AUTOMATED SIGN LANGUAGE TRANSLATION USING DEEP LEARNING

BY

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ABSTRACT

This project focuses on developing a system for automated static gesture sign language translation using deep learning. With the increasing demand for accessible communication tools, particularly for the hearing-impaired community, the need for reliable sign language translation systems is growing. The main challenge addressed in this project is the recognition and translation of static sign language gestures into text, which is less complex than dynamic gestures involving movement. The methodology involves processing images of static sign language gestures using hand landmark detection with MediaPipe. These landmarks are then normalized and input into a deep learning model, trained on processed dataset images, to predict the corresponding sign. The model architecture consists of multiple dense layers with batch normalization and dropout to ensure robust learning. The system is integrated into a user-friendly application that offers real-time sign language translation through a webcam feed, with features such as dynamic confidence threshold adjustment, translation history tracking, and a sign language dictionary. The results show that the system is capable of accurately recognizing and translating static sign language gestures with high confidence, as validated by the test dataset. The system is efficient, easy to use, and highly adaptable for future enhancements. This project demonstrates the potential of deep learning in bridging communication gaps for the hearing-impaired community and sets the groundwork for future work in dynamic sign language translation.

Area of Study: Deep Learning, Computer Vision
Keywords: Sign Language Translation, Static Gesture Recognition, Deep Learning, MediaPipe, Hand Landmark Detection

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LIST OF SYMBOLS

%	Percentage
@	Indicates a specific version or tag
>	Greater than
<	Less than
+	Addition or combination
-	Subtraction, negation, or separation
/	Division or separation
*	Multiplication or wildcard
=	Equals or assignment
&	Logical AND or conjunction
.	Decimal point or file extension separator
:	Separator
→	Implies or data flow direction
≈	Approximately equal to
x, y, z	Coordinate axes

LIST OF ABBREVIATIONS

MSL	Malaysian Sign Language
ASL	American Sign Language
ISL	Indian Sign Language
AR	Augmented Reality
HCI	Human-Computer Interaction
HMM	Hidden Markov Model
HOG	Histogram of Oriented Gradients
SVM	Support Vector Machine
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
GUI	Graphical User Interface
API	Application Programming Interface
RGB	Red, Green, Blue (color model)
BGR	Blue, Green, Red (color model)
FPS	Frames Per Second
IDE	Integrated Development Environment
CPU	Central Processing Unit
GPU	Graphics Processing Unit
RAM	Random Access Memory
SSD	Solid State Drive
NVMe	Non-Volatile Memory Express
CUDA	Compute Unified Device Architecture
cuDNN	CUDA Deep Neural Network
SGD	Stochastic Gradient Descent
ReLU	Rectified Linear Unit

Chapter 1
Introduction

1.1 Problem Statement and Motivation

In Malaysia, the communication barrier between the deaf and hearing communities is a prevalent issue, particularly for the Deaf community that uses Malaysian Sign Language (MSL). This gap in communication is not only a challenge within the local population but also extends to interactions with international communities, as MSL differs from other sign languages like American Sign Language (ASL) or Indian Sign Language (ISL). The difficulty in communication arises primarily from the lack of familiarity with MSL in the hearing population. This lack of understanding restricts the social inclusion of the deaf community and limits their access to essential services and opportunities, such as education and employment.

Moreover, the existing sign language recognition systems, although present in the research and development domain, are still limited in their capabilities. These systems often fail to address variability in gestures, such as those that differ between left and right hands. Additionally, most systems are designed to recognize signs from only one language or have limited language support, making them less versatile for real-world application, especially in multilingual societies like Malaysia. The lack of an efficient, accessible, and multilingual sign language translation system motivated this project. The aim is to bridge this communication gap by developing a system that automatically translates static MSL gestures into text, which can be understood by both the deaf and hearing populations. This project focuses on recognizing and translating static MSL gestures into text, leveraging deep learning and computer vision techniques to provide real-time translation in a user-friendly application.

By creating this system, the goal is not only to aid communication within Malaysia but also to enable the deaf community to communicate internationally. The multilingual aspect of the system (supporting English, Malay, Chinese, and Tamil) helps ensure that MSL signs can be translated into languages that are widely spoken, thus fostering better interaction not only within Malaysia but also across borders, especially where English serves as a common language. Ultimately, this system is designed to improve inclusivity and facilitate global communication, making MSL more accessible to a broader audience.

1.2 Objectives

The main goal of this project is to construct a deep learning system designed to identify and convert static Malaysian Sign Language (MSL) gestures into readable text as events unfold in real time. This system targets a broad range of gestures, including all letters from A to Z, numbers ranging from 0 to 10, and essential everyday words like "Drink," "Eat," and "Help." The focus lies on achieving a high level of accuracy, specifically exceeding 90%, by utilizing a standard webcam to capture hand movements under carefully controlled conditions. This setup ensures the system can process gestures reliably, providing a foundation for effective communication by translating visual signs into text instantly.

Another key aim is to develop a system capable of managing variations in handedness with precision. This involves recognizing sign language gestures performed with either the left hand or the right hand and translating them accurately into text. To accomplish this, the project employs preprocessing techniques such as landmark normalization, which adjusts the position and orientation of hand landmarks based on the wrist's location. This method helps the system adapt to different hand preferences, ensuring it works well for all users regardless of which hand they use to sign.

The system also intends to provide real-time translation capabilities into four distinct languages: English, Malay, Chinese, and Tamil. This feature aims to make the system accessible to a diverse audience, covering the major linguistic groups found in Malaysia and potentially beyond. By supporting multiple languages, the system addresses the needs of users from different cultural backgrounds, allowing them to receive translations in their preferred language as gestures are made, which enhances its practical application across various communities.

The project includes the creation of a straightforward graphical user interface using Tkinter to facilitate user interaction. This GUI serves as the main point of contact, offering a clear and simple layout that allows users to operate the system without confusion. It provides essential functions like starting the webcam, selecting translation languages, and viewing results,

making the technology approachable for individuals who may not have extensive technical experience, thus improving overall usability.

Another objective is to integrate real-time translation feedback and a history display into the system. This feature enables users to see the signs the system recognizes as they happen, along with a record of previously translated signs and their corresponding text outputs. The history display acts as a reference, letting users review past interactions to confirm accuracy or revisit earlier conversations. This addition supports continuous learning and communication, making the system a more reliable tool over time.

The system will also incorporate the ability to adjust its confidence threshold dynamically based on the clarity of the input. This means the system only proceeds with translating a sign when it is certain of the recognition, preventing errors from uncertain gestures. By fine-tuning this threshold, the project ensures the translations remain trustworthy, which is critical for maintaining user confidence and the system's effectiveness in real-world settings.

The final aim of this project is to deliver a fully functional sign language translation system that benefits the deaf community effectively. This system seeks to reduce the communication barrier between deaf individuals and those who do not understand sign language, as well as between different language and cultural groups. By providing a practical solution that operates smoothly and meets user needs, the project contributes to greater inclusion and understanding, fostering better interactions in everyday life.

