

**MALAYSIAN SIGN LANGUAGE & ALPHABETS
RECOGNITION USING DEEP LEARNING ALGORITHM AND
IMAGE PROCESSING TECHNIQUE**

MUHAMMAD FAUZAN BIN ABDUL HAKIM



UNIVERSITI TEKNIKAL MALAYSIA MELAKA

**MALAYSIAN SIGN LANGUAGE & ALPHABETS
RECOGNITION USING DEEP LEARNING ALGORITHM AND
IMAGE PROCESSING TECHNIQUE**

MUHAMMAD FAUZAN BIN ABDUL HAKIM

**This report is submitted in partial fulfillment of the requirements
for the degree of Bachelor of Electronic Engineering with Honours**



**Faculty of Electronic and Computer Engineering
Universiti Teknikal Malaysia Melaka**
UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2023

BORANG PENGESAHAN STATUS LAPORAN
PROJEK SARJANA MUDA II

Tajuk Projek : Malaysian Sign Language & Alphabets Recognition
Using Deep Learning Algorithm And Image
Processing Technique
Sesi Pengajian : 2022/2023

Saya MUHAMMAD FAUZAN BIN ABDUL HAKIM mengaku membenarkan laporan Projek Sarjana Muda ini disimpan di Perpustakaan dengan syarat-syarat kegunaan seperti berikut:

1. Laporan adalah hakmilik Universiti Teknikal Malaysia Melaka.
2. Perpustakaan dibenarkan membuat salinan untuk tujuan pengajian sahaja.
3. Perpustakaan dibenarkan membuat salinan laporan ini sebagai bahan pertukaran antara institusi pengajian tinggi.
4. Sila tandakan (✓):

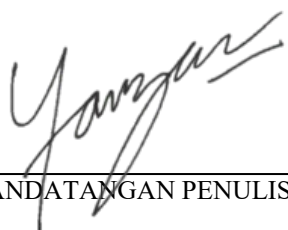
SULIT*

(Mengandungi maklumat yang berdarjah keselamatan atau kepentingan Malaysia seperti yang termaktub di dalam AKTA RAHSIA RASMI 1972)

TERHAD*

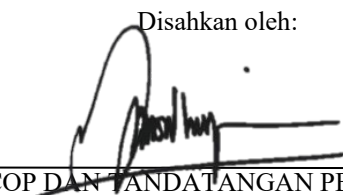
(Mengandungi maklumat terhad yang telah ditentukan oleh organisasi/badan di mana penyelidikan dijalankan.)

TIDAK TERHAD


(TANDATANGAN PENULIS)

Alamat Tetap: No 700, Jalan HJ
Buyong Bodeen,
Kg Tersusun
Sengat, Kg
Kepayang, Perak

Tarikh : 12 Januari 2023

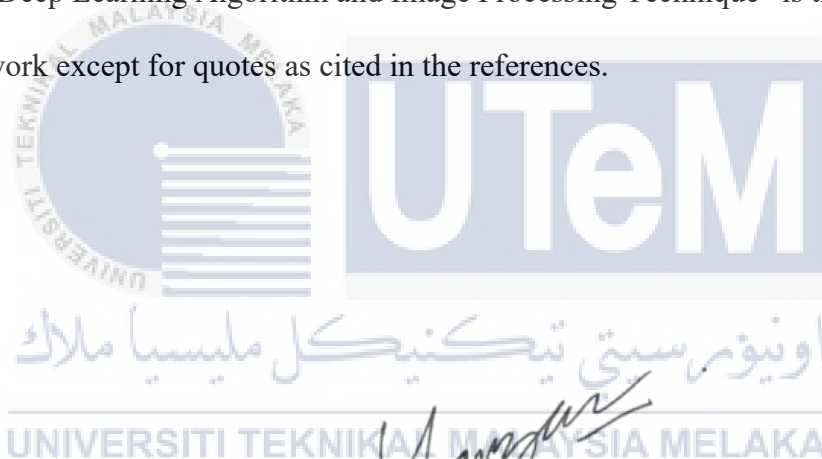
Disahkan oleh:

(COP DAN TANDATANGAN PENYELIA)

PROFESOR MADYA DR. MASRULLIZAM BIN MAT IBRAHIM
Profesor Madya
Fakulti Kejuruteraan Elektronik dan Kejuruteraan Komputer
Universiti Teknikal Malaysia Melaka (UTeM)
Hang Tuah Jaya
75100 Durian Tunggal, Melaka

Tarikh : 12 Januari 2023

DECLARATION

I declare that this report entitled “Malaysian Sign Language & Alphabets Recognition using Deep Learning Algorithm and Image Processing Technique” is the result of my own work except for quotes as cited in the references.



