partial fulfillment of the requirements for the Degree of

Electrical Engineering

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DECLARATION

This thesis is a presentation of my original research work. Wherever contributions of others are involved, every effort is made to indicate this clearly, with due reference to the literature, and acknowledgment of collaborative research and discussions. I also declare that this work is the result of my investigations, except where identified by references and, free from plagiarism of the work of others.

Signature: ………….

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Mujahid Iqbal

Date: ……………….

The undersigned hereby certify that they have read and recommend the thesis entitled "Distribution System Insulator Inspection By UAV And Machine Learning" by Adil Siddique & Mujahid Iqbal for the degree of BS Electrical Engineering System.

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DEDICATION

We dedicate this work to our last prophet Muhammad (Peace be upon him), my great hero and messenger of Allah Almighty. One of the most influential people, that humanity has ever witnessed.

LIST OF ACRONYMS

AL	Artificial Intelligence
AC	Alternating Current
DC	Direct Current
DOF	Degree Of Freedom
ESC	Electronic Speed Controller
HVDC	High voltage direct current
LI-PO	Lithium Polymer
ML	Machine Learning
mAH	Milli Ampere Henry
OHL	Over Head Lines
PVC	Polyvinyl Chloride
RPV	Remotely piloted vehicle
UAS	Unmanned aircraft system
UAV	Unmanned Aerial Vehicle

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ABSTRACT

Increasing demand for electricity due to technological advancement in every aspect of human life has increased the importance of the smooth operation of distribution lines. Distribution lines pass through mountains, deserts, forests and many other inaccessible zones. Therefore, the detection of present and future hazards to transmission lines due to the presence of anything on the line, human towns adjacent to the distribution lines, trees of forests, new plants nearer to the lines, and birds nest is an important concern. Conventionally, these lines were inspected by line men which consumes too much time, increases inspection cost because of the huge workforce, increases human life and safety risks, compromises the reliability of the data and take too much delay in the desired information. In order to cope with the aforementioned problems, an unmanned autonomous vehicle (UAV) is proposed in this study with an instant camera is proposed for distribution lines insulator inspection. This system can monitor the physical conditions of the insulator. This UAV-based system is capable to replace humans which reduces workforce costs and increases human life security and data reliability. In this study, a technician or any other expert maintains a distance and operates UAV to observe the lines. Further Machine Learning-Based algorithms help in fault classifications. It’s an easy, safe, and long-lasting way to analyze transmission and distribution lines. In the local market of Pakistan, the proposed system of inspection and fault detection through imaging of distribution lines can be used by wapda and a simple cwod-copter can be used for government agencies, military applications, disaster relief, etc. It can inspect distribution lines that are unreachable where manual labor cannot inspect.

CHAPTER # 1
INTRODUCTION OF FAULTS DETECTION AND UAV

Introduction:

In this modern world, it is impossible to think a moment without electricity. Transmission electricity cables, electricity pylon, are the important parts of the electrical transmission system or grid, and they are critical to the secure transmission of electricity between a grid station and a local distribution station [1]. These parts were exposed to bad weather (direct sunlight all day, strong winds, snow, rain, etc.), high mechanical stress and high temperature caused by high voltage, so they are likely to have to have physical flaws [2]. This is why the power line delivery system needs to be checked and fixed up on a regular basis.

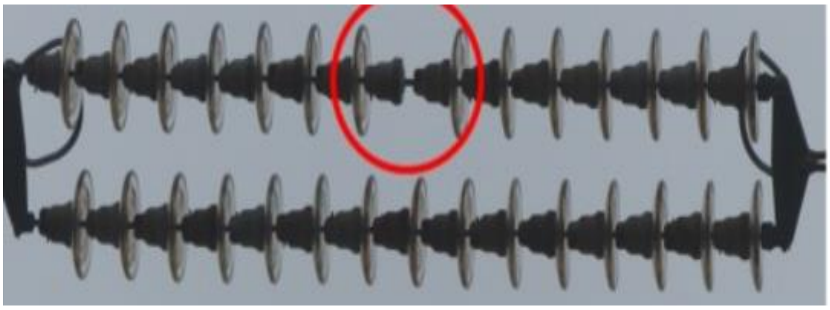

Figure 1.1: Faulty Insulator [1]

Increasing population and advancement in technology are increasing the electricity demand because it can transform in any other type of energy as per consumer need. This energy is generated on generating stations then supplied to the consumer through a wag transmission and distribution system. This all system is called the power system. These systems have a vital role in our daily life due to technological involvement in every aspect of human life. In any power system, it is preferred and designed to supply electricity to the customers in economical and reliable manners [3]. Furthermore, the bad environmental factor is also considered in this system. Generally. the power system has four main parts:

- Generation
- Transmission
- Distribution
- Consumers

Due to enhancement in transmission network, the methods for diagnosis, care, inspection and surveillance are being changed. In our proposed system, such method is being generated in which surveillance and fault detection of distribution lines insulator is detected using UAV.

A drone with image technology will be able to solve problems with overheating parts of the distribution line (focus on a conductor) and with not enough power going through the line. The suggested simplified inspection system makes sure that thermal images can be taken from the air no matter what the weather is like or how much load is on the power lines. The method gives a safe, high-quality, and cost-effective way to check the power lines from a distance and with flexibility [4].

Unmanned aerial vehicles (UAVs) also categorized as drones, are aerial vehicles that do not have an individual operator on land. Unmanned aerial vehicles (UAVs) are part of an unmanned aircraft system (UAS), which consists of a UAV, an earth-based controller, and a coordination device among both. UAVs can fly depending on whether they are controlled remotely by a human operator or independently by auto-flight mode.

The system consists of two parts:

1. Hardware design.
2. Software design.

The hardware part combines drone and interfacing of thermal and optical camera circuits with the help of control in order to capture and transmit the required data. Software part includes interpretation of the received data by different AI techniques. The data of different faults and scenario is then trained and the received data is then tested to detect the faults [5].

To be more specific, our suggested unmanned aerial vehicle (UAV) Perform Inspection and fault detection of transmission lines insulator over a fixed pattern. Because Insulators are critical components of the power distribution system, and their failure can cause power outages, safety hazards, and damage to equipment. Traditional inspection methods involve manual inspection, which is time-consuming, expensive, and poses safety risks for personnel. Using UAVs and machine learning algorithms for insulator inspection enables faster and more accurate identification of defects, such as cracks, corrosion, and contamination. The UAVs can capture images of insulators from multiple angles and distances.

The combination of camera and machine learning technology for distribution system insulator inspection has the potential to improve the safety and reliability of the power distribution system while reducing costs and downtime associated with manual inspections.

1.1 Problem Statement:

Traditional inspection methods may not be able to detect defects that are not visible to the naked eye, which can lead to insulator failure and power outages. The present models are that the feature selection has not been deployed for the fault detection of insulators because they use different robots which are specific to one direction only. But our proposed model has a wide-angle view due to which it can capture the picture of the insulator and also detect the fault in any direction. We aim to solve the success rate by capturing the actual fault of the insulator. Our model has been applied to many distribution lines, which is effective and reliable. We are also interested in the kinds of pictures that have complex backgrounds. The approach produces a poor recognition rate for photographs taken in conditions like rain, fog, and other difficult weather. Our proposed model collects maximum data in such conditions.

1.2 PROJECT OVERVIEW/GOAL:

- Fault detection through UAV.
- Optimization of UAV through ML.
- Differentiation of insulator.
- Detect which kind of fault in the distribution power line insulator.
    i. Crack
    ii. Broken
    iii. Healthy
- Train dataset.

1.3 Project Methodology:

To develop the system following methodology will be used:

- Collection of the required dataset.
- Training of hardware using dataset and AI
- Checking results
- If any error in result, then check our dataset and AI module
- Testing of hardware.

- Validation of results.
- Showing a working prototype.

Proposed Methodology Flow Chart Diagram:

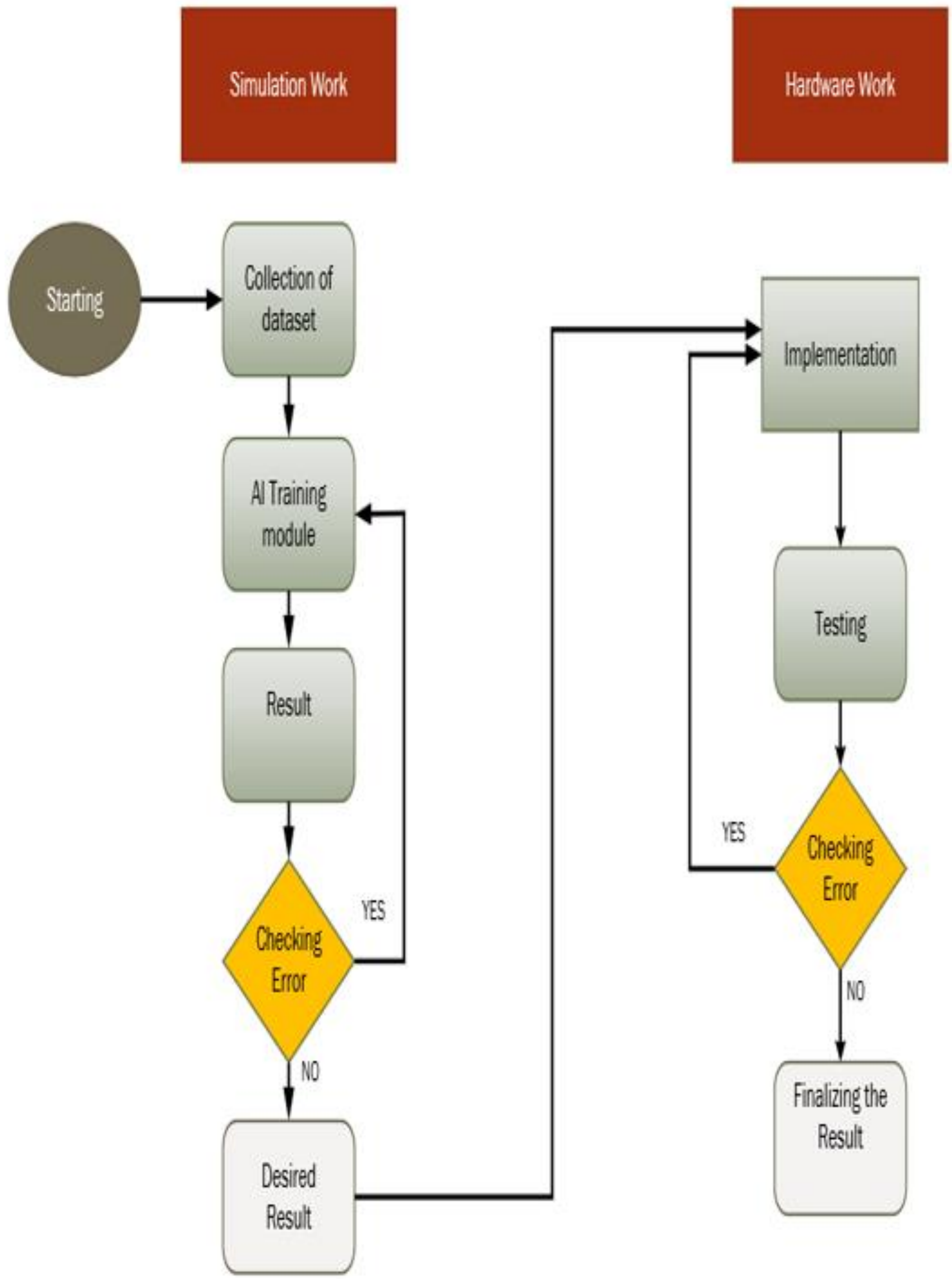

Figure 1.2: Proposed Methodology Flow chart

1.4 Work Division

Table 1: Work Division

Sr. No	Name	Work
1	Adil Siddique	Software logic development and Hardware design
2	Mujahid Iqbal	Software based simulation and Documentation

1.5 Conclusion:

The goal of this research is to develop and build an UAV capable of monitoring, examination and defect diagnosis. In this work, a new method to inspect distribution lines insulator is proposed. The new method comprises of a cwod-copter integrated a camera and controller which inspect distribution lines insulator visually.

