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## Novel Use of Neural Networks to Identify and Detect Electrical Infrastructure Performance

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**NOVEL USE OF NEURAL NETWORKS TO IDENTIFY AND DETECT  
ELECTRICAL INFRASTRUCTURE PERFORMANCE**

by

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B.S. December 2015, Old Dominion University

A Thesis Submitted to the Faculty of  
Old Dominion University in Partial Fulfillment of the  
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COMPUTER SCIENCE

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**ABSTRACT****NOVEL USE OF NEURAL NETWORKS TO IDENTIFY AND DETECT  
ELECTRICAL INFRASTRUCTURE PERFORMANCE**

Evan Pierre Savaria  
Old Dominion University, 2019  
Advisor: Dr. Danella Zhao

Electrical grid maintenance and repairs are crucial services that keep America's lights on. Electrical service providers make it their priority to uphold minimal interruptions to this service. Electricity is essential for modern technology within the home, such as cooking, refrigeration, and hot water. Organizations, such as schools, hospitals, and military bases, cannot properly function or operate without power. When analyzing the current electrical infrastructure, it is evident that considerable components of the power grid are aging and in need of replacement. Additionally, threats and damage continue to occur. These damages occur not only due to simple, single power line failure but also on a larger scale in the event of natural disasters. Instead of replacing current aging components or sending out crews of people for preventative maintenance and repairs, neural networks provide innovative technology that can improve these processes. With the use of unmanned aerial vehicles (UAVs), neural networks can identify and classify both normal functioning and damaged electrical power lines.

This thesis will investigate the use of convolutional neural networks and low-cost unmanned aerial vehicles (UAV)'s to identify and detect damage to power lines that carry electrical service to consumers called distribution lines. The UAVs can serve as a vehicle to supply neural networks with input imagery data and automatically evaluate the condition of power lines. These neural networks are comprised of many layers that have been configured for

this specific use and provide efficient identification and detection performance. Together, the UAV-neural network system can provide more efficient routine maintenance with wider coverage of areas, increased accessibility, and decreased time between identification of issues and subsequent repair. Most importantly, the use of neural networks will keep electrical crews safe and provide faster response in the setting of natural disaster. In this day and age, we must think smarter and respond more efficiently to serve continually growing areas and reach areas with less resources.

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This thesis is dedicated to the proposition that learning is a persistent process that must be taken  
one step at a time.

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I want to give a final thanks to my employer NAVSEA, for giving their employees the opportunity to pursue a higher education. NAVSEA has also allowed me to have a flexible schedule while I pursue my academic goals. This investment in my education will allow me to be more productive and ultimately provide continued innovation to the Navy's Warfighter.

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## CHAPTER 1

### INTRODUCTION AND MOTIVATION

The electrical grid is one of America's most important resources and is responsible for the daily well-being of its citizens. Everything you can think of from transportation, education, recreation, and medical care relies on electricity. Electricity flows from power plants across high voltage transmission lines down to substations that provide lower voltage electricity through distribution lines to its customers. It is the priority of all power companies nationwide to keep this service operational 24 hours a day and 7 days a week. Any interruption in this multi-trillion-dollar infrastructure can be devastating and incur costs for both the receiver and sender of electricity. [1] The majority of this electrical infrastructure was built during the 1950's and 1960's. [2] Unfortunately, much of this infrastructure has aged and is exceeding its recommended life expectancy. In fact, the American Society of Civil Engineers gave the electrical infrastructure in the United States a grade of D+ during their 2017 evaluation. [3] It has been estimated that it would cost over 5 trillion dollars to replace all of the recommended infrastructure. With a grade this low and a cost this high we must think of a smarter and more efficient way to maintain this infrastructure.

Thunderstorms, tornadoes, and other natural disasters are also a large contributor to the national average of electrical outages. It has been estimated that 90% of customer outage-minutes are due to events which affect local distribution lines. [4] In many situations all it takes is one tree to fall across a distribution line to interrupt this service for thousands of customers. The North American Electric Reliability Corporation (NERC) requires that all electrical utilities report events which cause power outages of more than 300 MegaWatts (MW) or affect 50,000 or more customers. [5] The University of Vermont has done the analysis and compiled a list from

the NERC data describing outages from years 1984 to 2006. [6] Results from this study indicate that almost 44% of the events in the period were weather-related. [5]

Replacing aging equipment and power lines in the United States is a nearly impossible task to start on the East Coast and finish on the West Coast. This maintenance service could be improved through the use of automated identification and detection methods. A solution is to utilize the flexibility of UAVs to provide imagery data as input into a neural network model that has been trained to identify electrical power lines and detect condition. This same approach can be used during storm or natural disaster outage inspections. UAVs can be sent into harm's way to complete an inspection task. Having the ability to identify and detect in a range of weather and lighting conditions could dramatically improve maintenance and repair times for this industry.

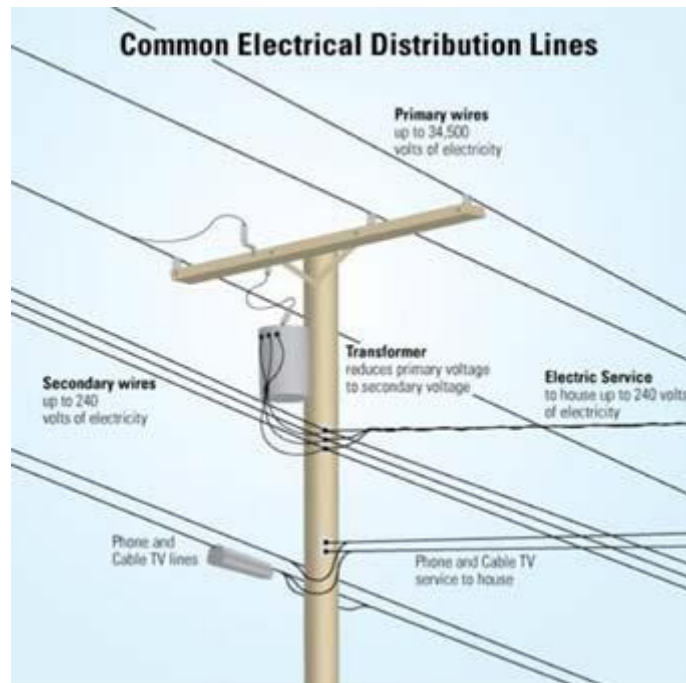
This thesis will investigate the configuration and performance of convolutional neural networks and low-cost unmanned aerial vehicles (UAV)'s to identify and detect electrical power lines in various light conditions with over 90% accuracy. The convolutional neural networks are comprised of many layers where certain aspects and objects are assigned a level of importance which is the differentiating factor of other images. [7] Training the model will focus on the scientific reasoning behind the configuration of network layers based on weather and light conditions. During testing of the model, performance metrics will be gathered to analyze the detection accuracy through classifying a damaged or non-damaged power line. This research can be leveraged in the industry to improve service and keep employees safe. This research in neural networks can revolutionize how artificial intelligence helps to provide uninterrupted electrical service.

## **CHAPTER 2**

### **BACKGROUND OF THE RESEARCH PROBLEM**

#### **2.1 ELECTRICAL DISTRIBUTION LINES**

Distribution lines are the final stage in the delivery of electricity to customers. [8] These lines can carry voltages ranging from 2400 to 34,500 volts. [9] Dominion Energy alone has nearly 57,000 miles of these lines that are part of a network consisting of medium-voltage power lines, substations, pole-mounted transformers, low-voltage distribution wires and meters. [8] Utility poles serve as a support for these public utility services. The three electrical lines affixed to the top of a utility pole make up the 3-phase power distribution system. Most distribution lines are made from high tensile strength aluminum due to being lightweight and cost effective. A transformer in some cases can be found below the distribution electric lines and serves as a power reduction device to provide electricity to homes and businesses. The lowest lines on the utility pole below the transformer, are lines reserved for telecommunications. These lines can be made from either fiber or copper material and are encased in a polymer conduit attached to a steel strand. [10]



*Figure 1: Electrical Distribution Lines*

*Adapted from 'Washington State Department,' n.d., Retrieved from <https://www.lni.wa.gov>*

## **2.2 ROUTINE MAINTANENCE AND REPAIR**

The most common method for inspecting a distribution line in the field today is by climbing a utility pole. For taller transmission lines connecting substations together a manned helicopter has to be used in order to view the lines. When inspecting over 100 miles of any type of line this process can take a group of workers months to complete. [3] With the expansion of the electrical grid, each year this task is becoming more challenging and time consuming. Frequency of service checks and service times can be challenging due to locations with limited accessibility. Repairs of electrical infrastructure can also become difficult when roads are blocked by storm debris or there are not enough repair crews for the number of outages. Unmanned aerial vehicle (UAV) technology coupled with trained neural networks is now being explored in the electrical industry to improve maintenance and repair tasks.