1.3 Project Scope

The scope of this project focuses on the development of a software application that recognizes and translates static MSL gestures into text. The system will be limited to recognizing and translating **static gestures** such as the alphabet (A-Z), numbers (0-10), and specific words like "Drink," "Eat," "Me," "Sorry," "You," "Wrong," and "Help." Dynamic gestures, such as those used for complex phrases or sentences, will not be addressed in this initial phase, as they present a much higher level of complexity that requires more advanced models and real-time processing.

The system will use a **webcam** to capture hand gestures and rely on **MediaPipe**, a powerful library for real-time hand tracking, to detect hand landmarks. These landmarks will be processed using a **deep learning model** that will be trained on a custom dataset of MSL gestures. **Preprocessing** techniques such as landmark normalization will be applied to ensure accurate recognition of gestures, regardless of whether the left or right hand is used. Additionally, the system will offer **multilingual translation** capabilities, translating recognized signs into English, Malay, Chinese, and Tamil, making it suitable for diverse linguistic needs within Malaysia and beyond.

The **GUI** will be simple yet functional, offering an intuitive interface for users to interact with the system. The system will provide real-time feedback, showing the recognized gesture and its translation, with an adjustable confidence threshold to filter out uncertain translations. The scope of this project does not extend to recognizing dynamic gestures or translating full sentences, but it provides a solid foundation for future work in these areas.

1.4 Contributions

This project brings meaningful progress to the fields of assistive technology and sign language recognition through several notable contributions. One key achievement is the effective use of an existing MSL dataset which downloaded from Kaggle. Since MSL datasets are limited and handedness is often overlooked in research, this project leverages this resource to address a critical gap, adapting it to support future studies in MSL recognition with careful application.

Another vital contribution lies in enhancing the preprocessing techniques to better manage handedness variations. Traditional sign language recognition systems often struggle with gestures from either hand, leading to inconsistent results. This project introduces a method that normalizes landmarks using the wrist position as a reference point, which allows for more uniform and precise gesture classification, ensuring the system performs reliably across different users.

The inclusion of a multilingual translation feature represents a major advancement in the project's scope. Unlike many sign language systems that focus on a single language, this

system offers real-time translation of MSL gestures into four widely used languages: English, Malay, Chinese, and Tamil. This capability extends the system's reach, making it a versatile tool for communication among diverse linguistic and cultural groups, not only within Malaysia but also in international contexts where these languages are spoken, thus broadening its impact.

The project also contributes by building a real-time translation system equipped with a user-friendly graphical user interface developed with Tkinter. This interface simplifies interaction by providing clear controls and displays, supported by features such as translation history, immediate feedback on recognized signs, and the option to adjust the confidence threshold. These elements enable users, even those with minimal technical knowledge, to engage with the system effectively. By connecting deaf and hearing communities through this accessible technology, the project offers a practical solution that enhances communication and supports social inclusion on a daily basis.

1.5 Report Organization

This report is organized to provide a comprehensive view of the development, evaluation, and testing of the automated MSL translation system. Chapter 2, **Literature Review**, will provide an in-depth exploration of the technologies, methodologies, and existing systems related to sign language recognition, with a particular focus on deep learning and computer vision approaches. It will also cover the hardware, software, and algorithms that are central to the project, setting the context for the technology used in the system. In Chapter 3, **System Methodology/Approach**, the overall approach taken in developing the system will be outlined. This chapter will explain the design decisions, the architecture of the system, and the specific methodology used to recognize and translate static MSL gestures into text. The design and functionality of the system will be further detailed in Chapter 4, **System Design**, where system diagrams and component interactions will be presented to provide a clearer understanding of how the system operates. Chapter 5, **System Implementation**, will focus on the technical setup of the system, including hardware and software configurations. It will provide insights into the steps involved in implementing the system, along with details on the challenges encountered during the process. In Chapter 6, **System Evaluation and Discussion**, the report will present the evaluation of the system, including performance metrics, testing results, and an analysis of the challenges faced during development. This chapter will also assess how well the objectives

of the project have been achieved. Finally, Chapter 7, **Conclusion and Recommendation**, will conclude the report by summarizing the key findings of the project, discussing the implications of the work, and offering suggestions for future improvements and research in the field of sign language recognition.

Chapter 2
Literature Review

2.1 Review of the Technologies

2.1.1 Dataset

Datasets provide the images needed to train models for sign language recognition. The Malaysian Sign Language Image Dataset includes 26 alphabet signs from A to Z, 11 number signs from 0 to 10, and seven single word signs such as "You," "Sorry," "Eat," "Drink," "Wrong," "Me," and "Help" [1]. Each category contains multiple .jpg and .png files, organized in subfolders for easy access. The images show hands in various poses against different backgrounds, offering a range of examples for the model to learn from. This variety helps the system handle real-world conditions, such as slight changes in lighting or hand angle. The dataset supports static signs, where each image captures a single gesture without movement. It ensures the model learns from relevant examples, like the distinct shapes for "A" or "drink."

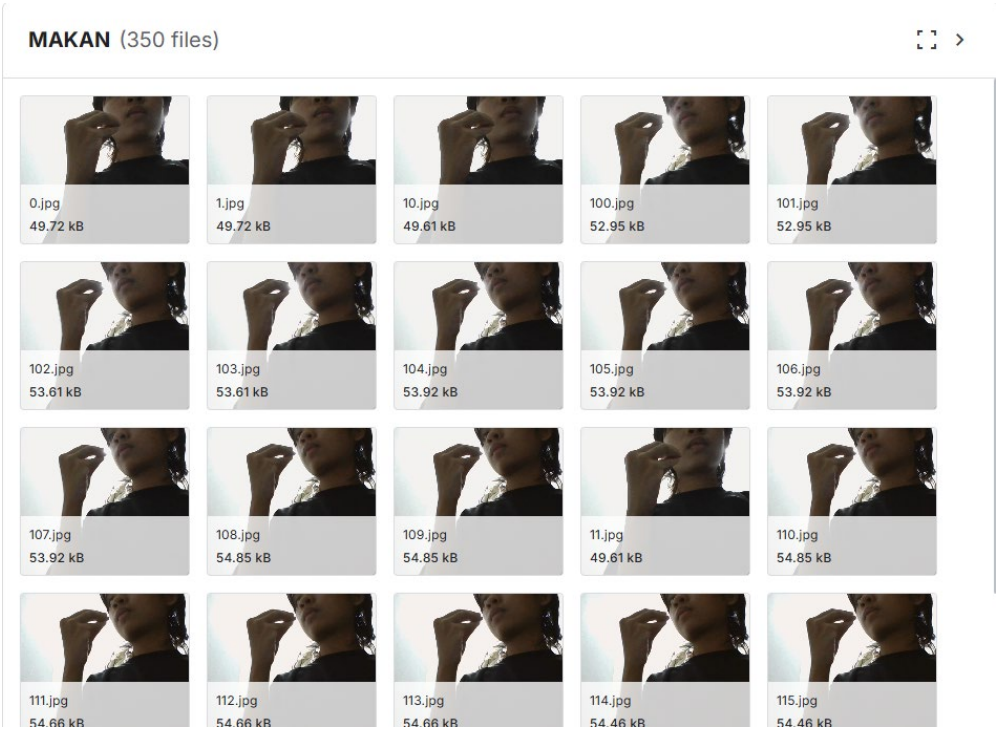

Figure 2.1.1 Sample MSL Dataset Images [1]

