



Faculty of Engineering

**AUTONOMOUS POWER LINE INSPECTION USING
COMPUTER VISION**

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Electrical and Electronics Engineering with Honours

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Grade: _____

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Final Year Project Report

Masters

PhD

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AUTONOMOUS POWER LINE INSPECTION USING
COMPUTER VISION

LAW JIN MING

A dissertation submitted in partial fulfilment
of the requirement for the degree of
Bachelor of Engineering
Electrical and Electronics Engineering with Honours

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To my beloved family and friends.

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ABSTRACT

This project aims to construct an autonomous power line inspection system using computer vision to classify and localise the normal and abnormal insulators. The traditional inspection methods, for instance, foot patrol inspection and helicopter-assisted inspection are time-consuming and dangerous. DenseNet-201 model is proposed as the base network to perform insulator fault detection autonomously. An algorithm with DenseNet-201 backbone consisting of two branches which are class label classification and bounding box regression is developed. The developed algorithm is trained on the augmented Chinese Power Line Insulator Dataset (CPLID) that consisted of normal and missing cap insulator images. The prediction results in classification accuracy of 100%. The average precision of detecting normal insulator and insulator missing cap has higher performance at threshold 0.3 which are 100% and 66.61%. The mean average precision at thresholds 0.3 and 0.5 are 83.31% and 64.62% respectively. The experimental results on the augmented CPLID dataset denote that the proposed model has high classification accuracy and it outperforms the ResNet model.

ABSTRAK

Projek ini bertujuan untuk membina system pemeriksaan talian kuasa autonomi menggunakan visi komputer untuk mengklasifikasikan dan menyetempatkan penebat normal dan tidak normal. Kaedah pemeriksaan tradisional, contohnya, pemeriksaan rondaan kaki dan pemeriksaan bantuan helikopter mengambil masa yang lama dan berbahaya. Model DenseNet-201 dicadangkan sebagai rangkaian asas untuk melakukan pengesanan penebat dengan regresi kotak-terikat secara autonomi. Algoritma dengan DenseNet-201 yang terdiri daripada dua cabang iaitu klasifikasi label kelas dan regresi kotak sempadan dibangunkan. Algoritma yang dibangunkan dilatih pada ‘Chinese Power Line Insulator Dataset (CPLID)’ yang terdiri daripada imej penebat topi biasa dan hilang. Model ini menghasilkan ketepatan klasifikasi 100%. Ketepatan purata pengesanan penutup hilang penebat mempunyai prestasi yang lebih tinggi pada ambang 0.3 iaitu 66.61%. Purata ketepatan purata pada ambang 0.3 dan 0.5 masing-masing ialah 83.31% dan 64.62%. Keputusan eksperimen pada set data CPLID menunjukkan bahawa model yang dicadangkan mempunyai ketepatan pengelasan yang tinggi dan ia mengatasi prestasi model ResNet.

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LIST OF ABBREVIATIONS

AI	-	Artificial Intelligence
ALS	-	Airborne Laser Scanner
AP	-	Average Precision
ATV	-	All-Terrain Vehicle
CMDELM	-	Correlation-Maximizing Deep Extreme Learning Machine
CNN	-	Convolution Neural Network
CPLID	-	Chinese Power Line Insulator Dataset
CPU	-	Central Processing Unit
CSPD	-	Cross Stage Partial Dense
DDN	-	Defect Detector Network
DenseNet	-	Densely Connected Convolutional Network
Faster R-CNN	-	Faster-Region-Based CNN
FCN	-	Fully Convolutional Network
FPN	-	Feature Pyramid Network
GAN	-	Generative Adversarial Network
GUI	-	Graphical User Interface
GVN	-	Gray-Scale Variance Normalization
HOG	-	Histogram of Oriented Gradients
IBF	-	Improved Burr Feature
IDCE	-	Intelligent Damage Classification and Estimation
IDE	-	Integrated Development Environment
ILN	-	Insulator Localiser Network
IoU	-	Interception over Union

LBP	-	Local Binary Pattern
LIDAR	-	Light Detection and Ranging
LRF	-	Local Receptive Field
mAP	-	Mean Average Precision
NIR	-	Near-Infrared
OpenCV	-	Open Source Computer Vision Library
PF	-	Projection Feature
PIL	-	Pillow
PRC	-	Precision-Recall-Curve
PTLs	-	Power Transmission Lines
PWA	-	Proportion of White Area
RAM	-	Random Access Memory
RGB	-	Red, Green, and Blue
ROI	-	Region of Interest
RPNs	-	Region Proposal Networks
RWP	-	Ratio of White Pixels
SAR	-	Synthetic Aperture Radar
SSD	-	Single Shot Multibox Detector
SWT	-	Square Wave Transformation
UAV	-	Unmanned Aerial Vehicles
VGG	-	Visual Geometry Group
VOC2007	-	Visual Object Classes Challenge 2007
YOLO	-	You Only Look Once