CHAPTER 2

LITERATURE REVIEW

Conventionally, field surveys are performed to monitor transmission lines. Several teams on foot or by using helicopters purely depend on cost perform this kind of inspection. Teams on foot type of inspection as shown in Figure 2.1 require too ‘much labour and time for problem detection. However, it has a higher rate of detection.

‘The other techniques based on helicopter also have detection rate because of the high speed of helicopter and limited capability of the team to concurrently detect all possible issues. These two methods based on human visual observations. Moreover, these days several types of video cameras to record videos could be used, “Airbome Laser ‘Scanning (ALS/Lidar)” is another vitally used data acquisition technique. Reed et. al and Axelsson proposed first studies on ALS [1].

Figure 2.1: Manual Inspection of transmission lines [3]

Cameras and Laser Scanners acquired digital data and made it feasible to segregate data by analyzing data. This data collection was capable to make it economical and reliable Furthermore, this data was stored to compare with other acquired long-term data, Initially, it was manual, but it increases the rate of problem detection. Previously several remote sensing techniques were prosed and used to monitor the lines. Mu Li et al. inspect power lines by photographs taken from “Coarse Satellite” and applied technique of the data science on gathered data, which helps inline inspection reliability EPRI proposed several cases and methods for future monitoring and evaluation of overhead lines. In this paper, several sensing methods were discussed and compared.

Miralles et al, reviewed several computer foresight methods concemed with transmission lines management.’The author talked about fault detection methods in lines and inspection methods of lines and the detection of the pylon. It was not specific to a platform, Afterwards, Synthetic Aperture Radars (SAR) were used. SAR is basically “active imaging sensors”. Generally, these images comprise of Radar Back scattering Intensity be determined by several parameters (SAR system and target Phase of Back scattered parameters) and have a vital impact on the image appearance, Signal and Sensor range to the target. In this approach, the intensity used to analyze the data, in the shape of the amplitudes of the images, and it could be monitored through any software having the capability to sense remotely. In Backs catering the parameters of the system influence intensity by effecting microwave consumed wavelength, the polarization of the signal, and the attainment of image geometry. Furthermore, to identify the deviation the parameters like wavelength, polarization and geometry of the image must be invariable. The monitored intensity highly depends upon the targeted image must be invariable. The monitored intensity highly depends upon the targeted point properties: which are roughness of the line surface, moisture level on the line surface, trees and plants in the vanity. In “SAR Interferometry and Polarimetry” depends upon the data of the phase where data is processed in polarimetry based on the polarization of radiation which is received and radiations which were transmitted.

In objects detection and classification and land-cover classes, SAR polarimetry could be used. SAR Interferometry” is a method where two images are taken from changed standpoints with several meter distance among satellites and the pixel-by-pixel phase changings among the images are transformed into elevation dissimilarities of the terrain. SAR Radar grammetry” depends on

”Stereoscopic measurement” of the images of SAR is another method to obtain elevation data from the data of radar. It uses the values of range and the intensity of the SAR data. In this method, even the images with too much high resolution are not good even focusing on a small component of the lines. This imaging technique was not good and very stimulating while observing complex line structures. It’s a side-looking ranging imaging system. Imaging geometry has too many impacts on the features. Parallel and in range, lines could be easily detected. SAR images side-looking geometry is good to detect vertical features like transmission towers.

Imaging Geometry relevant distortions particularly layover and foreshortening influence towers emergence in images. This SAR data is used to map power lines and towers. Several authors analyzed Radar back scattering from power lines relevant to avoid the collision of aircraft of any helicopters. These findings provide basic knowledge about power line observation methods. For observation purposes, the wavelength is no longer than SAR images. Sarabandi et al did

Polarimetric backs cattering measurements” for several kinds of conductors in several bands. Sarabandi and Park examined the detection of the power line which depended upon the coherence among polarized cross-polarized back scatter components. They also examined ice/water impacts. Except this airborne SAR data was also used in many studies for power transmission lines and towers mapping. In such type of studies, the authors explain their results by using a few amounts of figures. They did not perform greater tests or perform any numerical analysis. Carande et al proved that the poles of the power lines can be recognized from their heights and the X band originated consistent data.

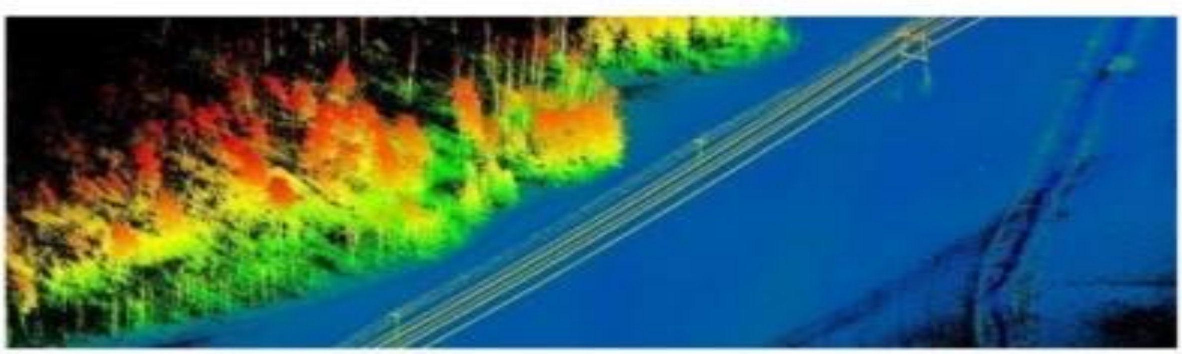

Figure 2.2: Remote sensing method through Radar imaging [4]

These DSMs were generated by the use of InSAR data without providing SAR data It was" Morphological filtering" based detection and shape, size and height-based criteria. Consequently, on the bases of Vertical Obstructions, the path of the transmission line was found by forming a line.

Furthermore, analysis of the height mistake and Erro source discusses were given as well. By using Polarimetric data Yang et al proposed a technique by using L band airborne data to detect towers. Deng et al use the same data any proposed method to detect power lines. A simulation model was presented, and the results show the line orientation effects in detecting. Ling et al proposed line visibility technique and Xie et al described the considerations" linear polarisation ratio" as well as "degree of linear polarization" to identify the towers used in transmission systems from the data of L band of the airborne. Afterwards, umanned helicopter/fixed-wing aircraft as shown in Figure 2.3 evident and Near-Infrared (NIR) wavelength were used to monitor lines by aerial images. Helicopters are usually used for power lines inspection. It can fly nearer to the

Figure 2.3: Transmission lines helicopter-based inspection [6]

lines, and hover nearby, so, it could make a clearer image of the object. However, fixed speed can fly faster and can cover more area with increased efficiency compared to helicopter. Usually. GSD is 5cm to 10cm of aerial images taken using fixed-wing which are very high in resolution.

In the monitoring of power transmission lines, 3D information has too much importance. Stereo Photogrammctry is used to generate height-related information from the images. However, if the images that were captured overlap" Stereo Matching" could be used for objects 3-D coordinated assumption. Triangulation technique was used for matching purposes if an object appears on one or more images. Then the position of 3-D is the point of intersection of multiple rays travelling through the pixels of the image to point out an object. The quality of the images particularly of the images taken by a lens having long focal length become weaker due to the motion of vehicle and vibrations that become the reason of image blurring. The helicopters angular motion due to the gust of wind could be counter weighed by using gym-stabilized gimbals to install camera.

Frank et al. used Hyper spectral data for experimental purposes. By using the appropriate configuration of the system and high-resolution camera many kinds of line components could be recognized through aerial images. It could help monitor the condition of the line components as well as line components factors like background, brightness, weather conditions and variations because of the season could be extracted automatically.

Thermal imaging as shown in Figure 2.4 is also a technique used for transmission lines monitoring; it is based on lines emitted infrared radiation with respect to their temperature. The thermal imaging technique depends upon the infrared radiations emitted by the objects as concerning objects temperature. According to" Stefan— Boltzmann" law objects emitted energy is the multiple of constant of "Stefan—Boltzmann" and temperature of the line. 3p micro meter to 14 micro meter spectral range is used for this imaging. Usually, a thermal camera having spectral range mid-wave infrared (3 to 5) or long-wave infrared (8 to 14) are used.

Cooled infrared could also be used it has high sensitivity and good image quality, but these cameras are expensive as compare to the un-cooled camera. 5 cm is the maximum gained images of spatial resolution through aerial inspection methods. it has been used by aerial, ground inspection and robotic inspection in which robots travel on lines to detect faults in components.

Lines having a very high temperature which is known as an electrical hot spot as well could be mapped due to long-wavelength infrared spectrum energy radiation. There are only a few studies conducted on power line analysis using thermal imaging. But it has several commercial applications and used to survey HV transmission and distribution lines. Faults on HV transmission lines could be found from the air but Stockton and Tache proved impossible the quantification of temperature measurements of the electrical fault even the readings were taken very closely. It was because of spot size grater measurement in parallel to the range of measurement, the reflection of the object and the conditions of weather. In a test, Blazquez used Probe Eye Scanner/Normal Color Video System (PESNVSr. In this experiment components having some faults were detected due to their high temperature in HV transmission lines. The result of these experiments was tallied with the ground survey. Mechanical and electrical components of power structure cause the rise in their temperature to compare to other nearby components in case of degradation. Forte et al. observed overhead transmission lines and observe performance by using HD thermography using ground-based measuring techniques.