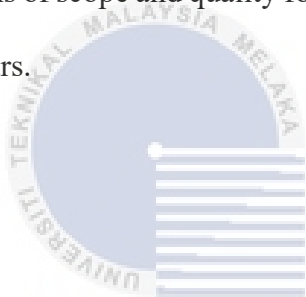
Signature :

Author : Muhammad Fauzan Bin Abdul Hakim

Date : 12/01/2023

APPROVAL

I hereby declare that I have read this thesis and in my opinion, this thesis is sufficient in terms of scope and quality for the award of Bachelor of Electronic Engineering with Honours.



Signature : 
UNIVERSITI TEKNIKAL MALAYSIA MELAKA

Supervisor Name : Assoc. Prof. Dr. Masrullizam Bin Mat Ibrahim

Date : 12/01/2023

DEDICATION

To my beloved family.



ABSTRACT

People who suffer from hearing difficulties use sign language as a way of communication and sign language translators quickly become inadequate to serve the entire deaf community, especially in Malaysia. To address the problem, this project aims to develop a Malaysian Sign Language recognition algorithm and translate it into text form. To achieve the objective, a dataset of Malaysian Sign Language and alphabets are constructed. Furthermore, image processing techniques to extract specific landmarks were used. The developed algorithm is trained using CNN architecture and PyCharm software is used to perform real-time gesture translation into text form. The algorithm shows a promising result with an accuracy of 96.16%. In addition, the result of precision, recall, and F1-Score for every predicted class is as high as 100%.

ABSTRAK

Orang yang mengalami masalah pendengaran menggunakan bahasa isyarat sebagai cara komunikasi dan penterjemah bahasa isyarat dengan cepat menjadi tidak mencukupi untuk berkhidmat kepada seluruh masyarakat pekak, terutamanya di Malaysia. Untuk menangani masalah tersebut, projek ini bertujuan untuk membangunkan algoritma pengesanan Bahasa Isyarat Malaysia dan menterjemahkannya ke dalam bentuk teks. Untuk mencapai objektif tersebut, set data Bahasa Isyarat Malaysia dan abjad dibina. Tambahan pula, teknik pemprosesan imej untuk mengekstrak tanda tempat tertentu telah digunakan. Algoritma yang dibangunkan dilatih menggunakan seni bina CNN dan perisian PyCharm digunakan untuk melakukan terjemahan gerak isyarat masa nyata ke dalam bentuk teks. Algoritma menunjukkan hasil yang menjanjikan dengan ketepatan 96.16%. Di samping itu, hasil ketepatan, ingat semula dan F1-Score untuk setiap kelas yang diramalkan adalah setinggi 100%.

ACKNOWLEDGEMENTS

Alhamdulillah, all praise be to Allah S.W.T. the Provider of Guidance, for lending me the strength and wisdom to complete this thesis.

I express my deepest appreciation to my supervisor, Associate Professor Dr. Masrullizam Bin Mat Ibrahim for his countless efforts and patience in helping me to complete this project. I am very grateful to my family, especially my parents, Abdul Hakim Bin Abdul Hamid and Marziana Es, Binti Abdul Manaf for their continuous support and encouragement throughout my studies. My special thanks go to the lecturers, friends, and all those involved in my project directly or indirectly. Last but not least, great appreciation must go to the Universiti Teknikal Malaysia Melaka (UTeM) for providing great facilities, amazing educators, and meaningful memories for me throughout my studies.