## 2.3 UNMANNED AERIAL VEHICLE SERVICES

UAV's provide a cost effective and low risk solution to today's electrical maintenance and repair requirements. There are two categories that this work can be split into, periodic and critical. [11] Periodic maintenance is the least risky of the two, as weather and lights conditions are usually favorable and there is no real sense of urgency as teams are only looking for defects that can be scheduled to be fixed at a later date. Critical maintenance presents a higher risk as there is likely damage to the electrical line caused by severe weather or devastating event. By sending a UAV out to a critical maintenance response rather than a human the calculated risk could drop significantly.



*Figure 2: UAV Going in Harm's Way*

*Adapted from 'TAdvisor,' n.d., Retrieved from <http://tadviser.com>*

A UAV alternative could also improve maintenance and repair times and coverage areas. The UAV can travel down miles of power lines without interfering with obstacles such as roads, houses, or debris. UAVs require very few prerequisites to operate and are not limited to how low they can fly. UAV maintenance is very inexpensive compared to trucks, equipment, and crew labor costs. These UAVs can be programmed to automatically deploy based on a routine

maintenance schedule. UAVs are likely to be uninterrupted by challenging weather conditions and can quickly be rescheduled for when flying conditions are favorable.

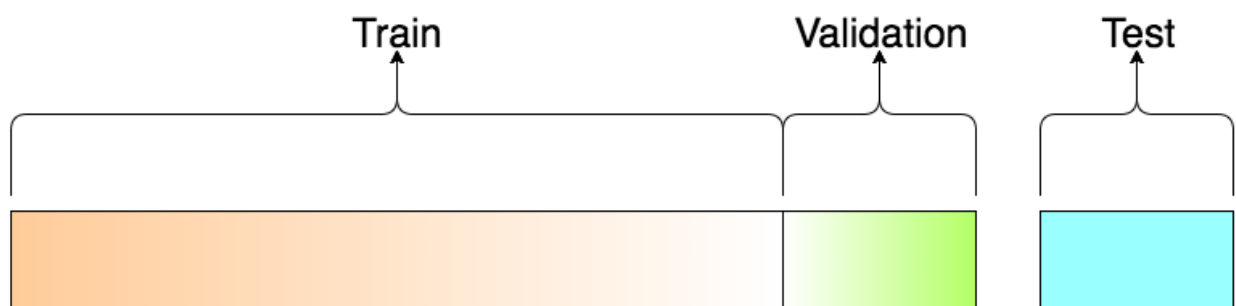
Through the integration of UAV's and neural networks, recorded imagery data of these electrical distribution lines can be provided to a trained deep learning model that can identify and detect electrical power lines in these varying weather and light conditions. When a fault or damaged power line is detected by the trained neural network, the power company could notify a repair or maintenance crew to resolve the issue.

## **2.4 CONVOLUTIONAL NEURAL NETWORK MODEL**

Being inspired by the human brain, artificial neural networks are composed of many artificial neurons that transfer information. [12] Neural networks are able to learn very complex relations in a dataset, instead of hardcoding hundreds of rules about the appearance of an object. The real advantage of neural networks over hardcoding image processing rules is that you can simply feed fit a neural network model with input data and not have to fully understand all of the requirements needed to classify an object reliably. The neural network will learn on a set of samples, generalize, and detect even previously unseen objects. It is important to understand the specific problem the neural network is solving when attempting to find the right hyperparameters for the model. This will help the neural network learn the features in an image on its own during the training process. Utilizing a neural network is more efficient than having a programmer check all images against code and make corrections to detect all the known cases. Even though the programmer and neural network may not always detect all cases, there is still a greater chance the neural network will give a higher chance of accurate detections and less positives through the ability to generalize.

Convolutional neural networks (CNN) are derived from the generic class of neural networks. Many times (CNN) algorithms are used for object identification and detection. [13] CNNs are two dimensional structures comprised from image input. [14] A combination of convolutional layers and pooling layers assists in finding a dense representation of the data. This method of reducing a picture's resolution is less CPU and memory intensive than hardcoding requirements using a large number of (IF) conditions and loops. Although the neural network is more sophisticated, it will not necessarily take more resources.

To train a CNN model, imagery data must be split into three datasets. The training dataset will be the input for the neural network to configure the weights and biases of the model's layers. Having a robust training dataset is optimal so that the model is able generalize accurately on the data. [15] Second, there is a validation dataset piece which is partitioned off of the training dataset and is used to provide an unbiased evaluation of the model. Validation testing gives engineers a gauge for how well the model will perform on the actual testing dataset. Third there is a testing dataset which is used to evaluate the final model's fit. The testing dataset contains samples of data spanning across various classes that the model may face in the real world. [16]



*Figure 3: Visual Representation of Dataset Split*

*Adapted from 'Tarang Shah,' n.d., Retrieved from <https://towardsdatascience.com>*

After each convolutional layer there is an activation layer utilizing a function called Rectified Linear Units (ReLU) which is responsible for introducing the nonlinearity to the system that was just trained on linear operations. [17] The ReLU layer applies the function  $f(x) = \max(0, x)$  to all of the values in the input volume and changes all of the negative activations to 0. [17]

A max pooling layer could be chosen by the programmer when down sampling is required. This layer uses a filter of a set size and applies it to the input data. This will output the maximum value in every subregion that the filter covers. [17] The last step in convolutional neural network is to attach a fully connected layer to the end of the network. This layer will take input and output an N dimensional vector where N is the number of classes the program can select. [17]

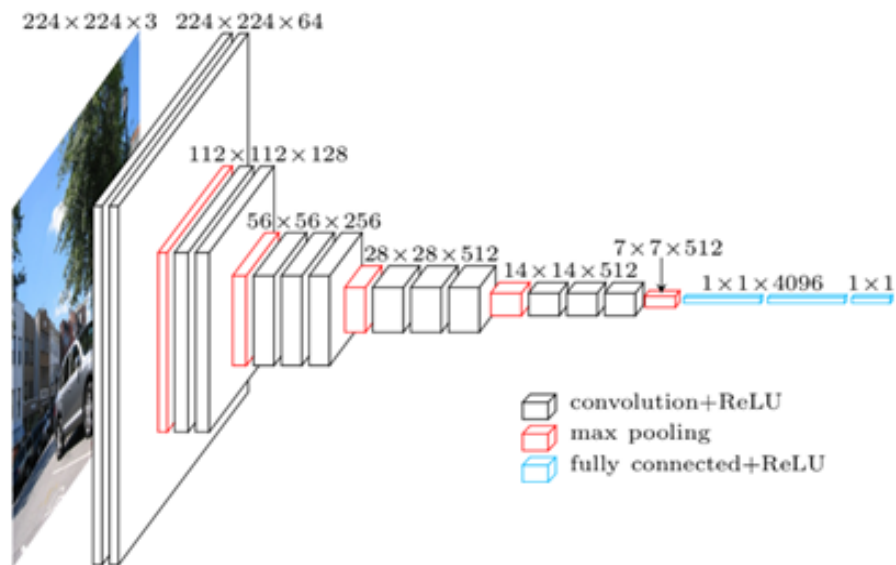


Figure 4: Convolutional Neural Network Layers

Adapted from 'Jeremy Jordan,' n.d., Retrieved from <https://www.jeremyjordan.me/>

## **CHAPTER 3**

### **RELATED WORK**

In recent years, UAVs have been incorporated into industries where there is a need for improved efficiency and safety of human life. For the electrical industry, UAVs are often coupled with deep learning algorithms to identify and detect power lines. Improvements to this service have been made recently to extend the duration of flight through methods such as perching. [18] Automatic Real-time detection has also been studied to improve response times to power outages, even in cluttered environments. [19] In order for all of these methods to be beneficial, neural networks must achieve high accuracy. Research has continued to improve detection accuracy through the development of models that can detect power lines only a few pixels wide. [20] Sano et al [21] has investigated a method for analyzing information represented in neural networks. In order to improve neural network accuracy, you must first fully understand what is going on in the neural network.

Ramesh et al [22] has contributed research to the area of UAV support for automatic detection of power lines for the electrical industry. In this paper power lines are detected from remote sensed images captured by a camera onboard the UAV. [22] They proposed pixel intensity-based clustering followed by morphological operations as a means for power line detection. Performance of this method was evaluated and the features derived from the confusion matrix were close to one indicating this was an effective classification method. [22]

Maxim et al. [18] proposed the use of power lines to charge UAVs. Battery power is a true limitation of a UAV's practical use. They propose a wireless charging method to transfer power to the UAV. More battery power means longer run times and more input data that can be

collected for the neural network. The experiment yielded satisfactory results and demonstrates the potential benefits of this approach for longer UAV battery life.

Siddiqui et al. [19] investigated a robust power line equipment inspection system based on convolutional neural networks to ensure uninterrupted electrical service to customers. This task was accomplished through the use of novel rotation normalization and ellipse detection methods which play a vital role in the classification of power lines based on features. The convolutional neural network is capable of detecting 17 different types of power line insulators in a highly cluttered environment. [19] One of the contributing factors to the performance of this model was the use of two cameras which capture images from nearby and faraway distances. The proposed system achieved up to 98% accuracy on a large evaluation dataset. [19]

D.K. Chaturvedi [23] proposed a method for analyzing information represented by a multi-layer neural network. A function must be defined to estimate the degree of dependence of output data based on input data. In other words, the value of this function can be used to determine if a trained network can detect the features that are most important for classifying an image. Neural Networks are generally considered a black box and so it is not a simple task to find the structure or function of each unit. This paper investigates how to improve performance based on the understanding a neural networks structure.