The data comes from Kaggle, shared by Isawasan to aid work on regional sign languages [1]. It totals thousands of files, giving enough samples for effective training. The images use

standard formats, which work well with libraries for loading and processing. This resource enables the creation of a balanced set, where alphabet signs teach letter recognition, numbers handle counting, and words cover basic terms. The dataset's design fits the needs of sign recognition systems, allowing classification of gestures with reliability. It reflects practical use, with hands positioned as in everyday signing. This setup makes it a key part of building accurate models.

2.1.2 MediaPipe

MediaPipe detects hands in images and videos. It analyzes frames to locate hands and mark 21 key points on each [2]. The tool works on standard computers without extra hardware. It handles up to two hands per frame and labels them as left or right. This feature supports signs that use both hands, like some numbers. The system sets a confidence level of 0.5 to balance speed and accuracy.

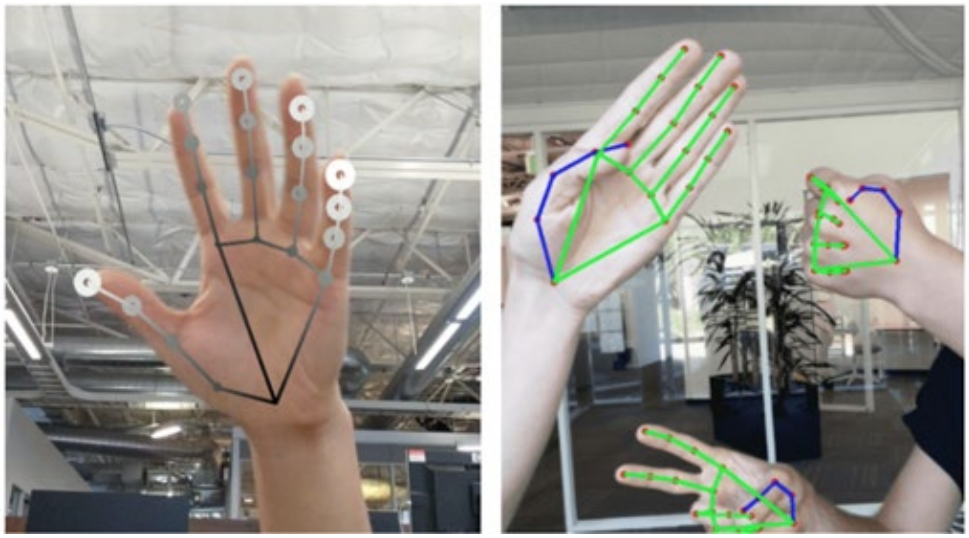

Figure 2.1.2 Hand Landmark Model [2]

MediaPipe extracts x, y, and z coordinates for each point, giving position and depth [2]. It normalizes these points to reduce differences from camera angle or hand size. The tool flips right-hand data to match left-hand patterns, creating uniform inputs. This adjustment helps models learn from all examples without bias. MediaPipe runs in a loop for video, updating every 30 milliseconds. This pace fits needs for quick responses.

2.1.3 OpenCV

OpenCV processes images and videos. It loads files from datasets and converts colors from BGR to RGB for other tools [3]. The library flips video frames to create a mirror effect for users. It draws lines between key points and adds text like "Success" or "Low Confidence" based on scores. This feedback shows if the detection works well.

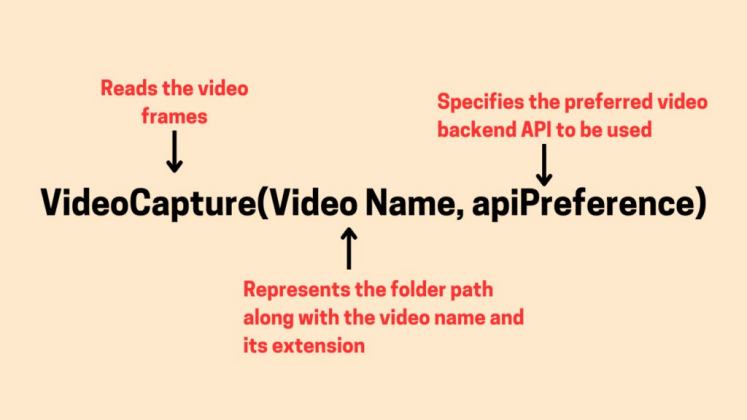

Figure 2.1.3 Capturing the video frame [3]

OpenCV resizes images to fit displays, such as scaling photos to 380 by 380 pixels [3]. It captures video from webcams, reading frames in loops for live use. The library supports rectangles around messages, using green for good detections and red for low ones. OpenCV works with arrays to handle data, ensuring smooth operation on standard hardware. This tool fits needs for frame management.

2.1.4 TensorFlow/Keras

TensorFlow and Keras build and train neural networks. Keras stacks layers with 384, 192, and 96 neurons, using ReLU activation [4]. The setup includes batch normalization to stabilize data and dropout to drop neurons at 0.25 and 0.15 rates. The output uses softmax to match sign classes. TensorFlow compiles with SGD at 0.002 learning rate and 0.9 momentum. Training runs 25 epochs with batch size 48, tracking accuracy.

The libraries load data as arrays, filtering classes with few samples [4]. Labels encode to numbers for classification. Data splits into training and testing sets, with 75% for learning. The

model saves for use in apps, where it predicts from landmarks. This setup identifies MSL signs with reliability. The libraries run on standard computers, supporting accessibility.

2.1.5 Tkinter

Tkinter creates desktop interfaces. It organizes elements like buttons, labels, and canvases in windows [5]. The tool uses frames to group parts, such as controls for language and confidence. It packs items to fill space, allowing the window to resize. Tkinter shows video on canvases, updating with new frames. It includes dropdowns for language choices and sliders for detection levels.