TABLE OF CONTENTS

| | |
|--|-------------|
| Declaration | |
| Approval | |
| Dedication | |
| Abstract | i |
| Abstrak | ii |
| Acknowledgements | iii |
| Table of Contents | iv |
| List of Figures | viii |
| List of Tables | xi |
| List of Symbols and Abbreviations | xii |
| List of Appendices | xiii |
| CHAPTER 1 INTRODUCTION | 1 |
| 1.1 Overview | 1 |
| 1.2 Problem Statement | 2 |
| 1.3 Objectives and Scopes of Project | 4 |
| 1.3.1 Project Objectives | 4 |

| | | |
|-----------------------------------|--|-----------|
| 1.3.2 | Scopes of Project | 4 |
| 1.4 | Organization of Thesis | 7 |
| CHAPTER 2 BACKGROUND STUDY | | 9 |
| 2.1 | Introduction | 9 |
| 2.2 | Malaysian Sign Language (MSL) | 10 |
| 2.2.1 | Overview | 10 |
| 2.2.2 | Body Parts Involved in Sign Language | 10 |
| 2.2.3 | Static/Dynamic Motions in Sign Language | 11 |
| 2.2.4 | Signing Space | 12 |
| 2.2.5 | Summary of the Characteristics of Malaysian Sign Language | 13 |
| 2.3 | Dataset for Sign Language Recognition algorithms | 13 |
| 2.3.1 | Related Works and Dataset on Sensor-Based SLR system | 13 |
| 2.3.2 | Related Works and Dataset on Vision-Based SLR | 14 |
| 2.4 | Sign Language Recognition algorithm | 16 |
| 2.4.1 | SLR algorithm based on Machine Learning | 16 |
| 2.4.2 | SLR algorithm based on Deep Learning | 17 |
| 2.5 | Real-time Sign Language Conversion into Text Form | 18 |
| 2.6 | Performance Analysis Method for Artificial Intelligence in SLR | 19 |
| 2.7 | Summary | 19 |
| CHAPTER 3 METHODOLOGY | | 21 |

| | | |
|---|--|-----------|
| 3.1 | Research Methodology | 21 |
| 3.2 | Dataset Construction | 23 |
| 3.2.1 | App to capture and label sign language | 23 |
| 3.2.2 | Technique to determine the RoI | 26 |
| 3.2.3 | Using the RoI and MediaPipe Holistic to determine the dataset image. | 28 |
| 3.2.4 | Construction of the dataset. | 31 |
| 3.3 | Modeling of the Neural Network | 31 |
| 3.3.1 | Convolutional Neural Network | 32 |
| 3.3.2 | Activation Function | 34 |
| 3.3.3 | Pooling and Downsampling | 35 |
| 3.4 | Simulation and Real-Time Testing | 35 |
| 3.5 | Performance Evaluation | 36 |
| 3.6 | Summary | 38 |
| CHAPTER 4 RESULTS AND DISCUSSION | | 39 |
| 4.1 | Malaysia Sign Language Dataset Construction | 39 |
| 4.1.1 | RoI Image Recorded and Post Processed | 41 |
| 4.1.2 | Dataset Organization | 42 |
| 4.1.3 | Malaysia Sign Language Dataset Summary | 43 |
| 4.2 | Development of Malaysia Sign Language Recognition Algorithm | 43 |
| 4.2.1 | Prediction Accuracy | 45 |

| | | |
|--|--|-----------|
| 4.3 | Conversion of Malaysia Sign Language to Text | 49 |
| 4.4 | Algorithm Performance Analysis | 52 |
| 4.5 | Discussion | 56 |
| CHAPTER 5 CONCLUSION AND FUTURE WORKS | | 58 |
| 5.1 | Conclusion | 58 |
| 5.2 | Project Impacts and Commercialization | 60 |
| 5.3 | Improvement and Suggestion | 63 |
| REFERENCES | | 65 |
| APPENDICES | | 69 |