The purpose of this method was to make a new method to produce the real temperature of a transmission lines. In this work, a comparison was made in between the simulations and measured values of the temperature. By considering inputs the current, the speed of the wind, direction and outside temperature a mathematical model was used to measure the temperature of the conductor.

Figure 2.4: Thermal Imaging of transmission lines [8]

Land-Based Mobile Mapping is another technique used for lines observation. In this technique, several types of positioning, navigation and imaging sensors are integrated to make a Mobile Mapping System (MMS) as shown in Figurc 2.5 mounted on a moving car or vehicle. In this method data set of images from a different angle and the point, the cloud is used. Laser scanners and the cameras are the most widely used sensors to gather data. In the navigation system.GNS and IMU are more significant parts to generate MMS and orientation of the sensor while collecting data 138). In any coordination system for georeferencing, the position of the system and the orientation at whichever interval of the time is used. All-Terrain Vehicles (ATV)", ships or yachts and the rucksacks could also be used other than cars with such kind of systems. An MMS using laser scanner as its major imaging part is knows as a" Mobile Laser Scanning (MLS)" system. It gathers denser point clouds because the divergence angle has very thin beam. GNSS-INS solution precision in ALS is used to find out the point of clouds accuracy. In urban as well as semi-urban areas, the accuracy of 2cm to 3 cm can easily be attained by using a good MIS system with an adequate number of satellites, and in open valleys, this accuracy could be accomplished through PLS method.

UAVs usage for power lines inspections more feasible option because it provides airborne data having a very good resolution, can monitor more closely due to flight nearer to lines. Furthermore, this option is cost economical in comparison with methods based on helicopters. From last few years, this method is gaining prominence researchers have proposed many techniques of lines inspection based on UAVs. However, many older methods-based m UAVs arc also easily available. Same as, many methods based on" Photogrammetry" as well as sensing of lines remotely presented in recent years. UAVs development is an emerging trending because these have much other application in agriculture, defence. espionage, and entertainment industry. However, in power lines inspection data acquired through UAVs were not proved very beneficial due to components limitations. But in the last few years increasing advancement in its components especially in battery life and technology improved its data reliability acquired from power lines inspection.

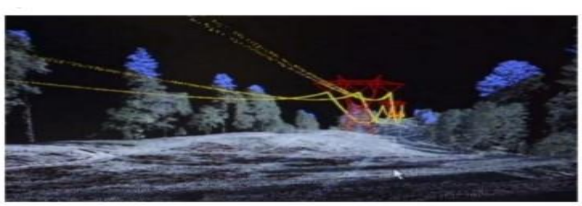

Figure 2.5: Mobile Mapping of transmission lines [11]

The invention of Lithium Polymer Battery" played a key role in UAVs development for this specific purpose of lines inspection because conventional methods were not appropriate for UAV due to vibrations. Furthermore, this battery enhances the flying time of the UAV as this type heavily varies concerning experiment performer and payload. Except for the battery. the inspection methods sensors availability enhanced UAVs capability to perform in more suitable manners in commercial applications. These all things vary country to country every country has its own set of rules for commercial availability of such devices [4]. Several developed UAVs have been tested and validated to perform several kinds of surveys of lines. Usually, UAV with fix wings is used to monitor vegetation as they can fly fast and higher.

Further these fixed wings vehicle could also be used for rough inspection of the lines. Helicopter and UAVs having multi-rotors could be used to get pictures of the line in which UAV hover nearer to the object and take pictures through the placed camera on it. The accuracy of the system could be increased by using some machine learning-based algorithms. Deng et al proposed a method in which a multi-platform system comprises of many distinct kinds of UAVs with distinct objectives. This was to prove the concept of line analysis through UAV and to analyse previously proposed methods of aerial monitoring based on ALS and UAV data. This system was more flexible and quicker as compared to previously proposed large remote monitoring systems. Toth and Gilpin-Jackson examined multiple images taken by backpack PLS systems in which the author found that the conductors for power transmission, insulators for attached in the transmission system and the poles providing support to the cables were easily detected from data gathered. Except this, the trees and plants grown around the lines were also identified. They also prepared the components list needed for UAV development for British Columbia Transmission Corporation, Canada". In the end, they explained UAV applications for civilians' services and discussed their limitations in term of technical issues, issues during their working like flight time, stability and reliability, financial bather (higher rate of UAVs due to expensive components) and some operational constraints. Hrabar et al worked in components required for UAV development. These components were enlisted specifically for UAV design to inspect transmission lines. Mostly proposed UAVs based monitoring system took optical images of the lines and detect fault from images or detect online transmission lines. Figure 2.6 shows how UAV monitored transmission lines. Except monitoring, detection of the power line is also essential to navigate the UAV hovering around the line in which this is assumed that the information is not presented. However. laser scanning of the lines through UAV has been proposed by a few authors but shows not much accuracy. In future small laser Scanning" system along UAV could be very powerful.

Figure 2.6: Transmission lines inspection through UAV [14]

Katragnik et al reviewed mobile robots and flying robots for the inspection of power lines. For UAVs author focused on UAVs technical aspects in which position control system of the UAV, attitude control system of the UAV and guidance system of the UAV were discussed. These technical problems were very important concerns for line inspection using UAV. Afterwards, Montambault et al. reviewed Vertical Take-Off and Landing (VTOL)" UAVs to inspect the power lines passing through forests and desserts. The author focused on UAVs as well. This review was purely focused on power systems inspection methods based on UAVs.

In this work, Hex-Copter is proposed which comprises of integrated Pi camera, Thermal camera and thermal sensor using Raspberry Pi. This hex-Copteris specifically designed to reduce man power, human error, and make process cost-efficient. This developed system is affordable by least developed states with good accuracy and user-friendly features. The previously developed and proposed systems are expensive, not afford able by developing states, and need a trained person to operate. That was bases on only a thermal camera or a simple camera or temperature sensor only. However, an integrated approach of these three with an HTML view makes this system novel.

The six propellers of a Hex-Copter offer the significant advantage that if any fails, the remaining propellers can maintain the craft to fly. The quad-copter will not be capable of flying if two propellers break, but the hex-copter will stay steady sufficient to land securely. Human monitoring is used for the thorough evaluation of overhead transmission. In last few periods, more study on auto power transmission monitoring has been carried out on a larger level. An automated detection approach for identifying defects in electric lines via UAV photos is implemented in this study, and this approach can efficiently examine electric power lines.

2.1 Existing Systems Features :

Robot has been used for surveillance of transmission lines. UAV, s is controlled manually with the help of remote control. In previous years, there is no mechanism used for continues long flight and which helicopter used for surveillance for distribution and transmission power line are very high cost. In recent research, optical camera is used for surveillance of transmission lines.

2.2 Our System Features:

UAV will be design for surveillance inspection of distribution lines insulator that autonomously performs surveillance inspection over a fixed pattern, without the requirement of a remote pilot and is powered mechanism for long flight time.

2.3 Conclusion:

The flight controller runs the UAV-based inspection system, which has a drone fly around the distribution lines and send live video data and pictures taken by an instant camera to a nearby host. Where the watcher checks the health of the distribution line insulators and sees which ones are broken or cracked. The results show that the fast camera is able to take stable pictures of the distribution lines insulator..

CHAPTER 3

SIMULATION & RESULTS

3.1 Introduction:

Sequential models can be used for insulator detection tasks through the use of Convolutional Neural Networks (CNNs). CNNs are a type of neural network that are designed to process insulator images and other multidimensional data. They consist of several layers of filters that perform convolution operations on the input data, followed by pooling layers that reduce the size of the output and improve computational efficiency.

In a sequential model for finding insulators detection, the CNN layers are usually followed by a set of fully connected layers that classify the insulator based on its features. The model is taught on a set of labeled images, where each insulator has a label that describes what is shown in the picture. During training, the model changes the weights of the filters and fully connected layers to get the gap between the labels it predicts and the real labels in the training data to be as small as possible. Once trained, the model can be used to predict the labels of new images. The input image is passed through the CNN layers, and the output of the final pooling layer is flattened and fed into the fully connected layers. The output of the final fully connected layer is a probability distribution over the possible labels, and the label with the highest probability is selected as the predicted label.

3.2 Proposed Framework:

This section is based on the proposed LF techniques and framework such as:

3.2.1 Convolutional Neural Network (CNN):

A Convolutional Neural Network (CNN) is a type of deep learning neural network that is designed to process insulator data and other multidimensional data like audio, video, and time-series data. CNNs are widely used in computer vision applications like image and video recognition, object detection, segmentation, and classification.

The key feature of a CNN is its ability to learn spatial hierarchies of features from the input data. It achieves this by applying a series of convolutional and pooling layers to the input insulator image. In the convolutional layer, a set of learnable filters is applied to the input image, producing a set of feature maps. These feature maps represent different aspects of the input image, such as edges, corners, and blobs.

The pooling layer is used to down sample the feature maps, reducing their spatial dimensions while retaining the important features. This reduces the computational complexity of the network and prevents overfitting.

After several convolutional and pooling layers, the output of the CNN is fed into a fully connected layer, which performs the classification task. The fully connected layer is typically followed by a SoftMax activation function, which converts the output of the layer into a probability distribution over the different classes.

In addition to the convolutional and pooling layers, CNNs may also include other types of layers, such as normalization layers, dropout layers, and activation layers, to improve the performance of the network and prevent overfitting.

Overall, CNNs have been highly successful in computer vision tasks and have achieved state-of-the-art performance on many benchmarks.

3.3 Gates of CNN:

3.3.1 Convolutional Gate:

This is the main gate used in a CNN. It performs convolution operation between the input image and a set of filters, each of which is small in size and designed to capture specific patterns in the input image. Convolutional gates are used to extract relevant features from the input image.

The convolutional gate applies a set of filters to the input image, producing a set of feature maps. Each filter is a small matrix of weights that is slid over the input image, computing the dot product between the filter and the corresponding region of the input image.

The output of the convolutional gate can be computed as:

First, we can apply a convolutional layer to X with filters F, kernel size k, and stride s:

$$Y = \text{Conv1D}(X, F, k, s)$$

Convolution is a process of sliding a small kernel or filter over the input image and performing a dot product between the kernel and the corresponding pixels of the input image.