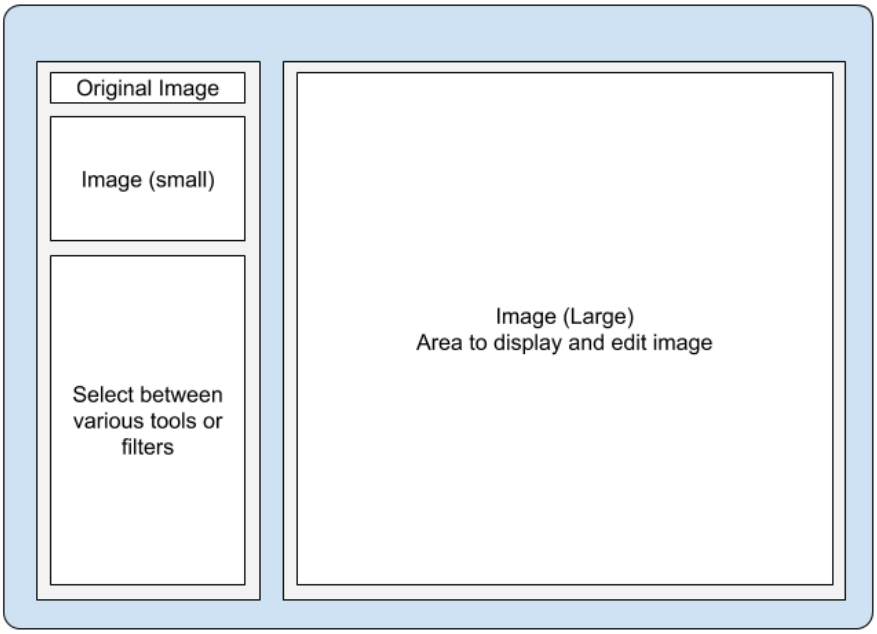

Figure 2.1.5 Tkinter Layout Example [5]

Tkinter handles events, like clicks to start cameras or change settings [5]. It supports text wrapping in labels for long history logs. The library uses styles for buttons, giving a clean look. Tkinter runs with Python, needing no extra installs. This tool fits needs for simple designs. The interface shows translations and history, aiding users in communication.

2.1.6 Googletrans

Googletrans translates text in the app. It uses Google's API to convert words like "drink" to "minum" in Malay [6]. The library maps names to codes, such as "ms" for Malay. It caches results to speed up repeats. The tool processes single words only, leaving alphabet and numbers

unchanged. This setup supports the app's multi-language feature, covering English, Malay, Chinese Simplified, and Tamil.

Googletrans works with a translator object, sending text and codes for output [6]. It handles errors by returning original text if translation fails. The library integrates with dropdowns, updating on language changes. This method ensures quick responses during use. The tool fits the project's needs for accessible translation.

2.1.7 Summary of the Technologies Review

The technologies form the project's core. The dataset supplies images for training, covering MSL signs [1]. MediaPipe detects hands and extracts landmarks, supporting preparation and recognition [2]. OpenCV processes video frames, enabling real-time updates [3]. TensorFlow/Keras trains the model, classifying signs from data [4]. Tkinter builds the interface, offering controls for users [5]. Googletrans handles translations, converting signs to languages [6]. These tools combine to create a reliable system.

The review shows each technology’s role in the process. Detection and extraction feed into training, which powers recognition. The interface delivers results to users, while translation adds language support. This setup ensures the system works as intended. Each tool brings a specific strength, making the system effective for its purpose.

2.2 Review of the Existing Systems

2.2.1 Static and Dynamic Hand-Gesture Recognition for Augmented Reality Applications

Reifinger et al. [7] explored the use of hand-gesture recognition in augmented reality (AR) applications, focusing on both static and dynamic gestures. The system recognized a predefined set of gestures using vision-based techniques and Hidden Markov Models (HMMs). Static gestures, such as hand poses representing commands (e.g., "stop" or "select"), were classified using feature extraction methods like contour analysis and orientation histograms. Dynamic gestures, involving motion (e.g., waving or circling), were modeled using HMMs to capture temporal patterns. The system was tested in an AR environment where users interacted with virtual objects, achieving a recognition accuracy of around 85% for static gestures and 78% for dynamic ones.

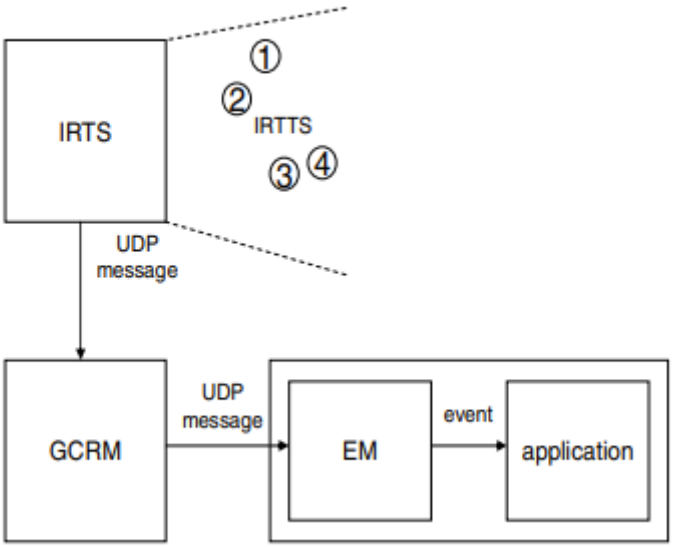

Figure 2.2.1: System Architecture for Static and Dynamic Gesture Recognition in AR [7].

The study highlighted the potential of gesture-based interfaces in AR but noted several limitations. The system required a controlled environment with consistent lighting and a plain background to ensure accurate feature extraction. Variability in hand orientation and speed of dynamic gestures also affected performance, as the HMMs struggled with non-uniform motion patterns. For the proposed MSL recognition system, this work provides insights into static gesture classification, which aligns with the project's focus on alphabets, numbers, and basic words. However, the reliance on traditional feature extraction and the lack of support for handedness variability indicate a need for more robust methods, such as deep learning and landmark-based detection, which are employed in this project.

2.2.2 Real Time Hand Gesture Recognition System for Dynamic Applications

Rautaray [8] proposed a real-time hand gesture recognition system for dynamic applications, focusing on human-computer interaction (HCI). The system used skin colour segmentation to detect hands in video frames, followed by feature extraction techniques such as edge detection and centroid distance to classify gestures. Dynamic gestures were tracked using a trajectory-based approach, where the movement of the hand's centroid over time was analyzed to identify patterns like swipes or circles. The system achieved an accuracy of 82% for a small set of predefined gestures but struggled with complex backgrounds and varying lighting conditions.