اونيورسيتي تيكنيكل مليسيا ملاك
UNIVERSITI TEKNIKAL MALAYSIA MELAKA

LIST OF FIGURES

| | |
|---|----|
| Figure 1.1: Number of publications based on sign language recognition by language [1]. | 4 |
| Figure 1.2: The scope of this project includes the Malaysian Sign Language alphabet except for the letter 'J' and 'Z'. | 6 |
| Figure 1.3: The five gestures that are also included in the project scope. | 6 |
| Figure 2.1: Hierarchy of typical sign language [4]. | 11 |
| Figure 2.2: Classification of typical sign language according to the number and movement of hands. | 12 |
| Figure 2.3: Typical signing space used by the signer. | 12 |
| Figure 2.4: Examples of using a sensor-based SLR system. | 14 |
| Figure 2.5: Example use of vision-based input that was recorded using the iPhone 6 [12]. | 15 |
| Figure 2.6: Example use of vision-based input that was recorded using the video camera with an accuracy of around 85 percent with 50 epochs [13]. | 15 |
| Figure 2.7: Machine Learning approach with Histogram of Oriented Gradient preprocessing applied [16]. | 17 |
| Figure 2.8: Real-time sign language conversion application for Indian Sign Language [20]. | 19 |
| Figure 3.1: Research Methodology of the project. | 21 |
| Figure 3.2: The process of acquiring images and labeling them. | 24 |
| Figure 3.3: The flowchart of how images are recorded. | 25 |

| | |
|--|----|
| Figure 3.4: The main technique of acquiring a large number of datasets. | 26 |
| Figure 3.5: The details of hand landmarks based on the MediaPipe Holistic framework. | 27 |
| Figure 3.6: The flowchart of determining the RoI without any offset. | 28 |
| Figure 3.7: Example of RoI drawn on an image based on the hand landmark. | 28 |
| Figure 3.8: The details of face landmarks based on the MediaPipe Holistic framework. | 29 |
| Figure 3.9: The data of RoI coordinates are extracted first before producing a new image can be done. | 30 |
| Figure 3.10: Example of new image saved from a 100x100 pixels canvas. It shows the hand landmark for the gesture 'G'. | 30 |
| Figure 3.11: Example of new image saved for the gesture word 'India' which includes hand and face landmarks. | 31 |
| Figure 3.12: Example of the CSV file used to store the information of the dataset. | 31 |
| Figure 3.13: Overall process of modeling the Malaysian Sign Language Recognition algorithm. | 32 |
| Figure 3.14: The CNN architecture using PyTorch. | 33 |
| Figure 3.15: Overall process of Real-Time Test using the saved Malaysian Sign Language Recognition algorithm. | 36 |
| Figure 3.16: Comparison between Binary-Class Confusion Matrix (left) and Multi-Class Confusion Matrix (right). | 37 |
| Figure 4.1: The layout of the GUI for recording images. | 40 |
| Figure 4.2: The left image shows a model demonstrating how to pose for a specific gesture. The right image shows the live feed when the image is recorded. | 41 |
| Figure 4.3: The process of getting the landmark view from the raw image. | 41 |
| Figure 4.4: The GUI for viewing recorded images. | 42 |
| Figure 4.5: Block Diagram of the developed CNN architecture. | 45 |

Figure 4.6: The graph of Prediction accuracy vs Number of epochs shows the rapid increase in accuracy from the 3rd epoch to the 6th epoch. 46

Figure 4.7: The figure shows that there is an angle that makes gesture U look similar to gesture R. 48

Figure 4.8: The figure shows that without the finger depth information, the only difference between the three classes is the position of the tip of the thumb. 49

Figure 4.9: The GUI for testing the trained model in real-time. 50

Figure 4.10: The accuracy (%) of the developed model when predicting each gesture in a real-time test. 51

Figure 4.11: The figure shows an example of determining the value of TP, FP, FN, and TN from a Multi-Class Confusion Matrix. 52

Figure 5.1: Some of the Sustainable Development Goals and their explanation. 62



LIST OF TABLES

| | |
|---|----|
| Table 3.1: The hyperparameter used in the training. | 32 |
| Table 3.2: Type of Activation Functions and its general formula [16] | 34 |
| Table 4.1: Description of different functions in the GUI (Record Image Tab) for recording images. | 40 |
| Table 4.2: Description of different functions in the GUI (View Image Tab) for recording images. | 43 |
| Table 4.3: The summary of the Malaysian Sign Language Dataset. | 43 |
| Table 4.4: The output shape and the number of parameters of each layer in the trained model. | 44 |
| Table 4.5: The prediction accuracy for the Training set and the test set for every epoch. | 46 |
| Table 4.6: The Multi-Class Confusion Matrix using the test dataset. | 47 |
| Table 4.7: Description of different functions in the GUI (Live Test Tab). | 50 |
| Table 4.8: Result of TP, FN, FP, and TN for every class that is derived from the Binary-Class Confusion Matrix based on Appendix E. | 52 |
| Table 4.9: The results of Accuracy, Precision, Recall, and F1-Score for each class. | 54 |
| Table 4.10: Accuracy comparison with other studies that used CNN architecture. | 56 |