3.3.2 Pooling Gate:

The result of the convolutional gate is sent through this gate to make it smaller. It makes the feature maps smaller while keeping the important elements. The max pooling gate is the most common type of pooling gate. It takes the highest value in a small area of the feature map.

The pooling gate is used to reduce the size of the feature maps while keeping the important features. It does this by taking a smaller sample of the output of the convolutional gate. The max pooling gate is the most common type of pooling gate. It takes the highest value in a small area of the feature map. Next, we can apply a pooling layer to Y with pool size p:

$$Z = \text{MaxPooling1D}(Y, p)$$

3.3.3 Activation Gate:

This gate applies a non-linear function to the output of the convolutional and pooling gates. The most commonly used activation gate is the Rectified Linear Unit (RLU) gate, which sets all negative values to zero and leaves positive values unchanged. Activation gates are used to introduce non-linearity into the network, which allows the network to learn complex representations of the input data.

The activation gate applies a non-linear function to the output of the convolutional and pooling gates. The most commonly used activation gate is the Rectified Linear Unit (RLU) gate, which sets all negative values to zero and leaves positive values unchanged.

The output of the RLU activation gate can be computed as:

3.4 Layers Of CNN:

A CNN consists of multiple layers, each of which performs a specific type of operation on the input data. The three main types of layers in a CNN are:

3.4.1 Convolutional Layer:

This layer performs a convolution operation on the input data using a set of filters (also called kernels or weights). The output of this layer is a feature map that represents the presence of certain features in the input image.

3.4.2 Pooling Layer: This is for feature map and its detail is given below.

This layer down samples the output of the convolutional layer by taking the maximum or average value in a small window of the feature map. This reduces the spatial size of the feature map and helps in reducing overfitting.

3.4.3 Fully Connected Layer: This layer takes the output of the previous layer and maps it to a set of output classes using a set of weights and biases. The output of this layer represents the probability of the input belonging to each of the output classes.

3.5 Proposed Integration Strategy:

Data Preparation: The first step in simulating a CNN is to prepare the data. This involves loading the image dataset and preprocessing it by resizing, normalizing, and splitting it into training and testing sets.

Model Creation: The next step is to create the CNN model. This involves defining the architecture of the CNN by specifying the number and types of layers, their hyperparameters such as the number of filters, kernel size, activation functions, and optimizer.

Model Training: Once the model is created, it needs to be trained on the training set. This involves feeding the training data into the model, computing the loss, and updating the model weights using backpropagation. The training process is repeated for a fixed number of epochs or until the model converges.

Model Evaluation: After the model is trained, it is evaluated on the testing set to measure its accuracy, precision, recall, and F1-score. This helps in determining if the model is overfitting or underfitting and if the hyperparameters need to be adjusted.

Model Prediction: Finally, the trained model can be used to make predictions on new unseen images. This involves feeding the new image into the model, computing the output probability vector, and predicting the class with the highest probability.

These steps can be repeated iteratively to improve the performance of the CNN by adjusting the hyperparameters, increasing the number of layers, or using a different optimizer or regularization technique.

3.6 Algorithm Flowchart:

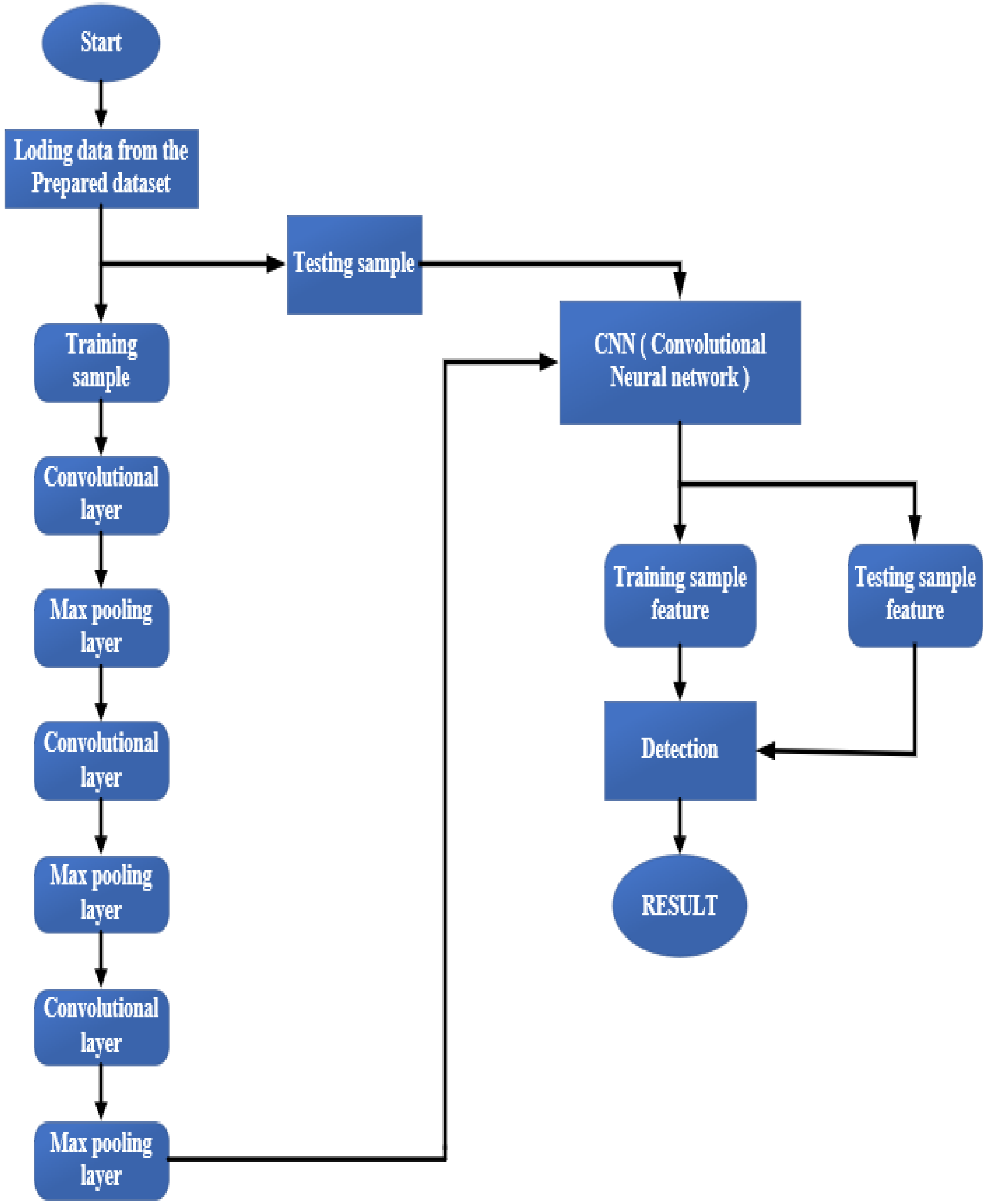

Figure 3.1: Algorithm Flowchart

3.7 Model Evaluation:

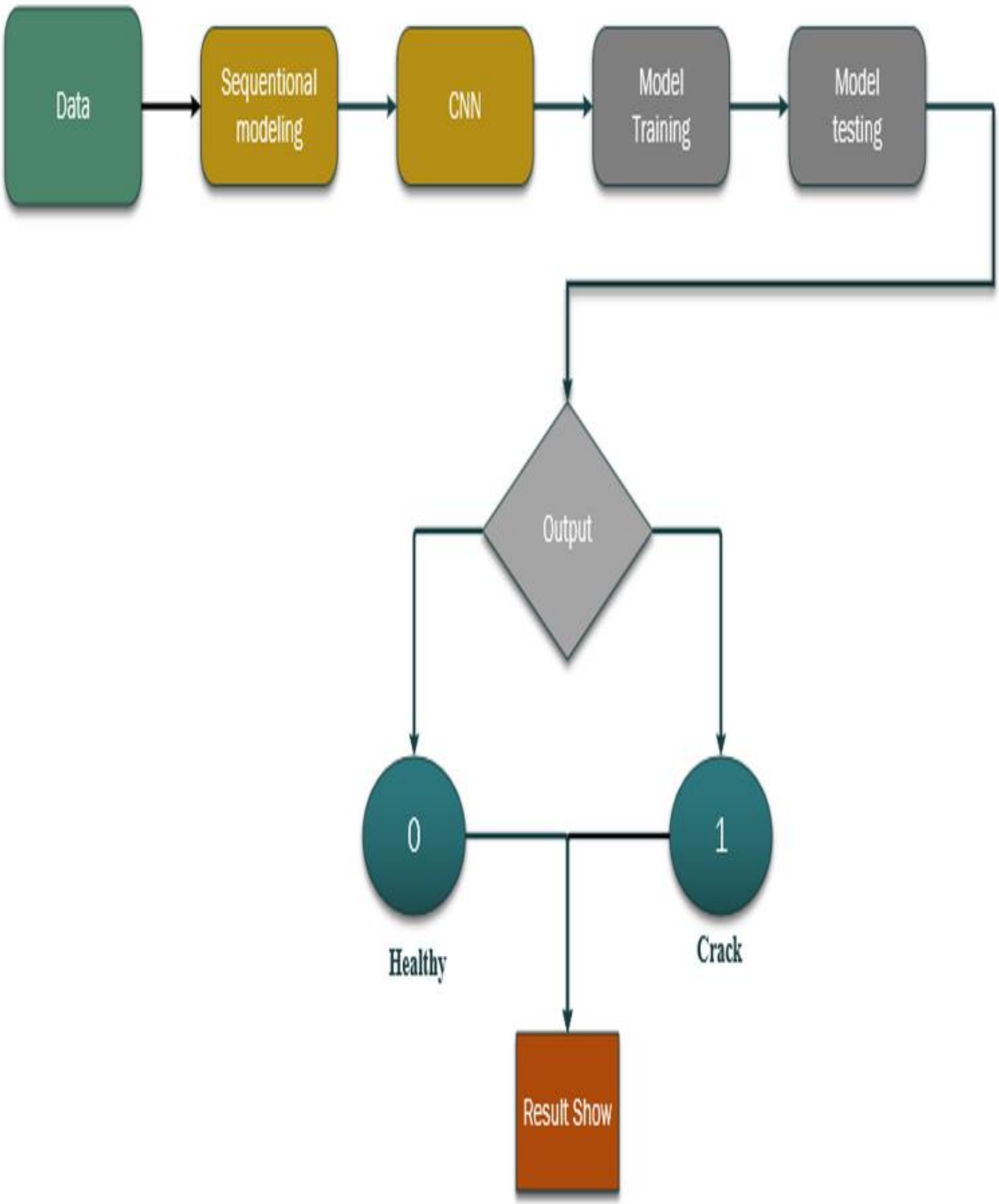

Figure 3.2: Model Evaluation

3.8 Data collection And Analysis:

Data provided for the testing and training of CNN model to improve the accuracy of results. There are two cases for healthy and unhealthy insulator testing through binary classification.