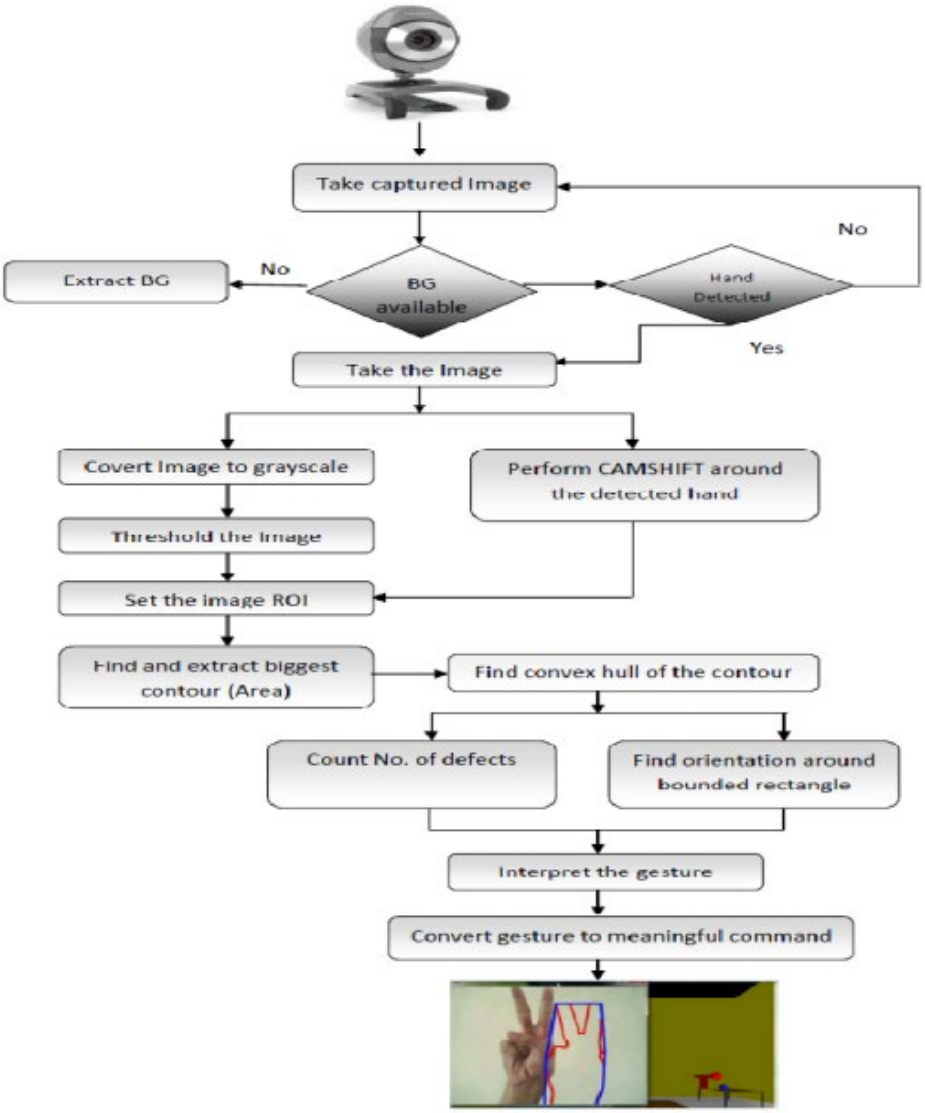

Figure 2.2.2: Workflow of Dynamic Gesture Recognition System [8]

The study emphasized the importance of real-time performance in HCI applications, a key requirement for the proposed MSL system. However, the reliance on skin colour segmentation made the system sensitive to environmental noise, a limitation also noted in other traditional approaches [9]. Additionally, the system did not address static gestures or handedness variability, both of which are critical for MSL recognition. The proposed system improves upon this by using MediaPipe for landmark detection, which is more robust to environmental variations, and a CNN for classification, enabling better handling of static gestures and handedness.

2.2.3 Signar: A Sign Language Translator Application with Augmented Reality Using Text and Image Recognition

Soogund and Joseph [10] developed Signar, an AR-based sign language translator application for Indian Sign Language (ISL). The system combined text and image recognition to translate static gestures into text, which was then overlaid in an AR environment using a smartphone camera. Gestures were captured via the camera, and a pre-trained model (based on traditional machine learning techniques like Support Vector Machines) classified the signs. The system supported a limited set of static gestures (e.g., alphabets) and achieved an accuracy of 80%. The AR interface allowed users to see translations in real-time, enhancing accessibility for hearing individuals interacting with deaf signers.

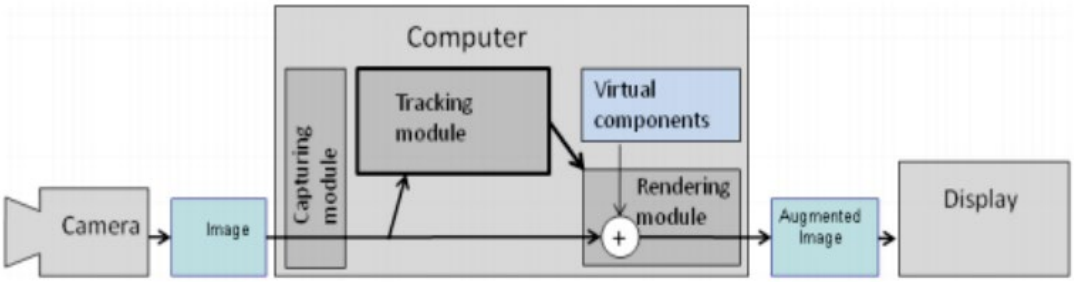

Figure 2.2.3: Signar System Overview [10]

While innovative, Signar faced challenges with scalability and robustness. The system was limited to a small gesture set and struggled with variations in hand orientation and lighting, as traditional machine learning models lacked the generalization ability of deep learning approaches. For the proposed MSL system, Signar's use of AR provides inspiration for potential future enhancements, such as displaying translations in an AR interface. However, the proposed system leverages deep learning and MediaPipe to achieve higher accuracy and support for both left and right-hand gestures, addressing the limitations of traditional methods.

2.2.4 American Sign Language Recognition Using Deep Learning and Computer Vision

Bantupalli and Xie [11] proposed an American Sign Language (ASL) recognition system using deep learning and computer vision. The system employed a CNN to classify static ASL gestures (alphabets A to Z) captured via a webcam. The dataset consisted of RGB images collected from multiple users, with preprocessing steps like image normalization and background subtraction to improve model performance. The CNN model achieved an accuracy of 92% on the test set, demonstrating the effectiveness of deep learning in handling variations

in hand appearance and orientation. The study also explored transfer learning by fine-tuning a pre-trained VGG16 model, which further improved accuracy to 94%.