## CHAPTER 4

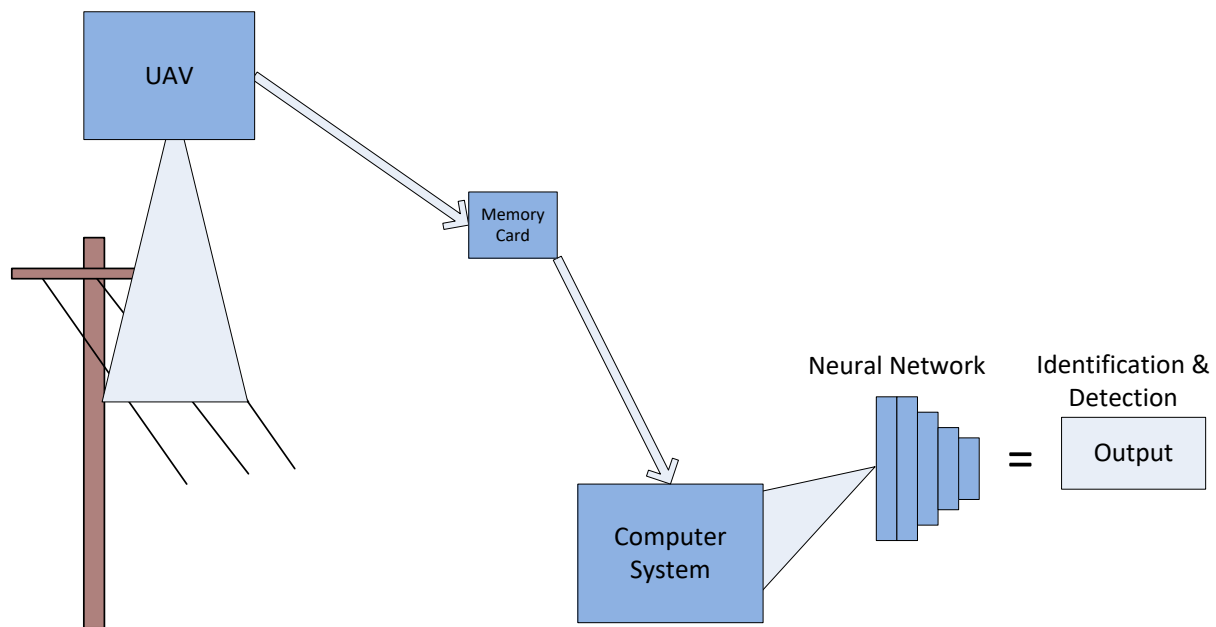
### PROBLEM DEFINITION

Maintenance and repair of the electrical infrastructure in the United States is an ongoing concern. There is simply not enough funding or personnel available to efficiently and effectively tackle this problem in its totality. The development of UAV assisted inspection of distribution lines is an alternative solution compared to traditional methods. This solution while impressive, is still in its infancy stage and requires additional refinement and testing before it will truly replace other methods. There are real life scenarios where these modern inspections systems still lack human ability. The neural network which processes the imagery data acquired from the UAV may not accurately understand the difference between electrical distribution lines and the telecommunication lines that run parallel across the same utility poles. Accurately classifying electrical lines from telecommunication lines is one example of a significant enhancement. Another challenge for these neural networks is the detection of power line performance in various light conditions. In many cases, distribution line repairs happen right after a storm where lighting conditions can vary from light to dark depending on the weather or time of day. These varying light conditions make it difficult for the neural network to detect the condition of a power line. Another enhancement is to configure and train the neural networks to detect the electric line condition in various light settings. A comprehensive system needs to be developed to take care of all these cases.

## CHAPTER 5

### TECHNICAL SOLUTION

The main goal of this neural network is to accurately identify electrical power distribution lines on a utility pole shared with other lines and have the ability to detect the performance of these lines under varying light settings. This neural network accepts input imagery data from a consumer grade UAV. Due to hardware limitations in various weather environments, lighting conditions are simulated by time of day. The neural network is written in Tensorflow and utilizes the TFlern library.



*Figure 5: Comprehensive System Overview*

#### 5.1 UNMANNED AERIAL VEHICLE (UAV)

The unmanned aerial vehicle (UAV) is a device used to record the video data of the distribution lines. This data is saved onto an onboard removable SD memory card capable of



holding 1 hour of video. The data saved onto the memory card is then uploaded to a computer where it will be processed as input into the neural network.

For the purposes of this experiment the DJI Spark UAV was chosen because it is lightweight of (300 grams), has a high-quality 1080p camera, and is affordable. The aerodynamic properties of this UAV are optimal for power line inspection. This UAV uses a standard quadcopter setup in a small form factor with a 2-axis stabilizer on the camera for smooth video recording. The runtime using the supplied 2970 mAh battery is approximately 16 minutes with the added benefit of removal batteries to increase flight time per day. Repairs for this UAV are minimal and convenient since all four propellers are replaceable with no tools required. The UAV Spark remote control provides accurate manual control of the UAV and allows for precision positioning of the aircraft. The controller can communicate with the UAV up to 1.2-mile operating distance and 120 meters altitude using frequencies 2.412-2.462 GHz, 5.745-5.825 GHz.

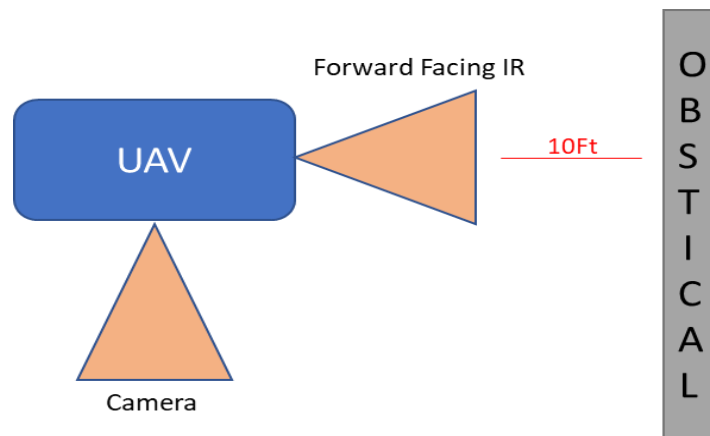


*Figure 6: DJI Spark UAV*

*Adapted from 'DJI,' n.d., Retrieved from <https://www.dji.com/spark>*

In order to obtain optimal results, the UAV was required to fly above the power lines with an altitude between 40 and 75 feet. Sample video recordings were taken at 40 feet, 75 feet and 100 feet. At a height of 40 feet the camera on the UAV recognized the power lines. At 75 feet the power lines became smaller; however, the UAV camera was still able to focus on the lines. At 100 feet the power lines were no longer visible.

An infrared detection system onboard the UAV is used to avoid obstacles in front of the path of travel. It is important to have two fields of view with one facing down toward the power line being observed and another facing forward to detect obstacles in the path of travel. If an object is detected within 10ft of the UAV's forward-facing sensor, then travel would stop and the operator could then pan the camera forward to determine the best approach to avoid the obstacle and damage to the UAV.



*Figure 7: UAV Obstacle Avoidance*

## 5.2 CONVOLUTIONAL NEURAL NETWORK

The second component to this solution is the software used for a machine learning Application Programming Interface (API), deep learning library, and computing environment to

build and run the convolutional neural network (CNN). The CNN is a bioinspired hierarchical multi-layered neural network that combines three architectural ideas: local receptive field, shared weights, and spatial or time subsampling [24]. Tflern, an opensource high level neural network API written for Python 3.7.2 is run on top of Google's TensorFlow library. Both are well supported and recognized in the artificial intelligence community. A Jupyter Notebook environment running on a container in Google's Colab cloud is utilized for the computing environment.

### **5.2.1 INPUT DATA**

Training and Testing input data for the convolutional neural network is acquired from video data captured by a camera onboard the UAV. The video editing software FFMPEG version 4.1.2 is used to extract individual images from the video. Parameters on the conversion software are set to control scaling and throttle the number of frames-per-second (FPS). The high frame rate camera used in this experiment generated a large set of input data.

Different locations are chosen to record input data so that the data is shuffled and over coverage is prevented. A string of power lines located on a rural grassy field are chosen as input data for the first dataset used to train the model. As the neural network begins to learn the meaningful features between a power line and telecommunication line, the input data complexity is then gradually increased through the recording of power lines near busy highways, buildings, and congested utility poles. Input data used for testing the model is done in a similar method. If the testing accuracy is reported high, then more complex testing data is provided as input into the model.