3.8.1 Healthy Insulator:

In this result when we enter the health image of insulator then our model tests the image and show output 0. In this result 0 mean that this is health insulator.

Figure 3.3: Healthy insulator

Figure 3.4: Healthy insulator

Code:

```
path=input ('enter the path of image")

test_image-cv2.imread(path)

test_image cv2.resize(test_image, (150,150))/255

 test image=np.expand_dims(test_image, axis=0)

predict_x= model.predict (test_ image)

classes_x=np.argmax (predict_x, axis=1)

print (classes x)

if classes x = = 0:

print("Insulator Healthy")

e1se:
```

print("Insulator is Unhealthy")

enter the path of image/content/drive/MyDrive/Insulator/c.jpg

1/1[= = = = = = = = = = = = =]-0s 32ms/step

Result:

[0]

Insulator is Healthy

Figure 3.5: Healthy insulator result

3.7.2 Unhealthy Insulator:

In this result when we enter the unhealth image of insulator then our model tests the image and show output 1. In this result 1 mean that this is unhealth insulator.

Figure 3.6: Unhealthy insulator

Figure 3.7: Unhealthy insulator

Code:

```
path=input ('enter the path of image")

test_image-cv2.imread(path)

test_image cv2.resize(test_image, (150,150))/255

 test image=np.expand_dims(test_image, axis=0)

predict_x= model.predict (test_ image)

classes_x=np.argmax (predict_x, axis=1)

print (classes x)

if classes_x = = 0:

print("Insulator Healthy")

e1se:

print("Insulator is Unhealthy")

enter the path of image/content/drive/MyDrive/Insulator/c.jpg

1/1[= = = = = = = = = = = = =]-0s 20ms/step
```

Result:

[1]

Insulator is Unhealthy

Figure 3.8: Unhealthy insulator result

3.8 Conclusion:

In conclusion, the use of Convolutional Neural Networks (CNNs) for object detection has revolutionized the field of computer vision. CNNs are a type of deep learning algorithm that can extract features from images and use them to identify and locate objects within an image. The simulation chapter on object detection using CNNs has demonstrated the effectiveness of these algorithms in detecting objects in complex and varied environments.

One of the advantages of using CNNs for object detection is their ability to learn and adapt to new data. Through the process of training, the network is able to extract relevant features from images and use them to identify objects, even in images it has never seen before. This makes CNNs particularly useful for applications such as surveillance, autonomous driving, and robotics.

The simulation chapter also highlighted some of the challenges associated with object detection using CNNs. One of the main challenges is the need for large amounts of annotated data for training the network. Annotated data refers to images that have been labeled with the location of objects within the image. This data is essential for the network to learn how to identify and locate objects accurately.

CHAPTER 4

HARDWARE DESIGN

Introduction:

In recent years, the rapid advancement of technology has revolutionized the way we approach various sectors, and the power distribution industry is no exception. Traditional manual inspection methods for distribution lines, such as visually inspecting insulators, can be time-consuming, costly, and potentially dangerous for technicians. However, with the advent of drones equipped with high-resolution cameras and advanced image processing techniques, the inspection process has been significantly streamlined and enhanced. This article explores the use of drones to collect images of insulators on distribution lines and transmit them through a Wi-Fi module for subsequent analysis using laptop software. In particular, we delve into the utilization of Convolutional Neural Networks (CNNs) for detecting healthy or unhealthy insulators, ushering in a new era of efficient and accurate distribution line inspections.

Step 1: The Role of Drones in Distribution Line Inspections

Distribution line inspections are vital for ensuring the reliability and safety of electrical power transmission. Insulators play a crucial role in maintaining the integrity of these lines by preventing electrical leakage and maintaining the necessary insulation levels. Traditionally, manual inspections involved sending technicians to visually assess the condition of each insulator, which was time-consuming and prone to human error. With the emergence of drones, this process has undergone a transformation.

Equipped with high-resolution cameras, drones can capture detailed images of insulators quickly and efficiently. These images provide valuable visual data that can be utilized for various analysis techniques, including computer vision algorithms. By leveraging the capabilities of drones, power distribution companies can enhance their inspection processes, improve maintenance planning, and ultimately reduce downtime and costs.

Step 2: Image Transmission via Wi-Fi Module

After capturing images of the insulators, the next step is to transmit this data to a central processing system for further analysis. Drones are equipped with a Wi-Fi module that enables seamless and wireless data transfer. This module establishes a connection with a laptop or computer, enabling real-time image transmission from the drone's camera.

The use of Wi-Fi for image transmission offers numerous advantages. It allows technicians and analysts to remotely monitor the inspection process, eliminating the need to physically access the drone's storage media. Additionally, the real-time transmission of images enables quick decision-making and immediate action if any critical issues are detected. This connectivity between the drone and the laptop software forms a crucial link in the inspection workflow, facilitating efficient analysis and processing of the collected images.

Step 3: Utilizing Convolutional Neural Networks (CNNs) for Insulator Detection

Once the images of the insulators are transmitted to the laptop software, advanced computer vision techniques, specifically Convolutional Neural Networks (CNNs), can be employed for automated analysis. CNNs are a type of deep learning algorithm widely used for image classification and object detection tasks. They excel in identifying patterns and features within images, making them highly suitable for identifying the health status of insulators.

In the context of distribution line inspections, CNNs can be trained using a large dataset of labeled images. These images can include examples of both healthy and unhealthy insulators, with labels indicating their respective conditions. By leveraging this dataset, CNN learns to recognize key visual cues and features associated with healthy or unhealthy insulators, enabling accurate classification.

Step 4: Simulation and Analysis of Laptop Software

The laptop software acts as a central hub for processing and analyzing the collected images using the trained CNN. Once the images are received via the Wi-Fi module, the software initiates the CNN-based analysis pipeline. This involves feeding the images through the pre-trained CNN model, which then predicts the health status of each insulator.

The software presents the results in a comprehensive and user-friendly interface, allowing technicians and analysts to review the findings efficiently. The system can provide detailed

4.1 List of components

Sr.No.	Components	Quantity
1	Drone	1
2	Arduino	1
3	Camera	1
4	ESP32	1
5	Battery	1
6	Motor Speed Controller	1

4.2 Drone

Drones, also known as unmanned aerial vehicles (UAVs), serve a variety of functions across different industries and sectors. Drones equipped with high-resolution cameras are used extensively for capturing aerial photographs and videos. They are employed in fields such as filmmaking, real estate, tourism, and sports to capture stunning aerial shots from unique perspectives.

Drones can be used for insulator image detection in the following ways:

Drones equipped with high-resolution cameras can capture detailed images of insulators mounted on power transmission lines or other infrastructure. These images can be used to detect any signs of damage, corrosion, or wear on the insulators. Drones can autonomously fly along power transmission lines, capturing images of insulators at regular intervals. The collected data can then be processed and analyzed using computer vision algorithms or artificial intelligence techniques to detect anomalies or patterns indicative of insulator degradation or failure.

Inspecting insulators using drones can be more efficient and cost-effective compared to traditional manual methods. Drones can cover large areas quickly, reducing the time and effort required for inspection. This enables utilities and maintenance teams to proactively identify and address potential issues before they escalate into major failures, leading to improved reliability and reduced downtime. Overall, using drones for insulator image detection enhances the speed, accuracy, and safety of inspections, enabling proactive maintenance and ensuring the reliable operation of power transmission infrastructure.

4.3 Arduino

Arduino is an open-source electronics platform that consists of both hardware and software components. The main function of Arduino is to provide a versatile and user-friendly platform for creating interactive electronic projects. Arduino boards are equipped with a microcontroller, which is essentially a small computer that can be programmed to perform various tasks. The microcontroller acts as the brain of the Arduino board and controls the input and output of signals.

When Arduino is connected to a drone for insulator image inspection, its functions, and role can vary depending on the specific setup and requirements. Here, Arduino is be used to collect data from sensors and devices attached to the drone. For insulator image inspection, it can receive inputs from cameras, thermal sensors, or other imaging devices mounted on the drone. Arduino can read the sensor data and transmit it to the ground station or store it for further analysis. Arduino can process the acquired data in real time or perform preliminary processing tasks.

Arduino can be utilized to control the drone's flight parameters and movements during the inspection process. It can receive commands from the ground station or incorporate autonomous algorithms to ensure the drone follows predefined flight paths, maintains stable positioning, and captures images from desired angles. Arduino can facilitate the transmission of image data or other relevant information from the drone to the ground station. It can handle communication protocols, such as Wi-Fi or radio frequency, to send data in real-time or in a batched manner, depending on the requirements of the inspection process. Arduino can act as an interface between the drone's onboard systems and external devices or software. It can facilitate communication between the drone's flight controller, camera systems, and other components, ensuring seamless coordination and data exchange. In the project, Arduino can be used to log and store acquired image data or other relevant information during the inspection. It can save the data to onboard memory or external storage devices, providing a backup or a reference for further analysis and evaluation.

4.4 Camera

When a camera is connected to Arduino for insulator image inspection, it serves several functions to capture and analyze images of the insulators. The camera captures high-resolution images of the insulators mounted on power transmission lines or other infrastructure. It records visual information of the insulators and surrounding areas, providing a detailed representation for analysis. The captured images are used for visual inspection of the insulators. The camera captures the surface conditions, such as signs of damage, corrosion, wear, or other defects that may affect the insulator's performance or safety. The camera's images can be processed and analyzed using image processing techniques. Arduino can handle image processing tasks such as noise reduction, image enhancement, edge detection, or segmentation to improve the visibility of relevant features or anomalies in the images.

By analyzing the captured images, the camera, and Arduino can extract relevant features of the insulators, such as their shape, size, and orientation. These features can be used to compare against known standards or reference images, enabling the identification of anomalies or deviations from the expected state. The camera images can be analyzed to detect anomalies or signs of insulator degradation, such as cracks, contamination, or partial discharges. Arduino can use algorithms to compare the captured images with predefined patterns or thresholds, triggering alerts or notifications when deviations are detected.

In the project, the camera, connected to Arduino, can transmit the captured images to the ground station or external devices for further analysis or storage. Arduino can handle communication protocols and data transmission between the camera and the receiving end. The camera and Arduino combination can provide real-time monitoring capabilities, continuously capturing and analyzing images during the inspection process. By connecting the camera to Arduino, the inspection process can be automated and streamlined, enabling efficient and accurate analysis of insulator images, and improving the overall reliability and performance of power transmission infrastructure.