CHAPTER 1

INTRODUCTION

1.1 Background

In 2000, Malaysia's population was around 23.3 million people while in 2013, the population had increased to 29.3 million which contributed to the rise in electricity usage [1]. The population in Malaysia has grown substantially every year until 32.7 million in 2021 [2]. As reported in Malaysia Energy Statistics Handbook 2020 by Malaysia Energy Information Hub (MEIH) [3], the electricity consumption by states in Malaysia is increasing from 2010 to 2018. Electricity is important for everyone in daily activities as most electrical appliances require electricity as power supplies. Therefore, electricity demand has been increasing gradually. The advancement of technologies and digitalization in society nowadays has caused the smart grid to experience rapid development. Thus, monitoring and maintenance of the electrical power grids are crucial with the increase in the dependency of society on electricity. This is to ensure that the power system works without interruption.

Power line inspection is needed to monitor the transmission line whether it is in good condition. Any fault in the power line may lead to power transmission system failure and problems like blackout, power outage, and economic losses. To avoid the problem of power outages or damage to the pole, inspection of the power lines is crucial for the safety of society. The most important component in distributing electricity in power grids is the power line. An insulator is installed between a current-carrying conductor and a tower. It plays a vital role in the electrical system to prevent unwanted current flows to the ground from the conductor. The insulator is crucial for the transmission lines and substations to operate safely. Since the insulators on the power line are outdoors and exposed to sunlight for a long time, they can be damaged or cracked [4]. The insulator fault usually occurs as influenced by lightning strikes, overloading, and material aging. Defects in the insulator are the most common accident found in power transmission [5]. The fault will cause harm to the safety of the transmission line and the power grids might experience huge economic

losses [6]. Thus, it is essential to detect the defects of power line components, especially insulators to maintain stability in the power system.

Traditionally, manual power line inspection methods such as foot patrol as shown in Figure 1.1 are commonly used as they are cheap and convenient. Although it is very convenient, it poses danger to the inspectors and consumes a lot of time [7]. There is a continuous development of helicopter-assisted, climbing robots, and unmanned aerial vehicles (UAVs) methods for performing inspection tasks. By comparing with the traditional inspection methods, the helicopter-assisted method performs on a large-scale area and is independent of the terrain environment [8]. However, due to its high movement speed, the accuracy of the inspection is affected. Among all, UAV is the most popular inspection method as it enhances inspection efficiency [8]. Previously, the overhead line inspection is done by visual inspection where the inspectors have to observe the overhead lines physically. With UAVs, the camera installed on them will capture the photos of power line components and send the photos to the workstation for the checking process. Hence, the inefficient traditional inspection methods are gradually replaced by UAVs. In power line inspection, there are four power line inspection tasks which are mapping and inspection of power line components, vegetation encroachment monitoring, disaster monitoring, as well as icing detection and measurement [9].



Figure 1.1: Manual inspection of power line [8]

Great achievements in computer vision have been made by Deep Learning (DL) especially in deep Convolutional Neural Networks (CNNs) in recent years [10]. Automatic vision-based power line inspections using computer vision have been introduced. Figure 1.2 shows the missing caps of insulators are detected automatically by using computer vision. With the autonomous vision-based power line inspection, the inspection efficiency and quality are improved. Much research on automated power line inspection was conducted in these few years. Unmanned aerial vehicles (UAVs), image processing, and deep learning are examples of state-of-the-art elements in power line inspection [8]. With the fast development of automation as well as artificial intelligence technologies, an alternative way of power line inspection is used which is drone-assisted inspection [7]. The automation of power line inspection is done by using UAV images, optical images, or LIDAR. The research is focusing on the mapping and monitoring of the power line components and lesser articles on fault analysis. This technology is implemented more in developed countries such as China. The power line inspection technology is still not advanced in Malaysia.

Moreover, this technology will encourage the industry to consider developing an autonomous power line monitoring system based on the use of UAVs instead of performing traditional inspection methods. With the autonomous line inspection using computer vision, the worker's workload is reduced where they no need to inspect the power line physically. Therefore, autonomous power line inspection using computer vision is beneficial to society. However, despite the research that has been done to perform power line visual inspection automatically, no completely autonomous vision-based inspection system that can detect various faults has yet to be produced.



