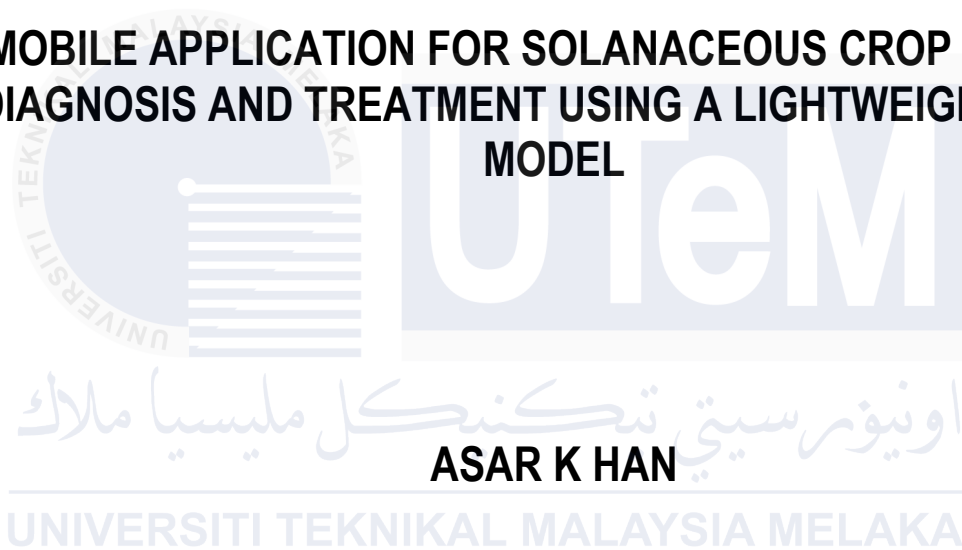




MOBILE APPLICATION FOR SOLANACEOUS CROP HEALTH DIAGNOSIS AND TREATMENT USING A LIGHTWEIGHT YOLO MODEL



MASTER OF SCIENCE IN ELECTRONICS ENGINEERING

2025



**Faculty of Electronics and Computer Technology and
Engineering**

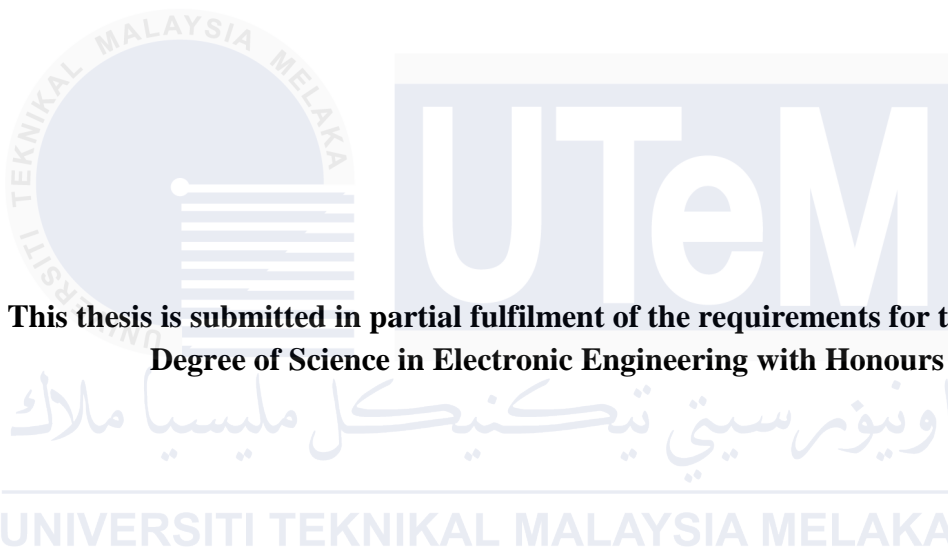
**MOBILE APPLICATION FOR SOLANACEOUS CROP HEALTH
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MODEL**

اونيورسيتي تيكنيكل مليسيا ملاك
UNIVERSITI TEKNIKAL MALAYSIA MELAKA
ASAR KHAN

MASTER OF SCIENCE IN ELECTRONICS ENGINEERING

**MOBILE APPLICATION FOR SOLANACEOUS CROP HEALTH DIAGNOSIS
AND TREATMENT USING A LIGHTWEIGHT YOLO MODEL**

ASAR KHAN



**This thesis is submitted in partial fulfilment of the requirements for the Master
Degree of Science in Electronic Engineering with Honours**