Weather conditions also play a factor in the accuracy of the neural network. This neural network is trained and tested on input data from scenarios in dark or light conditions. This type

of input data is used to simulate dark storm like conditions or a sunny day. The UAV-neural network system will be used in many different environments and conditions. The input data provided for this experiment covers all spectrums.

### **5.2.2 PREPROCESSING**

Preprocessing of the dataset occurs first before training of the neural network can begin. Preprocessed data is used to train the Tflern model. Individual images in the dataset are extracted and converted to a JPEG format that the model understands. All of the images are labeled and numbered (e.g. nondamaged.1.jpg). All of the filenames in the training folder are iterated over and return a [1, 0] and [0, 1] describing the classification labels based on the filename which explains the condition of the power line, damaged or non-damaged. Every image in the training dataset has to share equal dimensions. Images are converted to a grayscale format and resized to a useable scope. This reduces the number of random variables and improves variance. Image features are appended and the filename is created and added to a list. Images and their labels are shuffled so that they are ordered randomly. The labels and features are split into 2 lists of which all except a specified number images are used for the training dataset. These images are used for a testing dataset. The training and testing datasets are further separated into lists of features and labels. The lists are then iterated over such as [[features, label], [features, label], [features, label], [features, label], [features, label], ...] and only features are extracted to make a new list such as [features, features, features, features, features, features, ...] The same method is used for separating out the labels. These features and labels are split to fit the format required to train the model.

### 5.2.3 TRAINING MODEL

The neural network model is trained in Google's Colab GPU processing environment. The Tflern API provides the ability to build, train, and test models from standard layers. In the experiment 5000 training samples are extracted from the video data of which 1/10th or 500 were partitioned off for validation testing. All images in the dataset are resized to 150x150 in order for the neural network to see the power lines that are only a couple pixels in width. The learning rate which controls the magnitude of the weights is set to  $1e-3$ . There is no set optimal value for the learning rate, however it is common practice to start with an average learning rate of  $1e-3$  and gradually increase. Power lines are made of aluminum and show up as light gray on camera. Telecommunication lines are made of a plastic material and show up as darker.

### 5.2.4 TESTING MODEL

The validation testing and loss is measured from 500 training images that are tested against 4500 sample images. The testing accuracy and loss is measured against the testing dataset images. The validation testing does not influence how the model is trained; however, it does provide an analysis tool for estimating the accuracy of the neural network. It is healthy to see a validation loss decrease and validation accuracy increase over a period. A model that demonstrates high accuracy during validation testing, suggests that the model is valid for the experiment.

The software TensorBoard is used for analyzing the accuracy and debugging the neural network. TensorBoard will plot graphs of the testing and validation accuracy and loss. TensorBoard visual metrics and review summaries are helpful when debugging.

The neural network in this experiment consists of 6 convolutional filter layers. These layers transform the images into something more abstract so that each value can take into

account the pixel itself and the neighboring pixels. A defined number epochs were run which describes the number of full iterations over the samples in the network.

## CHAPTER 6

### EVALUATION OF DEVELOPED SOLUTION

The purpose of this neural network is to determine the performance benefits of a multi-layered model that can accurately identify a power line and detect the condition under varying light settings. Factors that affect the performance for this experiment include network complexity, problem complexity, and learning complexity as described by D.K. Chaturvedi [23]. The network complexity of this model is determined by the neuron complexity, number of layers, number of neurons, and type of interconnected weights. The problem complexity depends on the type of functional mapping, accurate and sufficient training input data, and the way the model is trained. Learning complexity depends on training algorithms, initialization of weights, error function, and initialization of training parameters. Metrics gathered during this experiment can be used to further the development of UAV assistance for the electrical industry.

#### 6.1 IDENTIFICATION & DETECTION FACTORS

These factors contribute greatly to the overall results of the model. Many of these factors are dependent on one another. Network, problem, and learning complexity factors that influence performance are listed in Table 1.

<b>Complexity</b>	<b>Factor</b>	<b>Influence</b>
Network	Neuron Complexity	Amount neuron is affected by input
Network	Neurons Per Layer	Complexity and speed of network
Network	Number of Layers	Number of layers until satisfactory performance is reached
Network	Number of Interconnected Weights	Number of connections made between layers
Problem	Normalization of Training Data	Min and Max of input data
Problem	Functional Mapping	Type of training pattern
Problem	Process for Training Model	Sequence of presenting data
Learning	Training Algorithms	Learning process
Learning	Initialization of Weights	Initial weights
Learning	Error Function	Calculation of error
Learning	Initialization of Training Parameters	Initial threshold levels

*Table 1 Complexity Factors*

### **6.1.1 NEURON COMPLEXITY**

This convolutional neural network utilizes the Rectified linear unit (ReLU) function that is widely used for linear activation. Precision of this model is determined by the reaction of each individual neuron. Another reason for choosing ReLU is that it will not be affected by gradient vanishing problems commonly found with sigmoid functions.

### **6.1.2 NEURONS PER LAYER**

The optimal number of neurons per layer was determined based on experimentation. Currently, there is not an algorithm that can select the optimal number of neurons for each



hidden layer. It depends on the size and type of dataset in the experiment. This neural network started out with a minimal number of neurons in each layer and during training, neurons and layers were added until optimal performance was achieved. Overfitting with too many neurons or underfitting with too little neurons is avoided.

### **6.1.3 NUMBER OF LAYERS**

There are 6 training layers in this neural network which include a combination of 2D convolutional and max\_pool\_2d pulling layers. The 2 main parameters were configured for this convolutional neural network are the filter size and stride. The size of the filter is important since the electrical lines are small and it can be difficult to find the optimal filter size. If the filter is configured too large then important features could go undetected. Stride is set optimal by default at size 1. This controlled the number of steps that the filter moves over the input image.

### **6.1.4 NUMBER OF INTERCONNECTED WEIGHTS**

Each layer in this neural network is interconnected to the previous layer by neurons that have an assigned weight. These weights are deterministic and are based on a learning rule. Configuration for this model is started by using a minimal size network and then adding additional neurons and layers until the optimal size is achieved. It has been proven that it is not necessary to connect every neuron with the other neuron in each layer. [23]

### **6.1.5 NORMALIZATION OF TRAINING DATA**

The input and output data in this neural network is normalized to the same order of magnitude for all variables so that there is equal significance. The weights within the training algorithm adjust to compensate for the order-of magnitude differences using techniques such as back propagation. In this neural network, there are multiple hidden layers with a normalization range between -0.9 to +0.9 for input and 0.1 to 0.9 for output.

### **6.1.6 FUNCTIONAL MAPPING**

The multiple similar grayscale images provided as input for this neural network share similar tasks. The model is simply determining what is a power line and how does it detect its condition. It can be helpful to map the similarities between inputs and tasks into one model. This will result in a neural network having multiple input and output layers. While this technic is not utilized here, it will be useful for larger datasets.

### **6.1.7 PROCESS FOR TRAINING MODEL**

The process for training this model is dependent on the training algorithms, initialization of weights, error function, and training parameters. These factors influence the performance of the neural network.

#### **6.1.7.1 TRAINING ALGORITHMS**

This multi-layered neural network uses the error back-propagation algorithm for training the model. This algorithm is based on error correction learning where the system output is compared to the expected output and influences how the network is trained. This process involves a front pass and back pass. The forward pass involves an input vector traversing through all neurons from the first layer to the last. During this forward pass weights are fixed. In the backward pass the weights are adjusted according to the error correction rule.

The back-propagation algorithm in this network provides an estimated guess to the trajectory in the error-weight space computed by the steepest decent method. [23] Weights are adjusted iteratively with a goal of moving towards an optimal solution. The neural networks learning rate of  $1e-3$  determines the networks magnitude weight adjustments. A slow learning rate is used initially for this model to achieve a smooth trajectory in the error-weight space.

Knowing when to stop training this network is determined by the generalization performance. After each epoch the network is tested for generalization. When optimal performance is reached or it is observed that the learning has peaked the training of the model is complete.

#### **6.1.7.2 INITIALIZATION OF WEIGHTS & BIASES**

For this neural network the biases are initialized with zero and the weights are initialized close to zero. With biases initially set to zero they will have no effect. Assigning values to weights close to zero provides a best guess expected value and the symmetry is broken to allow the algorithm to learn. The gradients that are calculated in back-propagation are proportional to the weights. This model avoided to use too small of weights that would require the network to run longer or never complete.

#### **6.1.7.3 LOSS FUNCTION**

For this multi-layered model, a softmax layer is used as the top layer as the loss function. This function is the cross entropy between training data distribution and the estimated distribution. Basically, this error function measures the distance between two distributions and minimizes the loss.

#### **6.1.7.4 INITIALIZATION OF TRAINING PARAMETERS**

Before the network can be trained parameters are set to initial values. For the training of this model no prior information is available. Therefore, all free parameters of the network are set to random numbers close to zero. Premature saturation is avoided by using weights that are not too large and that are uniformly distributed as described by Ramesh et al. [22] .

The initialization values chosen for this mode helped speed up convergence and gradient descent. The random initialization is used to break symmetry and ensure the hidden layers are learning at a sufficient rate.