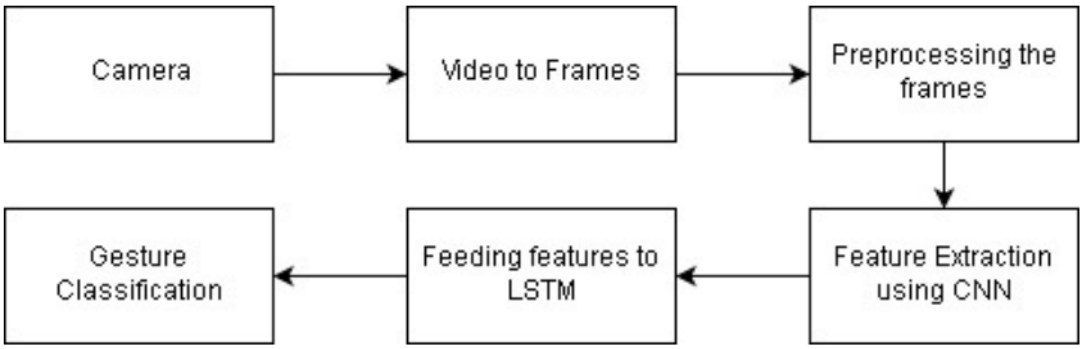

Figure 2.2.4: CNN-Based ASL Recognition Pipeline [11]

This work is highly relevant to the proposed MSL system, as it demonstrates the potential of CNNs for static gesture recognition, a core component of this project. The use of a diverse dataset and preprocessing techniques aligns with the proposed approach of creating a custom MSL dataset and normalizing hand landmarks. However, the system did not address handedness variability explicitly, a challenge the proposed system tackles through landmark normalization with MediaPipe. Additionally, the focus on ASL highlights the need for similar research on MSL, which remains underexplored.

2.2.5 Interactive Hand Gesture-based Assembly for Augmented Reality Applications

Radkowski [12] investigated hand gesture recognition for AR-based assembly applications, focusing on static gestures to control virtual assembly tasks. The system used a vision-based approach, extracting features like hand contours and finger positions to classify gestures such as "grab," "release," and "rotate." A rule-based classifier was employed, achieving an accuracy of 83% in controlled conditions. The study emphasized the importance of intuitive gesture interfaces in AR, allowing users to interact with virtual objects naturally.

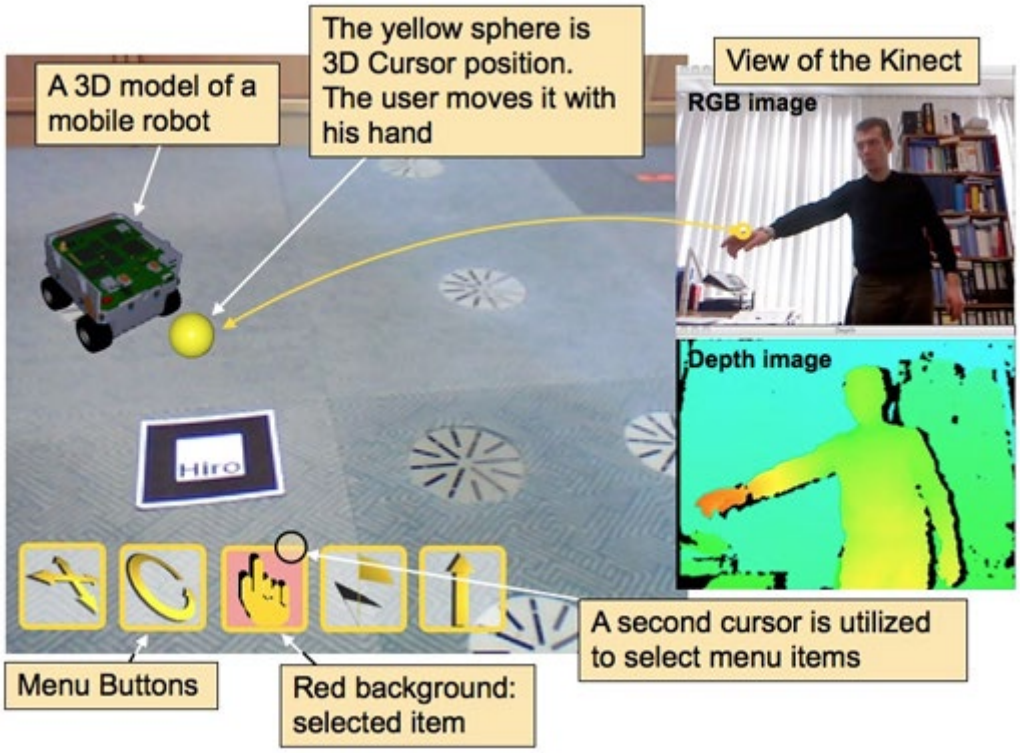

Figure 2.2.5: Gesture Recognition for AR Assembly [12]

The system's reliance on traditional feature extraction made it sensitive to lighting and background noise, similar to other early SLR systems [12]. It also lacked support for dynamic gestures and handedness variability, limiting its applicability to diverse user scenarios. For the proposed MSL system, this work underscores the potential of gesture-based interfaces but highlights the need for more robust methods. The use of MediaPipe and CNNs in the proposed system addresses these limitations, enabling real-time recognition of static MSL gestures with improved robustness to environmental variations.

2.2.6 Sign Language Recognition: A Deep Survey

Rastgoo et al. [13] provided a comprehensive survey of deep learning techniques in SLR, covering datasets, methodologies, and challenges. The study reviewed various deep learning architectures, including CNNs, Recurrent Neural Networks (RNNs), and 3D CNNs, for both static and dynamic gesture recognition. For static gestures, CNNs were found to be highly effective, with accuracies often exceeding 90% on benchmark datasets like the ASL Alphabet dataset. The survey also discussed the use of depth data and RGB-D cameras to improve recognition accuracy, particularly for complex gestures involving motion.