4.5 ESP32

ESP32 is connected to Arduino for insulator image inspection and the ESP32 collects images from n the scenario where an ESP32 is connected to Arduino for insulator image inspection and the ESP32 collects images from Arduino to send to a laptop for analysis, the ESP32 serves the following functions:

The ESP32 communicates with Arduino to receive the captured image data from the camera connected to Arduino. It collects the image data from Arduino and prepares it for transmission.

The ESP32 uses a communication protocol such as Wi-Fi or Bluetooth to establish a connection with the laptop. It transmits the captured image data from Arduino to the laptop for further processing and analysis.

The ESP32 manages network connectivity by connecting to a local Wi-Fi network or creating its own access point. It ensures a stable and reliable connection between the ESP32 and the laptop for data transmission. The ESP32 may implement a buffer to temporarily store the received image data before sending it to the laptop. This helps in managing the flow of data and ensuring smooth transmission without loss or corruption. The ESP32 can stream the captured images in real-time to the laptop, allowing for live monitoring and analysis of the insulator images. This provides immediate feedback and enables timely decision-making during the inspection process.

The ESP32 can handle any transmission errors or interruptions that may occur during data transfer. It may include error detection and retransmission mechanisms to ensure reliable delivery of the image data to the laptop.

The laptop, connected to the ESP32, plays a crucial role in the analysis of the insulator images. Here are the functions performed by the laptop:

The laptop compares the received image data from the ESP32 with the provided image data. It compares the features and characteristics of the captured images with reference or training data.

Machine Learning and CNN Training: The laptop may employ machine learning techniques, such as training Convolutional Neural Networks (CNNs), to learn patterns and features of healthy and non-healthy insulators. It trains the CNN model using labeled training data to classify the insulator images as healthy or non-healthy. The laptop applies the trained CNN model to the received image data and performs image analysis. It classifies the insulator images as either healthy or non-healthy based on the learned patterns and features.

The laptop presents the results of the insulator image inspection. It displays the classification results, indicating whether the insulator is healthy or non-healthy. This information can be used for further action, such as maintenance or repair of the identified non-healthy insulators. Arduino to send to a laptop for analysis, the ESP32 serves the following functions. ESP32 to collect and transmit image data from Arduino to the laptop, and employing machine learning techniques on the laptop for image analysis and classification, the system enables automated inspection and classification of insulator health, facilitating efficient maintenance and decision-making processes.

4.6 Battery

A heavier battery is required for a longer flying time due to the drone's heavier weight. Relying on preliminary study into several batteries, the best option appeared to be one with a 25 percent larger efficiency, which would extend the hex rotor's flight time. Trying to balance capacity and weight was a crucial concern. Since all the batteries had a comparable weight-to-capacity proportion, a battery was selected because it was expected to provide half an hour fly time.

4.7 Hardware

This is the picture of our hardware of distribution system insulator inspection by UAV by machine learning. A drone and healthy and unhealthy insulator shown in pictures and also it detects healthy insulator and unhealthy insulator. To overcome these challenges, this project proposes the use of unmanned aerial vehicles (UAVs) equipped with cameras and machine learning algorithms to automatically detect and classify insulator defects. Automating the insulator inspection process using UAVs and machine learning algorithms can improve the efficiency, accuracy, and safety of the inspection process.

Fig 4.1 Healthy and unhealthy insulator and drone

Fig 4.2 Hardware

4.8 Results

- Dataset Should be created in a picture.
- E.g. as shown in the figure it is as healthy

Our model compares with all data set and then show that this picture of insulator is healthy.

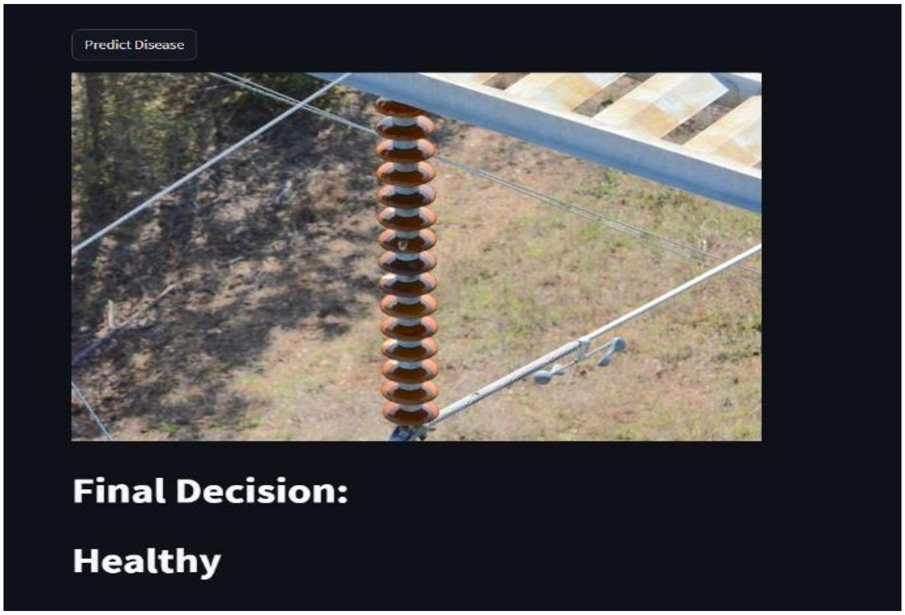

Fig 4.3 healthy insulator images

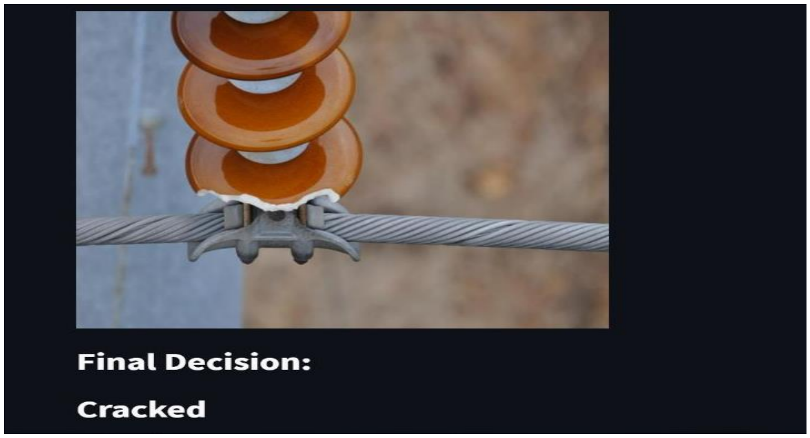

Fig 4.4 healthy insulator images

Fig 4.5 healthy insulator images

When we insert a picture of cracked or unhealthy insulator our model compares with our dataset and show that this is cracked insulator.

Cracked insulator also show in the picture.

Fig 4.6 Unhealthy insulator images

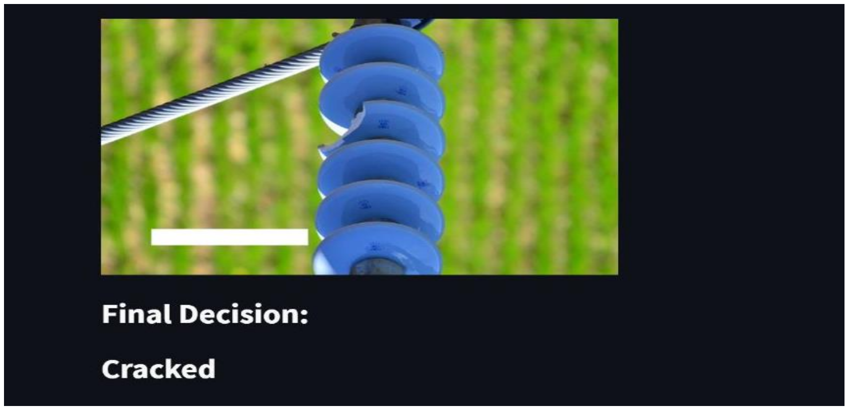

Fig 4.7 Unhealthy insulator images

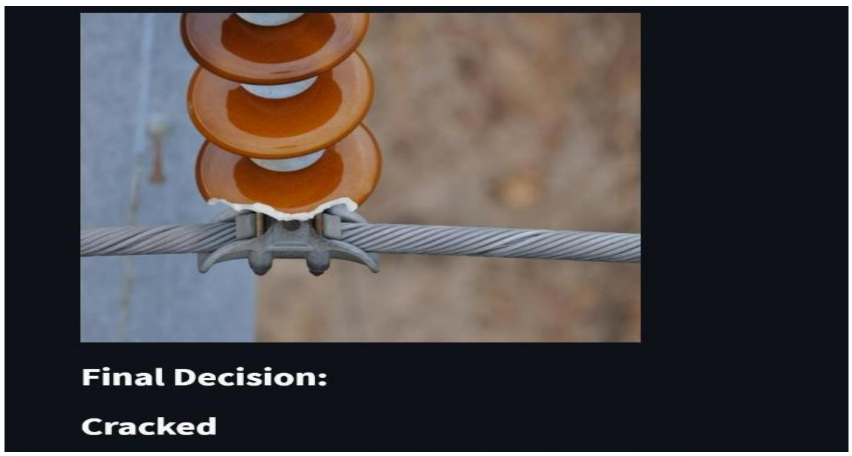

Fig 4.8 Unhealthy insulator images

When we insert a picture of any other thing but this picture is not insulator our model compares with our dataset and show that this is invalid image.

Because our model can detects healthy and unhealthy insulator.

Fig 4.9 Invalid image

Our model predict that this is invalid image because it is not a image of healthy or cracked insulator.

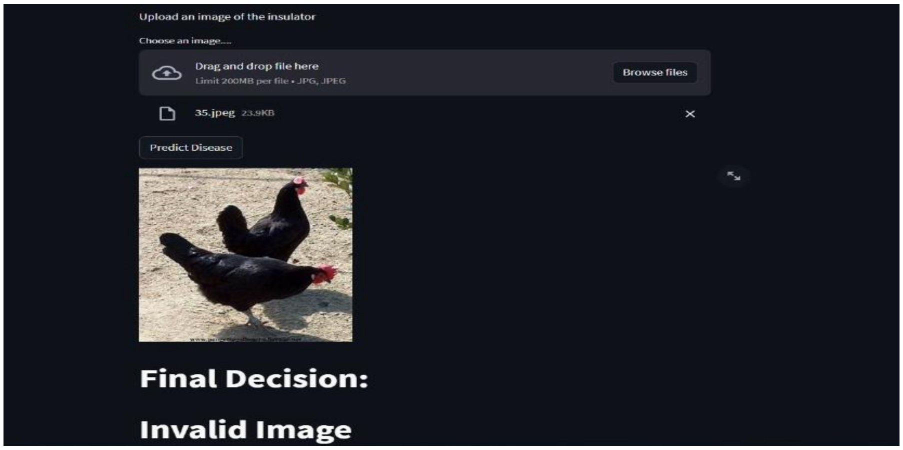

Fig 4.10 Invalid image

Because this is not a picture of insulator its a picture of car, so our model predict that it is an invalid image.