## **6.2 RESULTS**

In this section, the results will be explained with regard to the factors as described in previous sections, such as neuron complexity and training algorithms, and the results will also build upon prior research in the area of UAV detection of power lines. There were three objectives in this experiment: accurate identification of power lines, detection of power line condition, and true identification and detection in varying light conditions. Goal efficacy for each of these objectives was 90% or greater for this experiment.

### **6.2.1 IDENTIFICATION OF POWERLINES**

The first objective of this experiment involved identifying the difference between an electrical line and a telecommunication line that shared the same utility pole. With identification, the biggest challenge involved training the neural network to accurately identify the physical difference between electrical lines and the telecommunication lines. Electric lines are made of aluminum (Figure 8) and telecommunication lines are concealed in a plastic conduit (Figure 9).



*Figure 8: Aluminum Power line*

*Adapted from 'PeakDemand,' n.d., Retrieved from <https://peakdemand.com/>*



*Figure 9: Telecommunication Line*

*Adapted from 'Dreamstime.com', n.d., Retrieved from <https://thumbs.dreamstime.com>*

Video recordings of electrical lines and telecommunication lines were obtained with the use of a UAV. Images were extracted from the video and then provided as input data into the neural network. Then, the neural network was trained to identify the differentiating features of a power line and a telecommunication line. Convolutional layers were utilized to train the neural network how to filter the images with regard to spatial and temporal dependencies. Due to varying landscapes and terrains (Table 2), the neural network was also trained to filter these different background conditions.

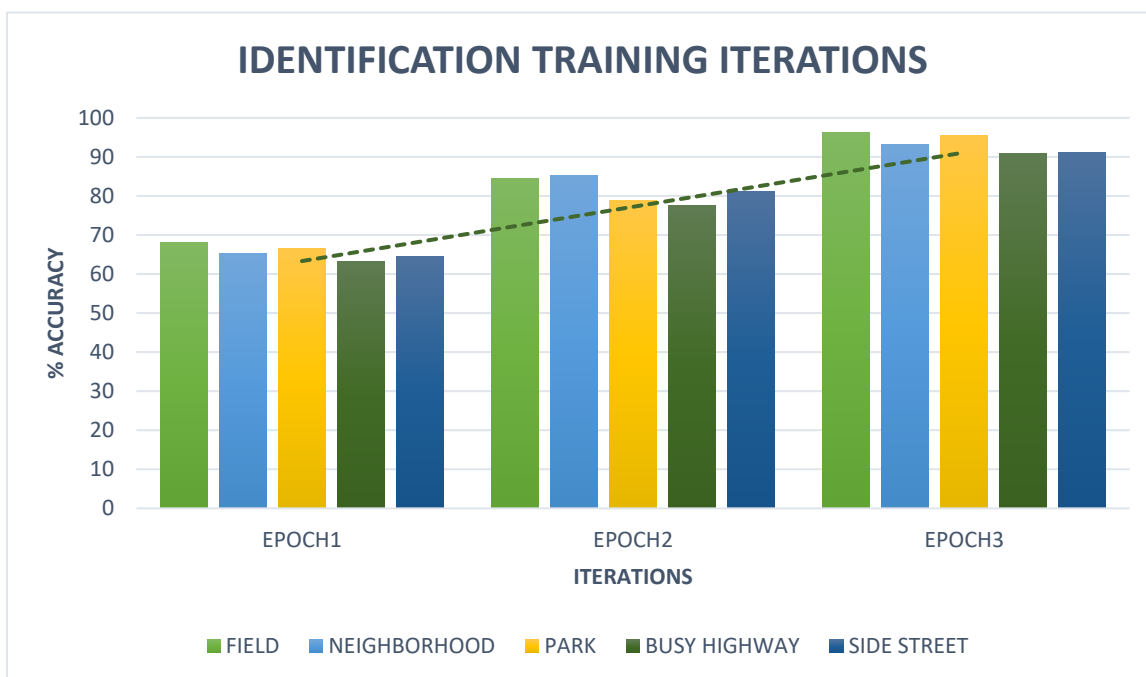
Location	Terrain
Field	Open Field
Neighborhood	Open with Houses
Park	Open with Trees
Busy Highway	Traffic, Road
Road	Some Cars and Trees

Table 2: Imagery Data Locations

### 6.2.2 POWERLINE IDENTIFICATION ACCURACY

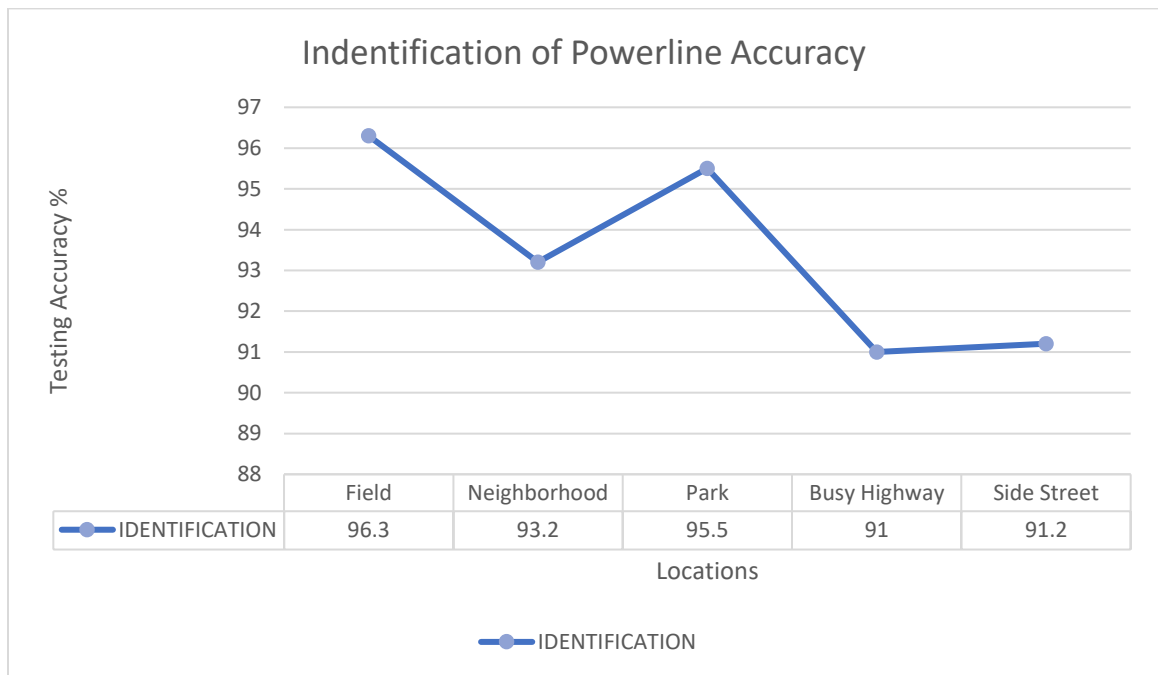
The neural network in this experiment was able to identify power lines with an accuracy of 90% or greater.

The neural network was provided input data of only power lines and only telecommunication lines. The learning rate was set to  $1e-3$ . Validation testing was conducted to minimize overfitting. This test verified that an increase in accuracy over the training dataset would yield an increase in the test dataset. Validation accuracy was counted after every epoch. One epoch was one iteration over training data during training. For this objective, three epochs proved sufficient to achieve 90% or greater during testing of the neural network.



*Table 3: Identification Training Epochs*

There were some issues during the early stages that contributed to loss or inaccurate classification of images. One of these issues included the overfitting of imagery data. This occurred in the early stages of the experiment when the back-propagation algorithm was shown different samples of power lines only being one color such as white. Introducing dissimilar objects, such as ground or guy wires, trained the algorithm to associate a parallel line to be that of a power line as well as the color white to be a power line as well. Therefore, when a darker power line was shown to the model, the model did not recognize it as a power line but instead recognized it as a telecommunication line.



*Figure 10: Identification Accuracy*

### **6.2.3. EFFECTIVENESS DETECTING POWERLINE CONDITION**

The second objective was to detect damaged and non-damaged power lines. For this part of the experiment, a missing power line was considered a damaged power line and when the power line was present this was considered a non-damaged power line. Similar to the inspection method, the neural network was provided input data of only damaged power lines and only non-damaged power lines. Validation testing provided feedback that the correct number of layers were sufficient. The neural network in this experiment was able to detect power line condition with an accuracy of 90% or greater.

When training the model to detect the condition of power lines, there was not an issue of overfitting. This was due to fixing this issue in the identification stage and the large amount of imagery data gathered for the training dataset used for comparing training and validation performance. Another way the model avoided overfitting was through the use of multiple algorithms to build a strong neural network using a smaller dataset.

For this objective, five epochs proved sufficient to achieve 90% or greater during testing of the neural network.