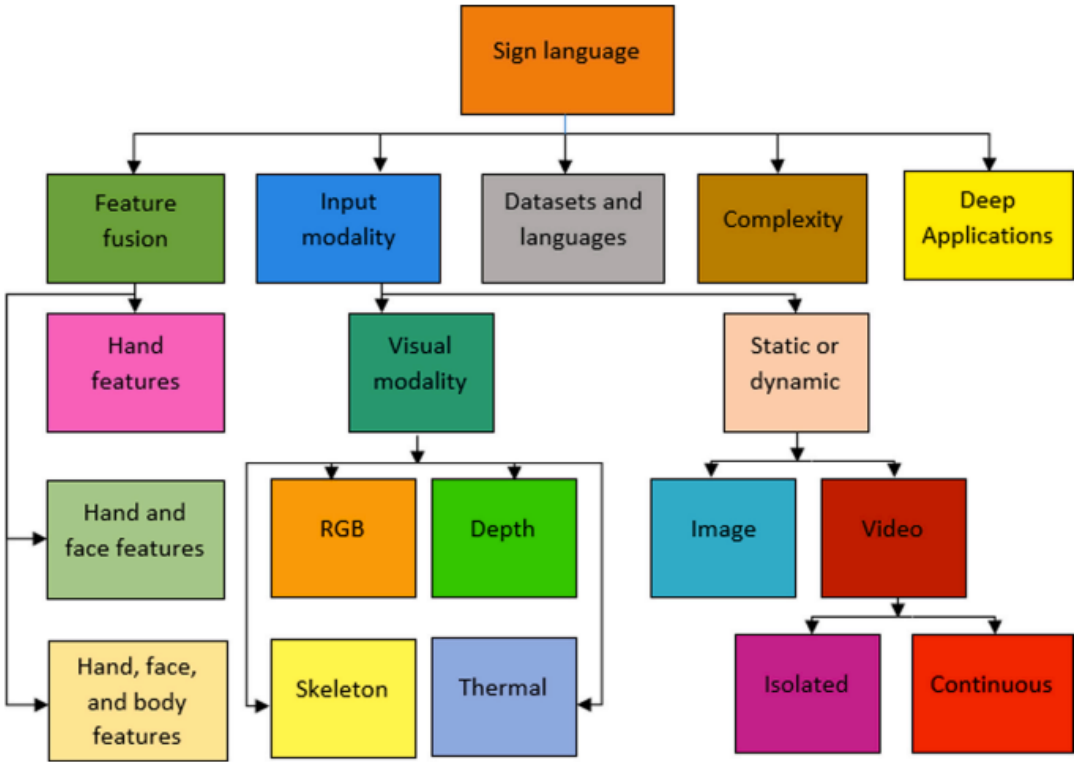

Figure 2.2.6: Deep Learning Architectures for SLR [13]

A key finding was the scarcity of datasets for less-studied sign languages, such as MSL, which hinders the development of accurate recognition systems. The survey also highlighted challenges like handedness variability and the need for real-time performance in practical applications. This aligns with the goals of the proposed MSL system, which addresses dataset scarcity by creating a custom MSL dataset and uses MediaPipe to handle handedness variability. The survey's emphasis on deep learning supports the proposed approach of using a CNN for gesture classification, ensuring high accuracy and real-time performance.

2.2.7 Real Time Indian Sign Language Recognition System to Aid Deaf-Dumb People

Rajam and Balakrishnan [14] developed a real-time Indian Sign Language (ISL) recognition system to assist deaf individuals. The system used a vision-based approach, capturing static gestures (alphabets and numbers) with a webcam. Features were extracted using Histogram of Oriented Gradients (HOG), and a Support Vector Machine (SVM) was used for classification. The system achieved an accuracy of 85% on a small dataset of 10 gestures. The study emphasized real-time performance, with a processing speed of 20 frames per second, suitable for practical applications.

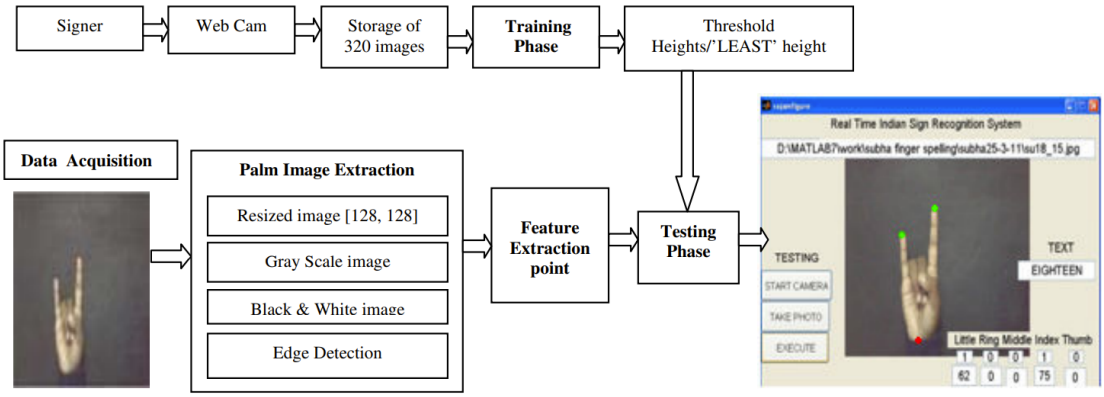

Figure 2.2.7: ISL Recognition System Workflow [14]

However, the system's reliance on traditional machine learning and HOG features limited its robustness to variations in lighting and hand orientation. It also did not address handedness variability, a critical challenge for sign language recognition. The proposed MSL system improves upon this by using deep learning (CNNs) for better generalization and MediaPipe for precise hand landmark detection, ensuring accurate recognition of static gestures performed with either hand.

2.2.8 A Real-Time System for Recognition of American Sign Language by Using Deep Learning

Taskiran et al. [15] proposed a real-time ASL recognition system using deep learning. The system employed a CNN to classify static ASL gestures (alphabets A to Z) captured via RGB images. The dataset included images from multiple users under varying conditions, with preprocessing steps like resizing and normalization to standardize input data. The CNN model achieved an accuracy of 93% on the test set, with a processing speed of 25 frames per second, making it suitable for real-time applications.

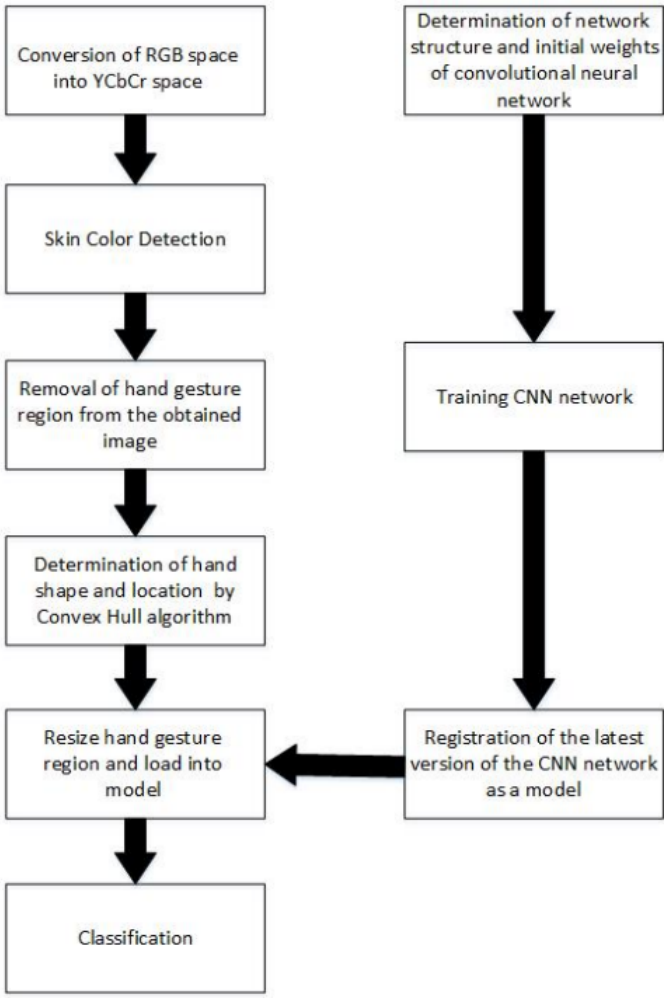

Figure 2.2.8: Real-Time ASL Recognition Using Deep Learning [15]

The study also explored the use of data augmentation (e.g., rotation, scaling) to improve model robustness, a technique that could benefit the proposed MSL system. However, the system did not explicitly address handedness variability, and the focus on ASL datasets underscores the lack of similar research for MSL. The proposed system builds on this work by using a custom MSL dataset and incorporating handedness normalization, ensuring broader applicability in the Malaysian context.