Fig 4.11 Invalid image

CHAPTER 5

BUSINESS DESCRIPTION

5.1 Form of Business

The form of our business will be Sole Ownership.

5.1.1 Team/Organizational Structure

All business starts from a low scale and after some time starts growing. Similarly, we will start our business on a small scale by making a unique drone for fault detection of insulator and trying to sell them all over the world. After some time, our business will start to grow and will surely make a reasonable profit. The following are the positions that will be assigned to the members of the company:

Adil Siddique will be the owner and Director of the company.

Mujahid Iqbal will manage the company and marketing.

5.1.2 Vision

The vision of distribution system insulator inspection by UAV and machine learning is to revolutionize the inspection process, making it more efficient, accurate, and cost-effective. By leveraging the capabilities of UAVs and advanced machine learning algorithms, the vision is to automate the inspection of insulators in distribution systems.

5.1.3 Mission

Our mission of distribution system insulator inspection by UAV and machine learning is to enhance the reliability, safety, and efficiency of electrical networks by leveraging advanced technologies. The primary objectives of this mission are as follows:

- Improve Inspection Accuracy
- Enhance Efficiency and Cost-effectiveness:
- Enable Proactive Maintenance
- Enhance Safety

- Foster Data-driven Decision Making:
- Promote Sustainable and Reliable Infrastructure:

Our mission of distribution system insulator inspection by UAV and machine learning is to transform the way inspections are conducted, ensuring the reliability and safety of electrical networks while optimizing operational efficiency and resource utilization.

5.1.4 Goal and Objective

Our goal of distribution system insulator inspection by UAV and machine learning is to develop and implement an automated and accurate inspection system for insulators in electrical networks. The objectives include:

- **Enhance Inspection Accuracy:** Develop machine learning algorithms to analyze visual and thermal data captured by UAVs and accurately detect insulator defects and anomalies.
- **Improve Efficiency:** Replace manual inspections with UAV-based operations to conduct inspections rapidly over a larger area, reducing labor costs and minimizing downtime.
- **Enable Proactive Maintenance:** Detect insulator issues at early stages to enable timely maintenance actions, prevent failures, and optimize the performance of the distribution system.
- **Ensure Safety:** Reduce risks by minimizing the need for human personnel to access hazardous or challenging locations for inspections.
- **Optimize Resource Allocation:** Provide data-driven insights to prioritize maintenance activities, allocate resources efficiently, and optimize the overall performance of the distribution system.

Contribute to a Reliable and Sustainable Infrastructure: Improve the reliability, safety, and sustainability of electrical networks through early detection, proactive maintenance, and optimize decision-making processes.

After this we can discuss industry and marketing analysis.

And then discuss Competitive Analysis.

And also about its accuracy.

5.2 Industry and Marketing Analysis

5.2.1 Industry Analysis

The distribution system insulator inspection industry is undergoing a transformation with the integration of UAVs and machine learning. There is a growing demand for efficient and accurate inspections, driven by the need for reliable electrical networks. Technological advancements in UAVs, such as improved flight capabilities and payload capacity, enable high-resolution data capture. Machine learning algorithms analyze this data to detect insulator conditions accurately. The industry benefits from cost reductions, time savings, enhanced safety, and data-driven decision-making. Market competition is increasing, with collaborations among UAV manufacturers, technology providers, and utilities. As regulations evolve, compliance and responsible UAV usage remain crucial for industry players.

- **Selection of sensors:** The system is totally based on the sensors so selection of sensors is very critical.

- **Others:** there are other issues like security, monitoring handling, and dealing with the emergency situation, etc. These are the critical flaws that we have to work hard to achieve our goals.

5.2.2 Competitive Analysis

The distribution system insulator inspection market using UAVs and machine learning is experiencing increasing competition. Key players include UAV manufacturers such as DJI, Parrot, and Yuneec, offering reliable and advanced platforms for inspections. Technology providers like Pix4D and Kespry offer software solutions and machine-learning algorithms for data analysis. Service providers like Precision Hawk and Cyberlaw deliver end-to-end inspection services using UAVs and advanced analytics. Startups and innovators bring niche technologies and specialized approaches to the market. Competitive factors include UAV performance, accuracy of algorithms, data processing capabilities, reporting quality, customer support, and cost-effectiveness. Partnerships and collaborations are expected to drive the development of integrated solutions tailored to industry needs.

5.2.3 Purpose

Our purpose is to develop a system that addresses the following problems:

- Enhance accuracy
- Increase efficiency
- Optimize resource utilization

5.3 SWOT Analysis

5.3.1 Strengths

- It is very beneficial for the IT and Power Industry development of a country.
- It takes less time for giving accurate output.
- More efficient than any other simple drone.

5.3.2 Weaknesses

- The communication errors can occur with the passage of time.
- Constantly required the Wi-Fi Connection.

5.3.3 Opportunities

- Introduction of new technology will attract people.
- The primary concern is to introduce modern ways in the field of the power sector.

5.3.4 Threats

- People will have accuracy concerns.
- It is difficult to influence the conventional mindset.

5.3.5 Marketing Objectives Follow

- Social media is a very much effective, powerful and economical source of advertisement nowadays.

- Electronic media (News Channel) is also a very much attractive and convincing source to advertise our product.
- We will target Power Sector for our project promotion.
- Letting the government know about its need and how it can fulfill their power sector requirements. .

5.4 Marketing Communication

In the next aspects of the public communications spectrum, the inherent strengths and shortcomings are taken into consideration and what they are incorporated, and how they are applied in this situation. By using social and electronic media which are nowadays considered as the most powerful and effective source of promotion and advertisement.

5.4.1 Advertising

It is an informal and sponsored means of educating consumers through, radio, news media, online portals, etc. about their goods and services. Advertising is one of the most commonly used marketing tactics in which the information about the goods and services of the business can be effectively conveyed to the vast target audience.

5.4.2 Personal Selling

Marketing involves selling of our project through videos and portals. Telling our customers how our system can fulfill their needs and how this bus can help them in making their work more easy, convenient, and more economical.

5.4.3 Direct Marketing

The efficacy of direct marketing can be directly calculated. Through inventing the technology, businesses use emails, faxes, and cell phones to connect with potential clients directly without including someone else.

5.5 Financial Plan

5.5.1 Resources Required

The resources are required:

- All the basic resources are required to start a business (i.e. Machinery, electronic equipment, a proper place etc.) Accessories.
- Human resources.
- Electricity (etc.)

Table 5.1: Initial Budget Expenses

Sr. No	Capital Nature Expenses	Amount(PKR)
1	Laptop (70000 x 1)	70000/-
2	Equipment (40000 x 1)	40000/-
	Revenue Nature Expenses	
3	Internet (4000 x 12)	48000/-
4	Misc. Expenses (1,500 x 12)	18,000/-
5	Electricity (10,000 x 12)	100,000/-
6	Purchase of Raw Material (10,000 x 10)	100,000/-
	Total: Initial Expenses (Budgeted)	328,000/-

Table 5.2: Statement of Comprehensive Income (Budged).

Sr. No		1st Year	2nd Year	3rd Year	4th Year	5th Year
1	**Revenue**	328,000/- (w-1)	360,000/- (w-2)	410,000/- (w-1)	430,000/- (w-1)	470,000/- (w-1)
2	**Cost of Production**	(80,000) (w-2)	(100,000) (w-1)	(130,000) (w-2)	(170,000) (w-2)	(200,000) (w-2)
3	**Other Operating Expenses**	(100,000) (w-3)	(100,000)	(105,000)	(111,000)	(135,000)
4	**Depreciation**	(5,000) (w-4)	(5,000)	(5,000)	(5,000)	(5,000)
5	**Misc.**	(4000)	4000	4000	4000	4000

6	**Marketing Expenses**	(8000)	(16000)	(16000)	(20000)	(20000)
7	**Profit before Commission**	30,000/-	40,000/-	60,200/-	89,800/-	110,400/-
8	**Commission**	(13,000) (w-5)	(18,000) (w-2)	(25,000) (w-3)	(35,000) (w-3)	(46000)(W-3)
9	**Profit After Commission**	**40,000/-**	**50,000/-**	**60,000/-**	**70,000/-**	**80,000/-**

5.6 Notes

5.6.1 Note-1

- All expenses & revenue are estimated.

5.6.2 Note-2

- Depreciation is provided on straight line method 10% on all Non-Current Assets.

5.6.3 Note-3

- Commission shall be given 10% in the basis of profit earned every year.

5.6.4 Note-4

- As the income in all years is less than the minimum prescribed limit as per "Income Tax
- Ordinance, 2001". So, no provision for tax is calculated.

5.6.5 Note-5

- Raw material contains sensors i.e. Arduino, Relay, Wi-Fi controllers etc. and other electrical equipment which are required.

5.6.6 Note-6

- Variable overhead vary with production depends on units produced in the year etc. electricity.

5.6.7 Note-7

- The all calculations are based on assumptions. So, there is a chance of imparity in these calculations.

5.7 Conclusion

In this chapter, the total business strategy is portrayed exhaustively alongside the five-year monetary arrangement. The undertaking's qualities and different highlights are additionally portrayed exhaustively. The design is to make it simple for the peruse to comprehend the financial worth and social remaining of this venture.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Conclusion

In conclusion, the integration of UAVs and machine learning algorithms for distribution system insulator inspection presents a transformative solution. The use of UAVs enables efficient and comprehensive inspections, eliminating the need for manual labor in challenging or hazardous environments. Equipped with high-resolution cameras, UAVs capture detailed visual data from multiple angles, facilitating accurate defect identification. Machine learning algorithms play a vital role in automating the analysis of the collected data. Through training and continuous learning, these algorithms can accurately detect and classify various insulator defects, such as cracks, corrosion, contamination, or physical damage. This automated process saves time and enhances the accuracy of inspections, allowing for timely maintenance actions.