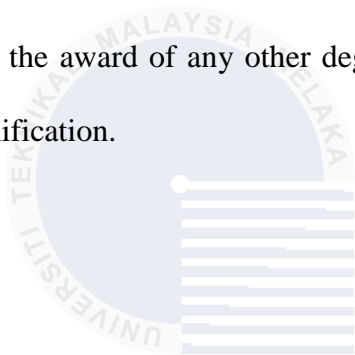
Faculty of Electronics and Computer Technology and Engineering

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2025

DECLARATION

I hereby declare that the thesis entitled “ Mobile Application For Solanaceous Crop Health Diagnosis And Treatment Using A Lightweight YOLO Model “ is based on my original research work, except where references have been cited. This thesis has not been submitted for the award of any other degree and is not under consideration for any other academic qualification.



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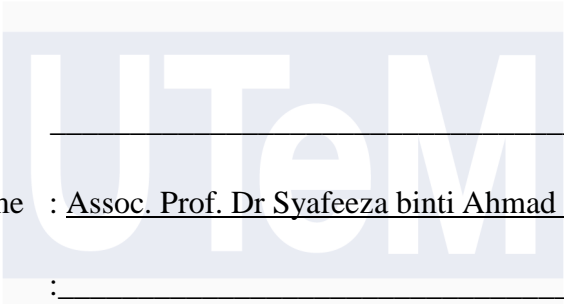
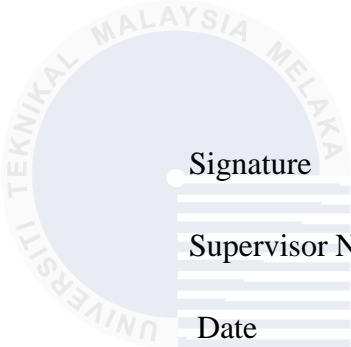
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APPROVAL

I confirm that I have read this thesis and, in my opinion, it fulfils the requirements in terms of both scope and quality for the award of Master of Science in Electronic Engineering.



Signature : _____

Supervisor Name : Assoc. Prof. Dr Syafeeza binti Ahmad Radzi

Date : _____

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DEDICATION

This work is dedicated to my beloved parents, brother, sister, other family members, dear friends, and valued students.



ABSTRACT

Agriculture, an extremely important industry for developing countries, but it is facing difficulties by plant disease, water insecurity, and rising temperatures. Traditional disease detection procedures is time consuming, require professional expertise, and can end in misdiagnosis, leading to poor treatment. In addition, the crop diseases looks similar although the diseases class is different. Therefore, this leads to the usage of Artificial Intelligence (AI) approach. With advances in AI especially deep learning, automated solutions appear to be a potential strategy to address these issues. There are remains a gap in accessible, accurate, and lightweight diagnostic tools that function efficiently on resource-constrained mobile devices. The goal of this research is to analyze and identify the best-performing optimized lightweight deep learning model among YOLOv5n, YOLOv7t, and YOLOv8n for identifying Solanaceous crop diseases specifically in these four types of plants used, peppers, potatoes, eggplants, and tomatoes. A total of 23 disease and healthy classes were considered, including Chili Anthracnose, Eggplant Cercospora leaf spot, Potato Common scab, Tomato Leaf mold, and others, which can result in significant financial losses. The models' performance is evaluated using important measures such as mean average precision (mAP), precision, recall, F1-score, inference time, and model size. Optimization was performed by fine-tuning hyperparameters such as (mini batch size, learning rate, loss functions, and weight decays), applying these techniques on data, and balancing performance with computational efficiency to enable on resource-constrained mobile devices. Using the PlantVillage dataset, which was processed through Roboflow for annotation and augmentation, the models were trained and tested on Google Colab, with YOLOv8n achieving the highest mean average precision (99.1% mAP), followed by YOLOv7t (98.6%) and YOLOv5n (98.5%). Based on these findings, a mobile application was developed to integrate the best-performing model, enabling real-time disease diagnosis from static images and providing treatment recommendations. This research contributes to precision agriculture by offering a cost-effective and efficient tool that empowers farmers with accurate disease detection and treatment guidance, ultimately improving crop health, increasing productivity, and supporting food security.