LIST OF SYMBOLS AND ABBREVIATIONS



| | | |
|------|---|------------------------------------|
| ANN | : | Artificial Neural Network |
| CNN | : | Convolutional Neural Network |
| CSV | : | Comma-Separated Values |
| GUI | : | Graphical User Interface |
| IDE | : | Integrated Development Environment |
| LSTM | : | Long Short-Term Memory |
| MB | : | MegaByte |
| MSL | : | Malaysian Sign Language |
| OS | : | Operating System |
| PC | : | Personal Computer |
| ReLU | : | Rectified Linear Unit |
| RGB | : | Red Green Blue |
| RNN | : | Recurrent Neural Network |
| RoI | : | Region of Interest |
| SDG | : | Sustainable Development Goal |
| SLR | : | Sign Language Recognition |

LIST OF APPENDICES

| | |
|---|----|
| Appendix A: Code for RoI Detection and Drawing Algorithm..... | 69 |
| Appendix B: Code for Dataset Preparation..... | 70 |
| Appendix C: Code for Training Neural Network..... | 71 |
| Appendix D: Code for Real-Time Test..... | 72 |
| Appendix E: Binary-Class Confusion Matrix Result..... | 73 |
| Appendix F: Sample Images Recorded in Dataset..... | 74 |

CHAPTER 1

INTRODUCTION



1.1 Overview

The deaf community cannot communicate with others through verbal communication. Since they do not possess the ability to hear, they lose the sense to control their voice. Hence, they have been using sign language to convey their intention, statement, feeling, and others. In Malaysia, the deaf community uses Malaysian Sign Language as the official sign language. However, sign language itself is typically learned by the deaf community only. The lack of awareness and effort from other communities to learn sign language causes the number of individuals who are not deaf that understand sign language still low. Communications between the deaf and others are inevitable since the deaf community still needs to attend court, counsel, or handle official matters. Hence, this complication raises the demand for sign language translators.

The sign language translator in Malaysia is trained to translate the Malaysian Sign Language into Bahasa Melayu. They provide the service of translation when the deaf community needed them. However, in Malaysia, the number of sign language translators is too low compared to the number of deaf people. Hence the process of acquiring a sign language translator becomes difficult. The service is typically needed to be booked and sometimes consumes a lot of time. Therefore the efficiency of the service is low since it cannot fulfill the service on demand. As a result, researchers have comes up with a better solution to automate the translation of sign language using artificial intelligence (A.I.) to reduce the need for a human sign language translator.

1.2 Problem Statement

The deaf community cannot communicate with people who do not understand Malaysian Sign Language. Typically, the Malaysian deaf community will learn Malaysian Sign Language from school. It enables them to communicate with each other and anyone who understands the language. However, the number of non-deaf people who understand this language is really low. This creates a communication gap between the deaf community and the non-deaf community. Since there are a lot of people who are reluctant to learn Malaysian Sign Language, there is a need to develop a device that can quickly translate Malaysian Sign Language without learning it.

Sign Language Recognition (SLR) system using a sensor-based system provide inconvenience restraint to the user and is expensive. There have been numerous efforts to develop a device that can translate sign language. Among them is the use of a sensor-based system. These sensors are attached to the signer to extract information during the signing process. However, the study shows that the implementation of the system makes the signer feel inconvenienced and restrains their movement. This

discourages the deaf community from fully committing to using the system. In addition, the number of sensors used can increase significantly when a higher accuracy of information from the signers is needed. Hence, it will increase the cost of the system. Therefore, an alternative to the sensor-based system, such as a vision-based system can be a solution to the problem.

There is a lack of research and system development focused on Malaysian Sign Language recognition. As for 2021, the number of research focused on Malaysian Sign Language Recognition made up less than 1% of the accumulated research for sign language recognition across the world [1]. The highest number of research is held by the American Sign Language Recognition system which is 32% as in Figure 1.1. This indirectly shows that the number of collected data to be used in Malaysian Sign Language Recognition is significantly lower compared to the rest of the world. Therefore, there is a need to support the lack of advancement in the area of the Malaysian Sign Language Recognition System. One of the solutions is to construct the Malaysian Sign Language dataset.