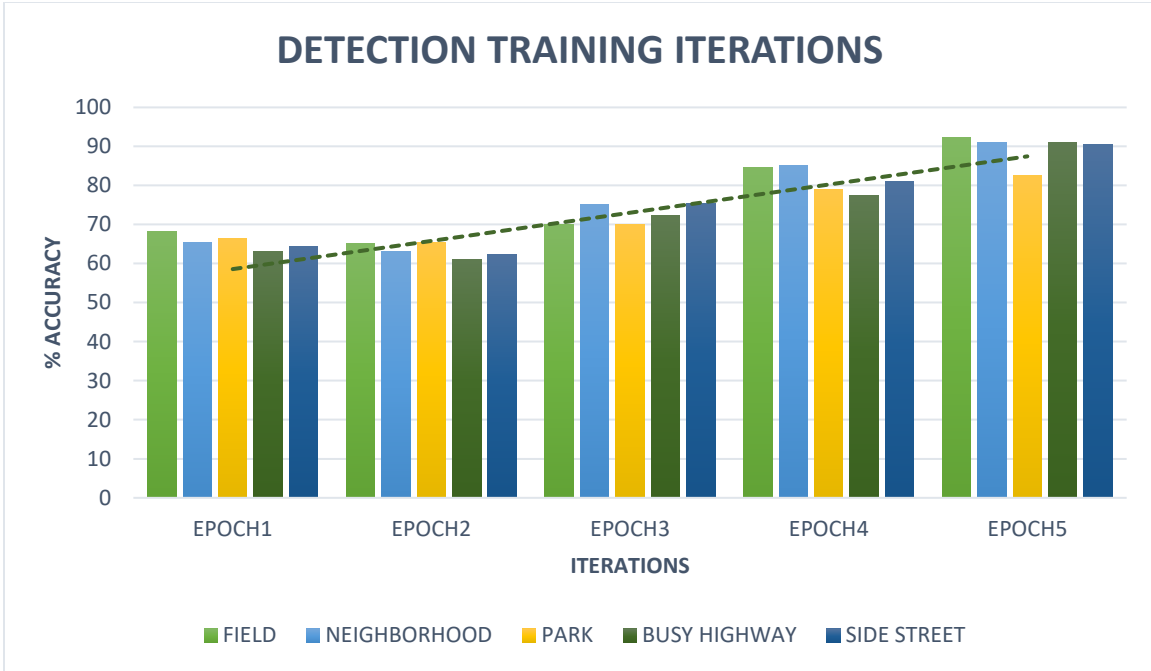


Table 4: Detection Training Iterations

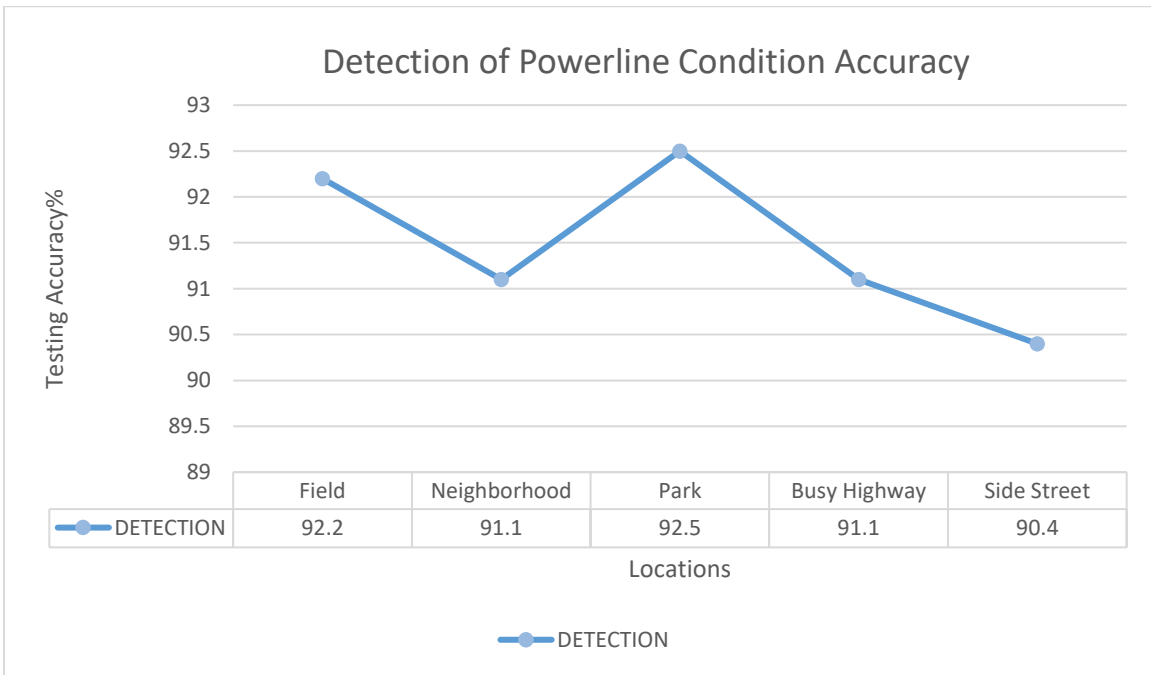


Figure 11: Detection Accuracy

#### 6.2.4 EFFECTIVENESS IN DIFFERENT LIGHT SETTINGS

The third objective was to identify and detect power lines in various light conditions. Light conditions made a large impact on the effectiveness of the neural network's ability to accurately identify and detect power lines. Success in both objective 1 and objective 2 had to be achieved before attempting the third objective. Testing between these two objects was conducted by the use of varying degrees of brightness or darkness in contrast. The telecommunication line was dark and the electrical line was white. Based on the results of validation testing, convolutional layers were configured and epochs were added until optimal results were achieved.

Distance also played an important role in the identification and detection of power lines. If the UAV was flown away from the power lines, the video became skewed and was found to sometimes only show two out of three of the lines. While greater altitude could improve the viewing angle, this could impede the camera's ability to focus on objects when above 75 feet. Below is an image captured demonstrating distortion of the power lines when at a viewing distance of 10 feet from the center of the power lines.



*Figure 12: Power line Image Skewing*

It was observed that a day with overcast was more difficult for the neural network to identify the difference between an electrical line and a telecommunication line. Below are three figures

which demonstrate the accuracy of identification and detection methods during light and dark conditions. The third figure demonstrates the average accuracy of identification, detection, and varying light conditions.