APLIKASI MUDAH ALIH UNTUK DIAGNOSIS DAN RAWATAN KESIHATAN TANAMAN SOLANACEOUS MENGGUNAKAN MODEL YOLO RINGAN

ABSTRAK

Pertanian, industri yang sangat penting untuk negara membangun, tetapi ia menghadapi kesukaran oleh penyakit tumbuhan, ketidakamanan air, dan peningkatan suhu. Prosedur pengesanan penyakit tradisional memakan masa, memerlukan kepakaran profesional, dan boleh berakhir dengan salah diagnosis, membawa kepada rawatan yang tidak baik. Selain itu, penyakit tanaman kelihatan serupa walaupun kelas penyakitnya berbeza. Oleh itu, ini membawa kepada penggunaan pendekatan Kecerdasan Buatan (AI). Dengan kemajuan dalam AI terutamanya pembelajaran mendalam, penyelesaian automatik nampaknya merupakan strategi yang berpotensi untuk menangani isu ini. Masih terdapat jurang dalam alat diagnostik yang boleh diakses, tepat dan ringan yang berfungsi dengan cekap pada peranti mudah alih yang dikekang oleh sumber. Matlamat penyelidikan ini adalah untuk menganalisis dan mengenal pasti model pembelajaran mendalam ringan yang dioptimumkan berprestasi terbaik di kalangan YOLOv5n, YOLOv7t dan YOLOv8n untuk mengenal pasti penyakit tanaman Solanaceous khususnya dalam empat jenis tumbuhan yang digunakan ini, lada, kentang, terung dan tomato. Sebanyak 23 penyakit dan kelas sihat telah dipertimbangkan, termasuk Cili Antraknosa, bintik daun Terung *Cercospora*, Kudis Biasa Kentang, acuan Daun Tomato, dan lain-lain, yang boleh mengakibatkan kerugian kewangan yang ketara. Prestasi model dinilai menggunakan ukuran penting seperti purata ketepatan (mAP), ketepatan, ingat semula, skor F1, masa inferens dan saiz model. Pengoptimuman dilakukan oleh hiperparameter penalaan halus seperti (saiz kelompok mini, kadar pembelajaran, fungsi kehilangan dan pereputan berat), menggunakan teknik ini pada data dan mengimbangi prestasi dengan kecekapan pengiraan untuk membolehkan pada peranti mudah alih yang dikekang sumber. Menggunakan set data PlantVillage, yang diproses melalui Roboflow untuk anotasi dan penambahan, model telah dilatih dan diuji pada Google Colab, dengan YOLOv8n mencapai ketepatan purata purata tertinggi (99.1% mAP), diikuti oleh YOLOv7t (98.6%) dan YOLOv5n (98.5%). Berdasarkan penemuan ini, aplikasi mudah alih telah dibangunkan untuk menyepadukan model berprestasi terbaik, membolehkan diagnosis penyakit masa nyata daripada imej statik dan menyediakan cadangan rawatan. Penyelidikan ini menyumbang kepada pertanian ketepatan dengan menawarkan alat kos efektif dan cekap yang memperkasakan petani dengan pengesanan penyakit dan panduan rawatan yang tepat, akhirnya meningkatkan kesihatan tanaman, meningkatkan produktiviti dan menyokong keselamatan makanan.

ACKNOWLEDGEMENT

In the Name of Allah, the Most Gracious, the Most Merciful.

Alhamdulillah, I am deeply thankful to Allah SWT for His kindness and for giving me the strength, knowledge, opportunity, courage, and capacity to finish my thesis. I would like to express my sincere appreciation to my supervisor, Associate Prof. Dr. Syafeeza Binti Ahmad Radzi, for her continuous guidance and valuable insights. I would also like to take this opportunity to sincerely thank everyone who helped me along the way, whether directly or indirectly, have greatly contributed to the improvement of my research.

Most importantly, I would like to thank my family, especially my loving parents, Qayem Khan and my Mother, my dear brothers, Bahroz Khan and Wazir Zada, my two sisters, and other family members. I am deeply grateful for their continuous ‘doa’, love, motivation, patience, strong support and encouragement in everything I have done.