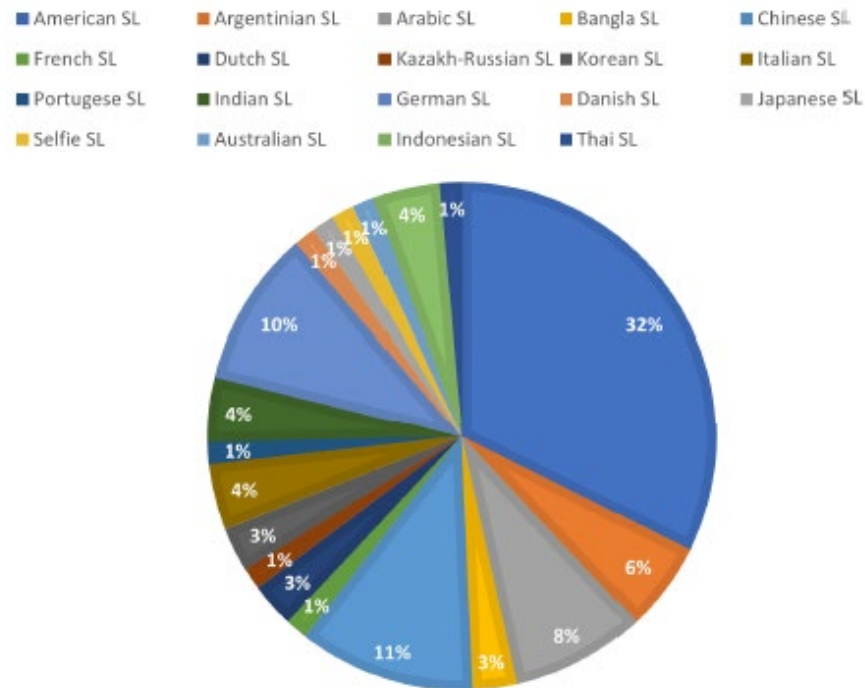


Figure 1.1: Number of publications based on sign language recognition by language [1].

1.3 Objectives and Scopes of Project

1.3.1 Project Objectives

The objectives of the project are as follows:

- i. To construct Malaysian Sign Language datasets with the label.
- ii. To develop a Malaysian Sign Language Recognition and alphabets algorithm using deep learning models and image processing techniques.
- iii. To convert the Malaysian Sign Language and alphabets into text form.
- iv. To analyze the performance of the Malaysian Sign Language Recognition algorithm.

1.3.2 Scopes of Project

To develop an artificial intelligence that can recognize Malaysian Sign Language and the alphabet, a set of data is collected. The data is a static image of people that

perform a specific Malaysian Sign Language and alphabet gesture. Hence, the device to capture the image is determined. To improve the effectiveness of the algorithm to be applied on a personal computer (PC), the camera of the PC itself is used to capture all of the images. Although the built-in PC camera has a lower quality compared to other types of cameras, this approach is used to ensure that the neural network is trained for the worst-case scenario.

Even though the initial data is accumulated in image format, the image then is processed to extract the hands and face landmarks. These landmarks then are used as the input data for the neural network. Instead of training the neural network based on the original image, the neural network is trained based on specific finger joints and facial features that are traced on an empty canvas. This approach is taken because the focus of this project is to classify a gesture according to Malaysian Sign Language and alphabet, hence the finger position and the facial features extraction are cleared before feeding to the neural network.

The neural network was trained based on a deep learning model. The deep learning model eliminates some of the pre-processing problems. Furthermore, the deep learning model can recognize features from its dataset without human interference. This project has used the Convolutional Neural Network (CNN) architecture in the neural network. This is because CNN architecture is excellent at finding strong features in image recognition.

Another scope of the project is that the algorithm can recognize 24 alphabets and 5 words in Malaysian Sign Language. Malaysian Sign Language can be divided into two categories which are the static sign and the dynamic sign. The static sign does not involve a moving gesture while the dynamic sign does. The static sign can be captured