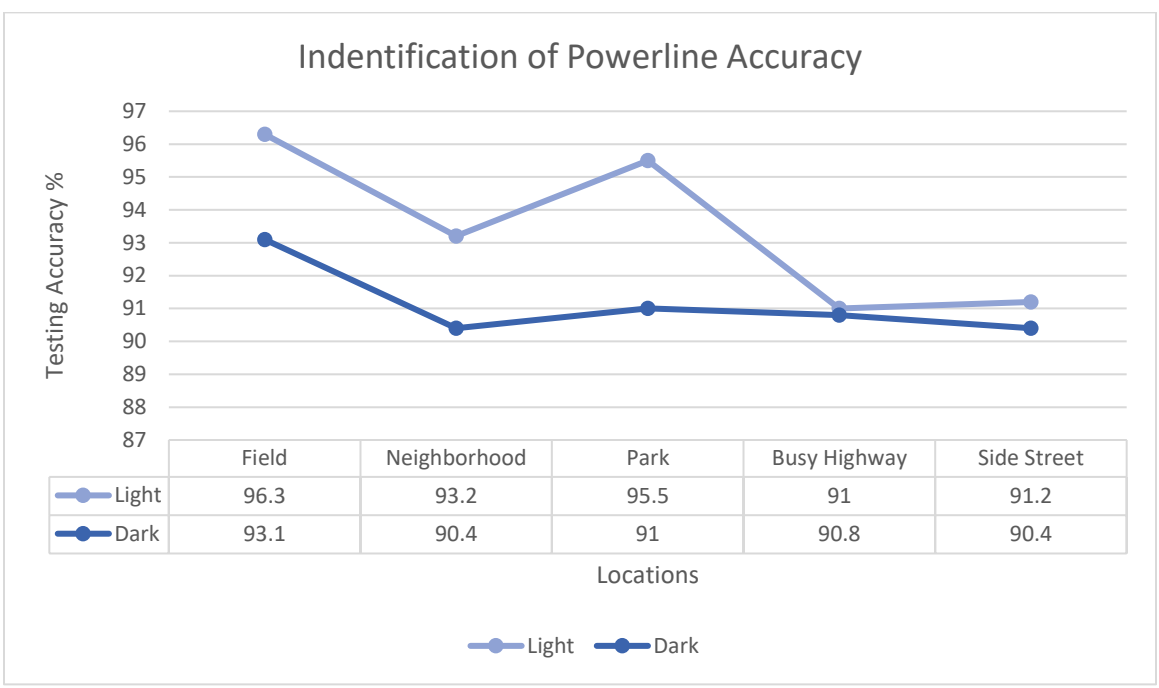
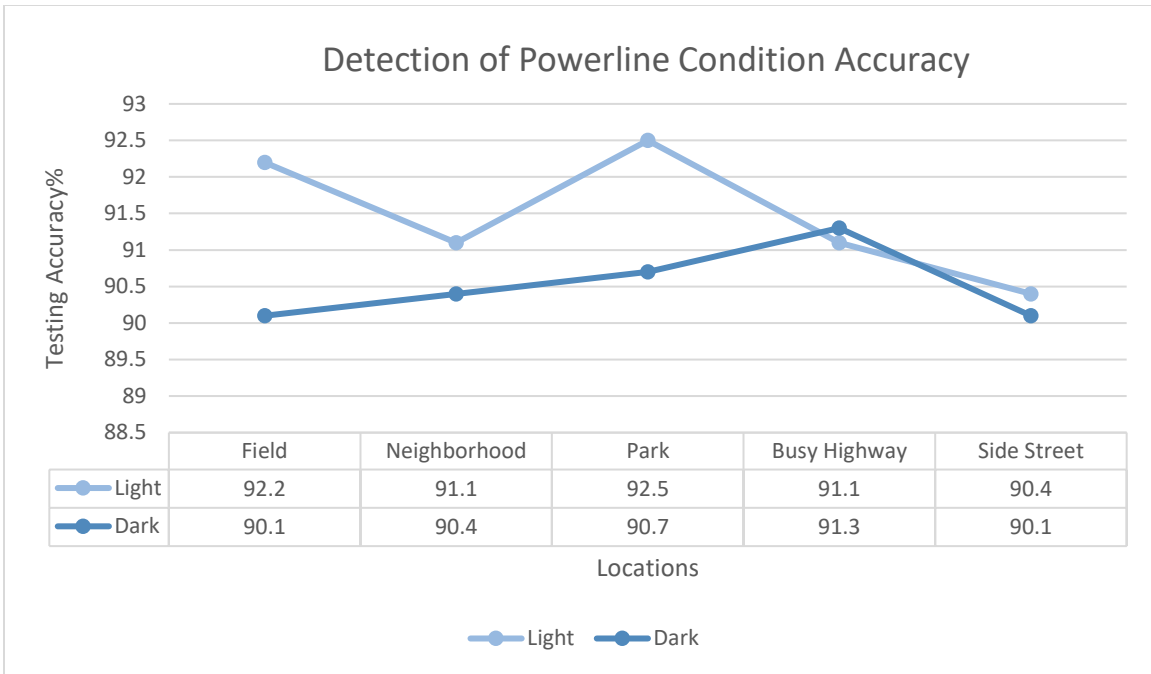
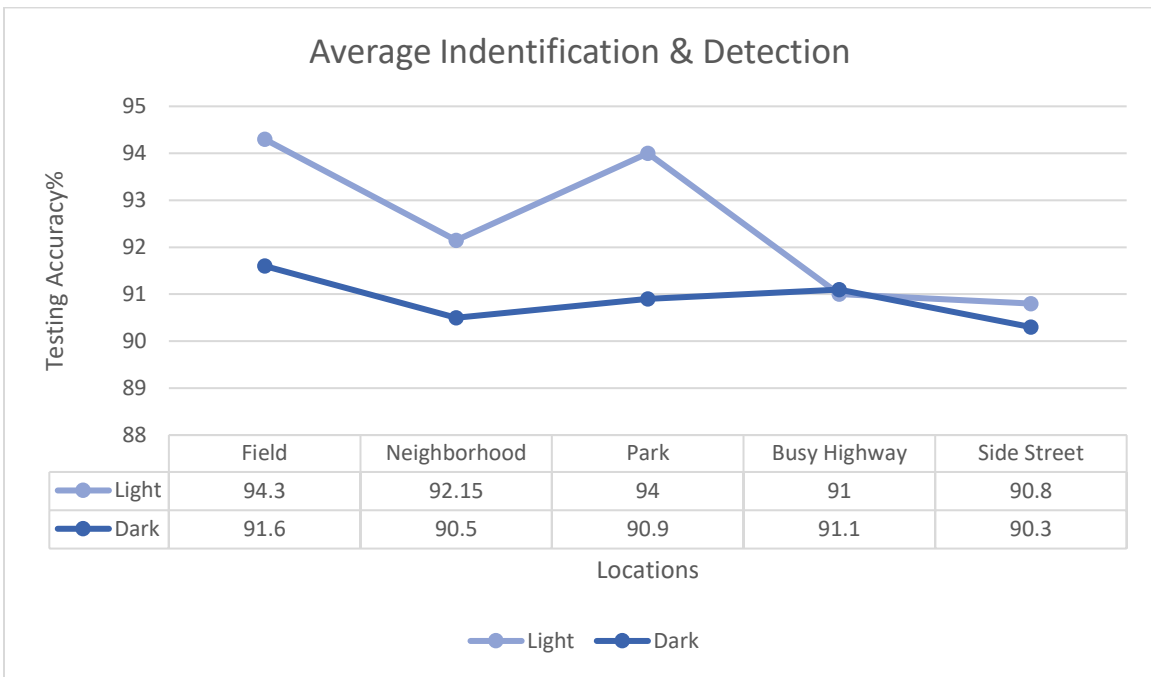


Figure 13: Identification Environment Accuracy



*Figure 14: Detection Environment Accuracy*



*Figure 15: Average Identification & Detection Environment Accuracy*

### 6.2.5 OPTIMIZATION OF OBJECT RECOGNITION

After repeated trials of identifying and detecting power lines, optimal results were achieved. The main idea behind convolutional layers is to apply filters to images until the optimal parameters for the network are achieved. One filter can scan the images for functional powerlines and another filter can scan for damaged powerlines. The resolution of these images can then be reduced by pooling and applying more convolutional layers until a very good dense representation of the data is reached. Once the best parameters for the network are found through training, a very smart and efficient equation will have been made. A technic used to improve efficiency and remove model complexity was to experiment using less filters, fewer layers, bigger step strides on the filters, and early pooling.

For the classification of damaged or non-damaged power lines, 4500 training samples proved sufficient. Out of the entire training dataset, 500 images were pulled and used for validation testing. The results from the validation test were above 90% accuracy. This level of validation accuracy provided confidence that the model had been configured closely to the minimal cost function. The actual testing results averaged 92% accuracy, which exceeded the goal of 90% accuracy.

<b>Dataset Type</b>	<b>Size (Images)</b>
Training Dataset	4500
Validation Dataset	500
Testing Dataset	8000

*Table 5: Model Dataset Attributes*

Different image sizes were tested throughout this experiment leading to the best image size of 150x150 pixels for this type of classification. Power lines look like thin parallel lines on

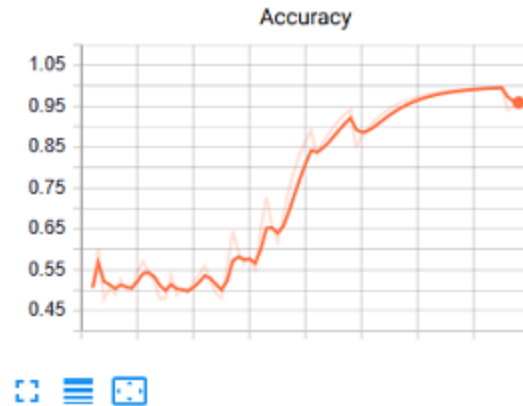
an image, thus making it difficult to recognize when an image is resized smaller than 150x150 pixels from the original 1920x1080 resolution. Different altitudes ranging from 100 feet down to 40 feet were tested. The closer the UAV was to the power line, while continuing to capture all three individual power lines in view, proved to be the best solution. In this case 40 feet was the optimal height for the camera onboard the UAV to capture the power lines of the 34ft power pole. This left a 6-foot air gap between the infrastructure and the UAV.

Different terrains also played a pivotal role in the object recognition. Tests proved that power lines viewed behind a white background, such as snow, were more difficult to recognize than power lines viewed behind a brown or darker background. Streets and intersections were also challenging when trying to classify what a power line is, as there are many parallel lines used for traffic management.

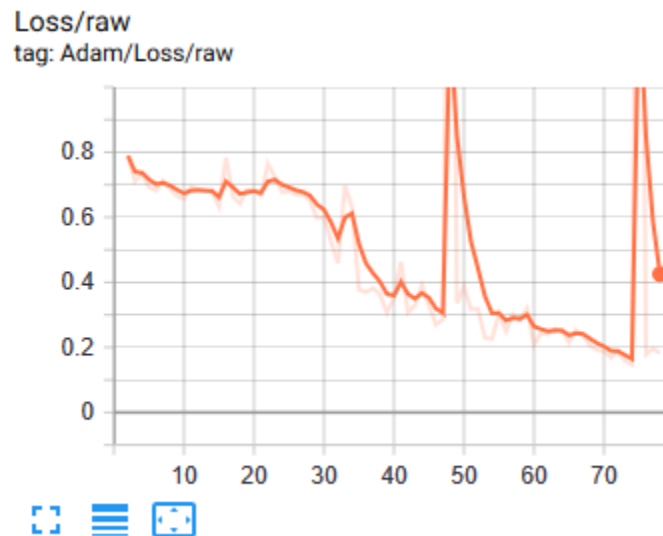
Semantic segmentation improves the accuracy through the use of an encoding and decoding image processing structure to classify objects in the image.