My greatest pleasure to my research colleagues and friends, Engr. Sana Ullah, Mr. Majid Rafiq, Dr. Irfan ur Rehman and those who indirectly involved for their kind help and supporting me directly and indirectly in completing this research. I am very fortunate to have these people during my ups and downs throughout this journey.

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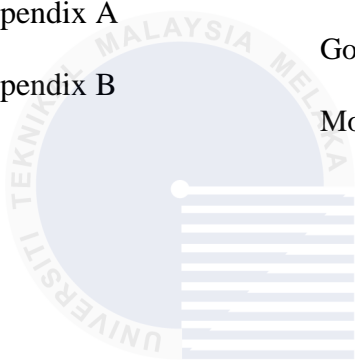
LIST OF ABBREVIATIONS

<i>Adam</i>	:	<i>Adaptive Moment Estimation</i>
<i>AI</i>	:	<i>Artificial Intelligence</i>
<i>AOT</i>	:	<i>Ahead-of-time</i>
<i>ANN</i>	:	<i>Artificial Neural Network</i>
<i>BCE</i>	:	<i>Binary Cross-Entropy</i>
<i>CNN</i>	:	<i>Convolutional Neural Network</i>
<i>Colab</i>	:	<i>Colaboratory</i>
<i>CPU</i>	:	<i>Central Processing Unit</i>
<i>DL</i>	:	<i>Deep Learning</i>
<i>FAO</i>	:	<i>Food and Agriculture Organization</i>
<i>GPU</i>	:	<i>Graphics Processing Unit</i>
<i>GUI</i>	:	<i>Graphical User Interface</i>
<i>IAM</i>	:	<i>Identity & Access Management</i>
<i>IoT</i>	:	<i>Internet of Things</i>
<i>IoU</i>	:	<i>Intersection over Union</i>
<i>KL/KL_DIV</i>	:	<i>Kullback-Leibler Divergence</i>
<i>mAP</i>	:	<i>Mean Average Precision</i>
<i>MDLAs</i>	:	<i>Mobile Deep Learning Applications</i>
<i>ML</i>	:	<i>Machine Learning</i>
<i>NAS</i>	:	<i>Network Architecture Search</i>
<i>ResNet</i>	:	<i>Residual Network</i>
<i>RF</i>	:	<i>Random Forest</i>
<i>RMSPProp</i>	:	<i>Root Mean Square Propagation</i>

<i>SDK</i>	:	<i>Software Development Kit</i>
<i>SDGs</i>	:	<i>Sustainable Development Goals</i>
<i>SGD</i>	:	<i>Stochastic Gradient Descent</i>
<i>SSD</i>	:	<i>Single Shot Detector</i>
<i>SVM</i>	:	<i>Support Vector Machine</i>
<i>UI</i>	:	<i>User Interface</i>
<i>VGGNet</i>	:	<i>Visual Geometry Group Network</i>
<i>YOLO</i>	:	<i>You Only Look Once</i>
<i>YOLOv5n</i>	:	<i>You Only Look Once version 5-nano</i>
<i>YOLOv7t</i>	:	<i>You Only Look Once version 7-tiny</i>
<i>YOLOv8n</i>	:	<i>You Only Look Once version 8-nano</i>

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LIST OF PUBLICATIONS

Below is a list of publications that are important to the research conducted on this thesis:

1. Khan, A., Ahmad Radzi, S., Mohd Zaimi, M.Z., Amsan, A.N., Mohd Saad, W.H., Abd Razak, N., Abdul Hamid, N. and Abdul Samad, A.S. (2024) 'Revolutionizing agriculture with deep learning: current trends and future directions', *The International Journal of Integrated Engineering (IJIE)*.
2. Khan, A., Syafeeza, A.R., Amsan, A.N., Abdul Hamid, N., Abd Razak, N. and Abdul Samad, A.S. (2025) 'Disease detection in solanaceous crops using one-stage detectors', *Journal of Advanced Research Design*. (Accepted for publication)
3. Khan, A., Syafeeza, A.R., Rahman, S., Wong, Y.C., Mohd Saad, W.H., Salam, A., Amin, F., de la Torre Díez, I., Osorio García, C. and Pascual Barrera, A.E. (2025) 'Development of lightweight deep learning-based disease detection model in plants for smart agriculture', *Scientific Reports*. (Submitted for publication)