The combination of UAVs and machine learning provides several significant benefits. It enhances inspection efficiency by covering large areas quickly and accessing difficult-to-reach locations. The proactive approach enables early detection of potential issues, enabling timely repairs or replacements, thereby reducing the risk of catastrophic failures and improving the overall reliability of the distribution system. Furthermore, the integration of UAVs and machine learning offers cost savings by reducing labor requirements and inspection time. The automation of the analysis process optimizes resource allocation and improves the utilization of maintenance personnel, tools, and equipment. This leads to more targeted and cost-effective maintenance actions, reducing unnecessary expenses and downtime.

Overall, the integration of UAVs and machine learning represents a groundbreaking advancement in distribution system insulator inspection. It enhances efficiency, accuracy, and safety while reducing costs and improving the reliability of the electrical grid. This technology-driven approach is poised to revolutionize the field of distribution system maintenance and contribute to the sustainable and reliable operation of power networks.

6.2 Future Work

While this study presents a distribution system insulator inspection by UAV and machine learning, there are several avenues for future research and development:

6.2.1 Integration of real-time data:

The integration of real-time data in distribution system insulator inspection using UAVs and machine learning offers immediate insights and actionable information. By capturing and analyzing data in real-time, potential defects or issues can be detected promptly, allowing for timely intervention. Real-time data enables rapid decision-making, facilitating efficient allocation of maintenance resources and reducing downtime. It also enhances the overall effectiveness of maintenance strategies by enabling continuous monitoring and adjustment based on evolving conditions. The integration of real-time data in insulator inspection enhances the reliability and performance of the distribution system, ensuring optimal operation and minimizing the risk of failures.

6.2.2 Hybrid models:

Hybrid models of real-time data integration in distribution system insulator inspection combine UAV-based data capture and machine learning algorithms to enable prompt defect detection, proactive maintenance, and efficient resource allocation, ensuring optimal system performance.

6.2.3 Optimization Strategies:

Optimization strategies for real-time data integration in distribution system insulator inspection using UAVs and machine learning focus on maximizing efficiency and effectiveness. These strategies involve:

Dynamic scheduling algorithms adjust inspection routes and priorities based on real-time data and evolving conditions, ensuring optimal coverage and resource allocation. Machine learning models analyze historical data to predict potential insulator failures, enabling proactive maintenance actions and minimizing downtime. Advanced algorithms analyze real-time data to pinpoint the exact location of insulator defects, facilitating targeted repairs and reducing response time. Optimization algorithms consider factors like UAV flight paths, battery life, and maintenance crew availability to optimize the utilization of resources and minimize idle time. Real-time data analysis provides decision support tools for maintenance personnel, helping them make informed decisions regarding inspections, repairs, and resource allocation. Machine learning models continuously learn from real-time data, improving their accuracy and effectiveness over time, leading to better defect detection and classification.

6.2.4 Demand-side management:

Demand-side management of real-time data in distribution system insulator inspection using UAVs and machine learning involves optimizing energy consumption based on insights from the data, ensuring efficient use of resources, and reducing overall energy demand.

6.2.5 Scalability and scalability considerations:

Scalability is a crucial factor in distribution system insulator inspection using UAVs and machine learning. Considerations include the ability to handle large volumes of data, accommodate increasing numbers of inspections, and scale the computational resources required for data processing and machine learning algorithms. Scalability considerations also involve developing efficient data storage and retrieval systems, ensuring seamless integration with existing infrastructure, and addressing potential challenges related to network connectivity and data security as the scale of operations expands.

REFERENCES

[1] X. Xie, Z. Liu, C. Xu, and Y. Zhang, "A multiple sensors platform method for power line inspection based on a large unmanned helicopter," *Sensors (Switzerland)*, vol. 17, no. 6, Jun. 2017.

[2] X. Huang *et al.*, "Design and Application of Insulator Detection Robot System for UHVDC Transmission Line," *International Journal of Mechanical Engineering and Applications*, vol. 7, no. 4, p. 106, 2019, doi: 10.11648/j.ijmea.20190704.13.

[3] Pagnano A, Ho¨pf M, and Teti R. A roadmap for automated power line inspection, maintenance and repair. Proc Cirp 2013; 12: 234–239.

[4] Malaver, A., Motta, N., Corke, P., Gonzalez, F. (2015). Development and Integration of a Solar Powered Unmanned Aerial Vehicle and a Wireless Sensor Network to Monitor Greenhouse Gases. Sensors, 15(2), 4072–4096. doi:10.3390/s150204072 (II Recd. M. D. Landry. C. E. Werther. K. C. (2020 April).

[5] The application of air and ground-based laser mapping systems to transmission line corridor surveys. In Proceedings of Position, Location and Navigation Symposium-PLANS196 (pp. 444-451). IEEE. 14.

[6] Axelsson, P. (1999). Processing of laser scanner data—algorithms and applications. ISPRS Journal of Photogrammetry and Remote Sensing. (2018 June).

[7] DI mu. C. Fens. Y. Cai. J., Yu. J. (2009. October). Overview of powerlines extraction and surveillance using remote sensing technology. In MIPPR 2009: Remote Sensing and GIS Data Processing and Other Applications (Vol. 7498. p. 74981 M). International Society for 62 Bibliography 63 Optics and Photonics. IQ Li. B. Wu. D. Cong. Y. Xia. Y. Tang. Y. (2012. December).

[8] A method of insulator detection from video sequence. In 2012 Fourth International Symposium on Information Science and Engineering (pp. 386-389). IEEE. 151 Liu, Y., Li, Z., Hayward, R., Walker, R., Jinn, H. (2009, December).

[9] Classification of airborne lidar intensity data using statistical analysis and Hough transform with application to power line corridors. In 2009 Digital Image Computing: Techniques and

Applications (pp. 462-467). IEEE. 161 Miralles, F., Poulet, N., Montambault, S. (2014, October).

[10] State-of-the-an review of computer vision for the management of power transmission lines. In Proceedings of the 2014 3rd International Conference on Applied Robotics for the Power Industry (pp. I.6). IEEE. 171 Deng, C., Wang, S., Huang, Z., Tan, Z., Liu, J. (2014).

[11] Unmanned aerial vehicles for power line inspection: A cooperative way in platforms and communications. J. Conium, 9(9). 687-692.

[12] Deng. S., Li, P., Dung, J., Yang, 1. (2012). Power line detection from synthetic aperture radar imagery using coherence of co-polarisation and cross-polarisation estimated in the Hough domain. 1ET Radar. Sonar Navigation, 6(9), 873.880. m Yang. W. Zhang. H. Chen. J. Sun. H. (2007. April).

[13] Automatic detection of power transmission series in full polarimctric SAR imagery. In 2007 IEEE Radar Conference (pp. 789-793). IEEE

[14] Performance evaluation of electrical transmission line detection and tracking algorithms based on image processing using UAV. IEEE 17 Sept. 2017

[15] Jani Reagan Vivek, Marzipan's, Michael Jesus Rickson Autonomous Quadcopter for Surveillance and Monitoring relational Journal of Advanced Research in Computer Engineering Technology (IJARCET) Volume 7, Issue 4, April 2018, ISSN: 2278 – 1323.

[16] Self-Powered Solar Aerial Vehicles Vol. 08, No. 02, pp. 95-117 (2020).

[17] Stability and Control of Quadcopter IJSRD - International Journal for Scientific Research Development Vol. 7, Issue 03, 2019 ISSN (online): 2321-0613

[18] Tayebi, A., and S. MacGilvray, "Attitude stabilization of a VTOL quadrotor aircraft," IEEE Trans. Control Syst. Technol., Vol. 14, pp. 562–571 (2006).

[19] Tang, Y. R., and Y. Li, "Dynamic modeling for high-performance controller design of a UAV quadrotor," IEEE Int. Conf. Informant. Automation, Lijiang, China, pp. 3112–3117 (2015).

[20] Asl, H. J., and J. Yoon, "Bounded-Input Control of the Quadrotor Unmanned Aerial Vehicle: A Vision-Based Approach," Asian J. Control, Vol. 19, No. 3, pp. 840–855 (2017).

[21] Zeng, X., H. Peng, J. Wu, and J. Wei, "Quad-Rotor Modeling and Attitude Control Using StateDependent ARX Type Model," Asian J. Control, Vol. 16, pp. 1403–1415 (2014).

[22] Mahony, R., V. Kumar, and P. Corke, "Multirotor Aerial Vehicles: Modeling, Estimation, and Control of Quadrotor," IEEE Robot. Autom. Mag., Vol. 19, pp. 20–32 (2012).

[23] Wang, L., and H. Jia, "The Trajectory Tracking Problem of Quadrotor UAV: Global Stability Analysis and Control Design Based on Cascade Theory," Asian J. Control, Vol. 16, pp. 574–588 (2014).

[24] Fritsch, O., P. De Monte, M. Buhl, and B. Lohmann, "Quasi-static feedback linearization for the translational dynamics of a quadrotor helicopter," Amer Control Conf., Montreal, QC, Canada, pp. 125–130 (2012).

[25] Ghandour, J., S. Aberkane, and J. C. Ponsart, Feedback Linearization approach for Standard and Fault Tolerant control: Application to a Quadrotor UAV TestbedPhys Conf. Series, Vol. 570, pp. 082003 (2014).

[26] Lee, D., H. Jin Kim, and S. Sastry, "Feedback linearization vs. adaptive sliding mode control for a quadrotor helicopter," Int. J. Control Autom. Syst., Vol. 7, pp. 419–428 (2009).

[27] Lin, Q., Z. H. Cai, Y. X. Wang, J. P. Yang, and L. F. Chen, "Adaptive Flight Control Design for Quadrotor UAV Based on Dynamic Inversion a Neural Networks," Third Int. Conf. Instrum. Meas. Comp. Commun. Control, Shenyang, China, pp. 1461–1466 (2013).

[28] Prasenjit, M., and W. Steven, Direct Adaptive Feedback Linearization for Quadrotor Control," AIAA Guid. Navig. Control Conf., American Institute of Aeronautics and Astronautics, Minneapolis, Minnesota, (2012). https://doi.org/10.2514/6.2012-4917

[29] Zhou, F., Z. Zhang, J. Liang, and J. Wang, "Feedback linearization and continuous sliding mode control for a quadrotor UAV," 27th Chinese Control Conf., Kunming, China, pp. 349–353 (2008).

[30] Zhou, Q.-L., Y. Zhang, C.-A. Rabbath, and D. Theilliol, "Design of feedback linearization control and reconfigurable control allocation with application to a quadrotor UAV," Conf. Control Fault-Tolerant Syst (SysTol), Nice, France, pp. 371–376 (2010).

[31] Choi, Y. C., and H. S. Ahn, "Nonlinear Control of Quadrotor for Point Tracking: Actual Implementation and Experimental Tests," IEEE/ASME Trans. Mechatron., Vol. 20, pp. 1179–1192 (2015).