### **6.2.6 PERFORMANCE COMPARISON**

When gauging the performance of this model it was important to understand the entire path of performance and not just the end result. As depicted in the image below, the accuracy significantly increased on the second iteration of the identification training process and the training dataset loss decreased over time. This graph shows a snapshot that the model was configured for the correct number of training iterations for identification, detection, and varying light conditions. This same method was used for detection and varying light conditions as well.



*Figure 16: Training Dataset Accuracy*



*Figure 17: Training Dataset Loss*

When comparing the validation test results to the actual test results it was common to see a trend. As described in the graph below, it is clear that as the validation loss went down, the accuracy increased. The validation results were similar to the actual test results and confirmed the model did not overfit while training.

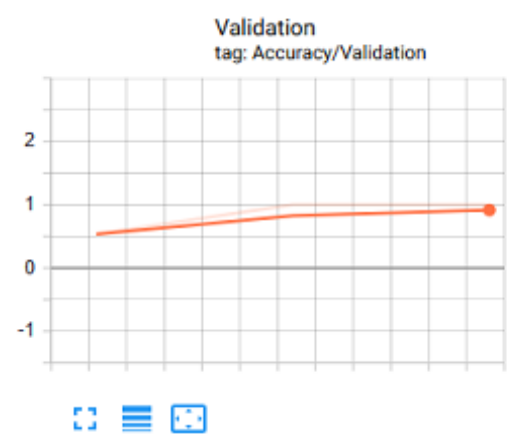


Figure 18: Validation Dataset Accuracy

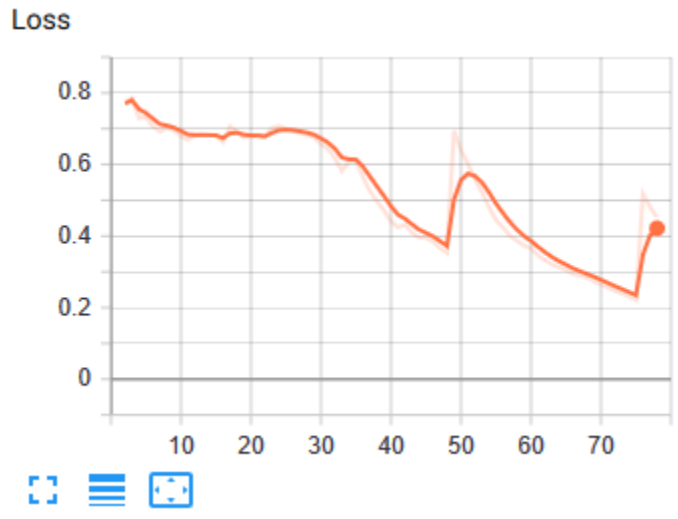


Figure 19: Validation Dataset Loss

### 6.2.7 SUMMARY OF RESULTS

Many of the factors that contributed to the results of this experiment were learned through trial and error. Machine Learning is still a science that is filled with untouched theories and practices that could further expand this study. I learned quickly that classifying imagery through the use of software requires experimenting with different training models to recognize every characteristic and feature of an object. A complex and robust neural network does not



always mean it will perform faster or produce more accurate results than a smaller network. Models should be individually configured in a way that fits the input data best. In my model, convolutional layers were used to identify parallel edges of the power lines. This strategy proved to be the best approach. Since my images started out at a high-resolution size of 1080p, it was critical to resize the images to a level that the neural network could handle based on the computing hardware being used to run the program. After determining the optimal amount of training iterations the network needed to be successful, I was able to achieve accurate results. The experiment's main objective was reached, and images of damaged and non-damaged power lines were correctly identified in various light and terrain conditions.

## CHAPTER 7

### MAJOR CONTRIBUTIONS

This thesis expanded on the method of using UAV's to identify power lines. The convolutional neural network in this experiment is configured to identify the difference between power lines and telecommunication lines that are sharing the same utility pole. Furthermore, the ability to identify and detect the condition of power lines in various light conditions is also an improvement over current methods that could prove useful in various weather conditions. This UAV-neural network system has proven to be efficient.

Tasking a low-cost UAV to inspect power lines could bring much-needed technological advancements to the industry. These power lines could be used as a highway for UAVs to collect data. By using multiples of this tool, a network of inspection UAVs could be established to collect more frequent electrical infrastructure data for the service provider. The advancements this system brings would put less people in harm's way, ultimately decreasing the number of causalities or injuries experienced by employees in this industry.

## **CHAPTER 8**

### **CONCLUSIONS**

#### **8.1 CONCLUDING REMARKS**

There were many questions that were answered from this experiment. The first is that imagery data captured from UAVs can be used as valid input data for training a Neural Network to identify and detect power lines in varying light conditions. The second is that Neural Networks can be trained using convolutional layers to recognize the difference between a damaged or non-damaged power line. The final is that low cost UAV's are a viable solution for accurately and efficiently inspecting power lines.

The camera affixed to the UAV was capable of seeing the thin aluminum power lines stretched across the utility poles. At first the UAV captured video data at an altitude of 75 feet however due to the resizing of imagery data later in the neural network, that input data could not be used as the power lines could barely be seen. A second attempt was made at an altitude of 40 feet which was effective as training data for the neural network. It was also learned that the angle and height at which the UAV captured the data affected the accuracy of classification.

The most effect layers inside the neural network are 2D convolutional. These layers are the filters that are designed for minimal processing with the ability to extract features from the input image. Just as performed in this experiment, features from the power lines were extracted from the input image and classified by the model. Once generalization based on the images that were injected into the network was reached, the training process was complete.

The greatest achievement for this experiment was the combining of all three of these components together which includes the UAV, imagery data, and neural network to form a low-cost UAV solution for power line inspection. This solution in time should prove beneficial to the

electrical industry. This system is capable of improving response times, and reducing cost. Ultimately it will keep humans safe which is everyone's top priority.

## **8.2 FUTURE IMPROVEMENTS**

As with any system, there is always room for improvement. Improvements for this system range from longevity of flight and maneuvering, to improvements of object recognition. While these improvements will require time and funding, the benefits will be significant.

A high priority future improvement would be to have a longer flight capability. The average flight time of the DJI Spark UAV is only 16 minutes based on manufacturer recommendations. This duration of flight is not yet sufficient for commercial application of this UAV. The UAV also has limited flight time and requires frequent charging of the battery. Improvements in battery life would allow for longer flight time and maximum usage of the memory card. Ideally there should be a balanced ratio between battery life and data recording. Fewer battery changes means more flight time and more efficient inspection services. There have been studies on UAV "Perching" which allow the UAV to charge its battery on a power line quickly and proceed with its route. [24] The proposed study suggests utilizing the electromagnetic fields which surrounds the power line to wirelessly charge the UAV in flight. [24]

Another future improvement would be the ability to use real-time processing to capture imagery data and classify objects with an aircraft's neural network. UAV's are a challenging platform to implement processing of data due to their limited payload and power requirements. Recent advances in Field Programmable Gate Array (FPGA) hardware architectures have shown favorable results. [25] For example, a vision-based control system was implemented on a custom low-power FPGA board designed for a quad-rotor UAV. [25] The use of parallel hardware

structures provides the computational real-time performance. FPGA is also less expensive to manufacture and requires fewer design time than other architectures. One limitation, however, is that FPGAs are only capable of 10% to 20% of the performance of an Application Specific Integrated Circuit (ASIC) [25]. Therefore, ASIC may still be the best choice for performance reasons. Future research in this area could allow for partnerships with UAV search and rescue organizations where additional datasets could be used to train and test neural network classification accuracy.

This solution would most likely require a mobile charging platform due to the great power demand. The power consumption of the UAV can be configured through efficient programming technics such as multi-core and multi-thread utilization. Having this embedded processing capability on the UAV would provide real-time results to the command station and would increase the effectiveness of this inspection service.

### **8.3 ECONOMIC IMPACT AND SUSTAINMENT**

The economic impact of a new system is important on many levels. A system that improves the economy is more likely to be accepted and adapted to current standards. The sustainment of this system will also determine the lifecycle of a system and its practicality in its working environment.

UAV inspection of power lines saves its owner labor and material costs. The customer of this system does not have to hire a team of inspectors to assess the electrical infrastructure. The UAV can do the job of a team faster and at a much lower cost. With the ability to inspect power lines more frequently, many avoidable issues that cause electrical service interruptions can be detected and solved. This provides less repair costs for the electrical company and allows the customers it serves to use more of its service. This ultimately also benefits the electrical

company. Since everything runs on electricity, businesses and residents will be more productive when their electrical service is not interrupted. This would produce a positive economic impact.

Sustainment of this system will be determined on how well the industry accepts this tool. Since UAV inspection is less expensive and more efficient than current methods, the probability of sustainment would likely be high. [26] Since the UAV inspection systems uses low cost UAVs and open source software, the system is expected to have an overall low sustainment cost. This is a positive characteristic to have especially if a company owns multiples of this system.

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