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CHAPTER 1

INTRODUCTION

1.1 Background

Agriculture plays a crucial role as well as it is considered to be the backbone of the economic system for developing countries. But this sector faces multiple challenges such as climate change, water shortage, and plant disease, which negatively impact on the world's food supply. In addition, the increasing demand for sustainable and environmentally friendly practices require new solutions to ensure the long term sustainability of agricultural systems. Improving product quality and quantity while reducing costs and increasing profits is the aim of agricultural research (Bharman *et al.*, 2022). Ensuring people's dietary demands has become important due to the significant population rise. Additionally, the sector plays a crucial role in providing employment opportunities and ensuring food security, making it a vital component of the national economy (Altalak *et al.*, 2022).

Solanaceous crops such as tomato, potato, pepper, and eggplant are an essential source of food for millions of people worldwide. However, these crops are susceptible to various diseases, which can cause significant economic losses to farmers. Traditional methods for diagnosing and treating diseases are often difficult and need specialized knowledge. Plant disease significantly reduce crop quality and cause yield losses up to 20% to 40% of the loss in worldwide food production, according to the Food and Agriculture Organization (FAO) (Ahmad, Saraswat and El, 2023). Plant diseases represent a serious threat to global food security. To minimize crop losses and ensure timely intervention, early

identification and detection are critical. These diseases are caused by bacteria, fungi, and other disease (Agarwal *et al.*, 2023). In addition to direct yield losses, plant diseases can also lead to increased production costs, reduced market access, and decreased food availability.

In the past, farmers relied heavily on visual observations and manual methods to identify plant diseases. However, manual identification increases the chances of misdiagnosis, which can lead to significant production losses. These traditional methods are often slow and labor-intensive, requiring considerable time and effort to complete tasks (Shoaib *et al.*, 2023). Furthermore, it is difficult for farmers to shift between different disease management strategies. The conventional approach, where experts rely on naked-eye observation can be costly, time-consuming, and prone to errors (Sharma *et al.*, 2022). Therefore, proper agricultural education and training in modern farming techniques are essential for farmers.

Recent advancements of computational systems as well as in Graphical Processing Unit (GPU) embedded processors, Artificial Intelligence (AI) applications have obtained exponential growth which leads to new methodologies and models of various pattern recognition problems. Deep learning, as a subset of AI, has gained significant attention in academic and industrial sectors due to its automatic learning and feature extraction capabilities. Deep learning is widely utilized in various domains, including image processing, video processing, voice processing, and natural language processing (Li, Zhang and Wang, 2021). Inspired by the human brain, deep learning is particularly good at evaluating large and complicated agricultural information. It can provide weather predictions, breeding improvement, and pest and disease identification. The parallel processing power of GPUs makes it possible to quickly train and implement deep learning

models, which is essential for analyzing massive amounts of agricultural samples in real-time (Rao *et al.*, 2022). Deep learning method improves disease detection in a variety of crops, guaranteeing quick and precise diagnosis. These technology developments assist farmers and the agricultural sector overall by streamlining disease control and boosting agricultural output and quality. Due to it provides an accurate diagnosis with less time and resource complexity, an automated intelligent strategy utilizing deep learning (DL) through Convolution Neural Networks (CNN) has become more and more popular in recent years (Verma *et al.*, 2022).

Several studies have explored the use of deep learning for plant disease detection and diagnosis, demonstrating high accuracy rates in detecting diseases such as tomato leaf mold, cucumber mosaic virus, and apple scab. For example, a deep learning algorithm based on MobileNet V2 that achieved over 90% accuracy for detecting diseases in potato leaves to control disease in the plants (Zaki *et al.*, 2020). Similarly, another study developed a deep learning model for detecting diseases in potato leaves. Other deep learning architecture, InceptionV3 was chosen for mobile deployment due to its lower memory requirements. In real environmental conditions, the created technology showed 94% confidence in detecting diseases, helping smallholder farmers in early disease diagnosis for improved production (Feng *et al.*, 2023) (Sanga, Machuve and Jomanga, 2020).

Inspired by other related works, this research aims to develop a cost-effective and time-efficient solution for Solanaceous crop diseases. This research aims to detect the Solanaceous crop diseases by leveraging deep learning techniques through a user-friendly mobile application. The research output is to provide small-scale farmers with a mobile app that has a user-friendly interface, reducing dependence on expensive technology. However,