Figure 1.2: Fault detection of insulator using deep learning [6]

1.2 Problem Statement

As mentioned earlier, traditional inspection method such as foot patrol inspection poses many disadvantages and limitation. In traditional operations, whenever there is a fault in the electrical transmission system, the localisation of damaged lines requires shutting down the entire distribution grid. The technicians are required to power the damaged line part by part to discover the ground fault. The checking process is time-consuming as it requires a few hours or even days to locate the fault. Although the foot patrol inspection method is widely implemented in inspecting the power line due to its high detection rate, it is not favourable in bad weather conditions [9]. The bad weather conditions will further make strenuous to the inspection process. In Malaysia, the geographical location restricts the work of power line inspectors. Traditional power line inspection method may risk their life and increase difficulties in their work. Other than being risky and time-consuming, a traditional operation such as the foot patrol inspection method does not allow remote control on the power line.

Traditional image processing technology in power line inspection is having low accuracy [6]. In previous research, the technology has been used by many researchers with aerial images to detect insulators and faults. It is done by segmenting the insulators via specific features such as texture, colour, shape, and gradient. A matching algorithm is then used to perform insulator fault detection. Nevertheless, in complex backgrounds, multi-scale detection is inappropriate as the image processing technology relied on classification features that are designed manually. The detection result poses low accuracy due to the uncertainty of the features of insulators in aerial images.

The unmanned aerial vehicle (UAV) inspection method is superior to other power line inspection methods in terms of efficiency and quality [11]. However, UAV-based power line inspection requires manually checking on a huge amount of aerial images captured by UAV to locate the abnormal components [12]. Prior knowledge of the power line components is required to perform manual checking on the captured aerial images. It relies on inspectors' experience and becomes a significant burden for inspectors.

1.3 Objectives

This project aims to develop an algorithm for a system that automatically detects the faults of the insulator which is the insulator missing caps by using computer vision.

To realise the goal of this project, the following objectives need to be achieved:

1. To study the existing work on autonomous power line inspection.
2. To develop an algorithm for autonomous power line inspection using computer vision to identify the faulty insulator with missing caps.
3. To validate the performance of the autonomous power line inspection algorithm.

1.4 Project Scope

The focus of this project is to develop an algorithm for autonomous power line inspection using computer vision. In this project, the development of the deep learning algorithm is focusing on insulator fault detection. The purpose is to classify the normal and abnormal insulators with a missing cap as well as localise the targeted object. Thus, the dataset used in this project consists of both normal and abnormal images of the insulator.

Moreover, this project is a fully software-based project using Python as the programming language. Other than Python, deep learning libraries are required in developing the algorithm. The libraries selected are OpenCV and TensorFlow in which OpenCV will be used for data augmentation while TensorFlow will be used for developing the deep learning algorithm for insulator fault detection.

Before using the insulator dataset in training the deep learning model, data augmentation techniques are performed on the dataset to increase data size. Brightness, contrast, and saturation changes are the data augmentation techniques performed in this project. This can be done by using OpenCV and other libraries such as Scikit-image in Python. In this project, the total number of augmented images is following the experimental setting used in a previous research paper. Then, the augmented dataset is annotated and distributed into three sets which are test, training, and validation sets. The labelled training set is used to train the deep learning model.

DenseNet model is the selected convolutional neural network in developing the algorithm for insulator fault detection. DenseNet neural network will learn the common

features from the labelled training set while the extracted features are used to perform classification and bounding box regression. The detail of the proposed method is discussed in Chapter 3 methodology.

Lastly, the performance of the trained model is evaluated by using the evaluation metrics such as accuracy, precision, recall, and average precision (AP). Object detection's performance is based on Intersection over Union (IoU) of the ground truth and predicted bounding box. The developed algorithm is compared with other algorithms such as ResNet model. The developed system will be further improved to improve the reliability of the system.

1.5 Report organisation

In this report, five chapters will be presented which are introduction, literature review, methodology, results, and discussion as well as the conclusion and recommendations. The outline of each chapter is stated below:

Chapter 1: Introduction

Chapter 1 discusses the background of the project, the current problems that the world is facing, objectives, project scopes, and the project outlines. The goal of this project is mentioned in the objectives.

Chapter 2: Literature review

Chapter 2 presents the background studies related to autonomous power line inspection using computer vision. It reviews the existing methods of power line inspection and different types of algorithms used as well as the result in previous studies based on journals, articles and conference papers.

Chapter 3: Methodology

Chapter 3 explains the hardware and software as well as the method that is used in this project. The developed algorithm is presented and the flow of the algorithm is explained. The project workflow is represented in a flow chart. Moreover, the parameters used in