2.2.9 Real-Time American Sign Language Recognition Using Desk and Wearable Computer Based Video

Starner et al. [16] presented one of the earliest works on real-time ASL recognition, using desk and wearable computer-based video systems. The system captured gestures via cameras mounted on a desk or worn by the user, focusing on dynamic gestures for sentence-level recognition. Features were extracted using colour-based tracking and motion analysis, and an

HMM was used for classification. The system achieved an accuracy of 85% for a small set of ASL sentences but required users to wear colored gloves to improve tracking accuracy.

This work laid the foundation for vision-based SLR but highlighted several limitations. The reliance on wearable devices and colored gloves made the system intrusive, and the accuracy dropped in uncontrolled environments due to lighting variations. For the proposed MSL system, this study provides historical context but underscores the need for non-intrusive methods. The use of MediaPipe and deep learning in the proposed system eliminates the need for wearable devices, enabling more practical and accurate recognition of static MSL gestures.

2.2.10 Strengths and Weakness of the Existing Systems

The reviewed works demonstrate a range of approaches to SLR, each with distinct strengths and weaknesses. Reifinger et al. [7] offer a strong integration of static and dynamic gesture recognition within an AR context, providing valuable insights into gesture-based interfaces. However, their reliance on traditional feature extraction methods like contour analysis and HMMs results in a notable sensitivity to environmental noise, such as lighting variations, and a significant lack of support for handedness variability, which limits its applicability to diverse user scenarios like those in MSL recognition. Rautaray [8] excels in its real-time performance for dynamic applications, making it suitable for HCI scenarios with a processing speed that supports practical use. Yet, the dependence on skin colour segmentation introduces a critical weakness in handling complex backgrounds and lighting changes, and the absence of static gesture support and handedness consideration makes it less relevant for the proposed MSL system.

Soogund and Joseph [10] demonstrate an innovative use of AR to display real-time translations, enhancing accessibility for hearing users interacting with deaf signers. However, the system's limited gesture set and reliance on traditional machine learning (SVM) lead to poor robustness against variations in lighting and hand orientation, hindering scalability for broader applications like MSL. Bantupalli and Xie [11] achieve a high accuracy of 92–94% using a CNN for static ASL gestures, showcasing the effectiveness of deep learning and the benefit of transfer learning with pre-trained models like VGG16. Despite this, the lack of explicit handling of handedness variability and the focus on ASL datasets reveal a gap that the proposed MSL system addresses through handedness normalization and a custom dataset.

Radkowski [12] provides an intuitive gesture interface for AR assembly tasks, highlighting the potential of gesture-based control in virtual environments. However, its sensitivity to lighting and background noise due to traditional feature extraction, combined with the absence of dynamic gesture support and handedness variability, limits its practicality for diverse scenarios like MSL recognition. Rastgoo et al. [13] offer a comprehensive survey of deep learning in SLR, providing a broad perspective on methodologies and identifying the critical issue of dataset scarcity for less-studied sign languages like MSL. As a survey, it lacks implementation details, but its insights directly inform the proposed system's focus on deep learning and dataset creation.

Rajam and Balakrishnan [14] achieve real-time performance with a processing speed of 20 fps for ISL recognition, a strength for practical applications. However, their reliance on HOG features and SVM results in limited robustness to lighting and orientation variations, and the lack of handedness support is a notable drawback compared to the proposed system's approach. Taskiran et al. [15] demonstrate a high accuracy of 93% and real-time performance at 25 fps for ASL recognition, enhanced by data augmentation techniques like rotation and scaling. Yet, the absence of handedness handling and the focus on ASL datasets highlight gaps that the proposed system addresses with MSL-specific data and normalization techniques.

Starner et al. [16] provide a pioneering contribution to real-time ASL recognition, laying the foundation for vision-based SLR with early innovations in dynamic gesture recognition. However, the intrusive nature of requiring colored gloves and wearable devices, along with sensitivity to lighting variations, significantly limits its practicality, a weakness the proposed system overcomes with non-intrusive methods using MediaPipe and deep learning.

2.2.11 Summary of the Existing Systems

A table compares prior works with key aspects, focusing on methodology, gesture type, handedness support, dataset focus, and real-time performance. This comparison highlights the strengths and limitations of existing systems.

Study	Methodology	Gesture Type	Handedness Support	Dataset Focus	Real-Time Performance	Key Limitations
Reifinger et al.[7]	Contour analysis, HMMs	Static & Dynamic	No	General gestures	Yes	Sensitivity to lighting, no handedness support.
Rautaray [8]	Skin colour segmentation	Dynamic	No	General gestures	Yes (20 fps)	Environmental noise, no static gestures.
Soogund and Joseph [10]	SVM, AR overlay	Static	No	ISL	Yes	Limited gesture set, lighting sensitivity.
Bantupalli and Xie [11]	CNN, transfer learning	Static	No	ASL	Yes	No handedness support, ASL focus.
Radkowski [12]	Rule-based classifier	Static	No	General gestures	Yes	Lighting sensitivity, no dynamic gestures.
Rastgoo et al.[13]	Survey (CNNs, RNNs, 3D CNNs)	Static & Dynamic	Varies	Multiple languages	Varies	Lack of implementation.
Rajam and Balakrishnan[14]	HOG, SVM	Static	No	ISL	Yes (20 fps)	Lighting sensitivity, no handedness.
Taskiran et al.[15]	CNN, data augmentation	Static	No	ASL	Yes (25 fps)	No handedness support, ASL focus.
Starner et al. [16]	Colour tracking, HMMs	Dynamic	No	ASL	Yes	Intrusive (gloves), lighting sensitivity.

Table 2.2.11 The Summary of Existing Sign Language Recognition System

The existing systems show progress in sign language translation. DeepASL handles ASL sentences with wrist cameras [17]. SignAR uses augmented reality for ISL on mobiles [10]. The ASL real-time system classifies alphabets with CNNs [15]. Bantupalli and Xie focus on vision-based ASL recognition [11]. TSPNet translates BSL videos to text [18]. The machine learning translator covers ISL gestures [19]. Rastgoo et al. survey deep learning methods [13]. These works advance the field, using deep learning for recognition and translation.

The systems vary in scope, from isolated signs to sentences. They rely on cameras and networks for processing. Common challenges include lighting and data limits. The review highlights how these tools inform the project's design for MSL.

Chapter 3

System Methodology/Approach

3.1 System Design Diagram

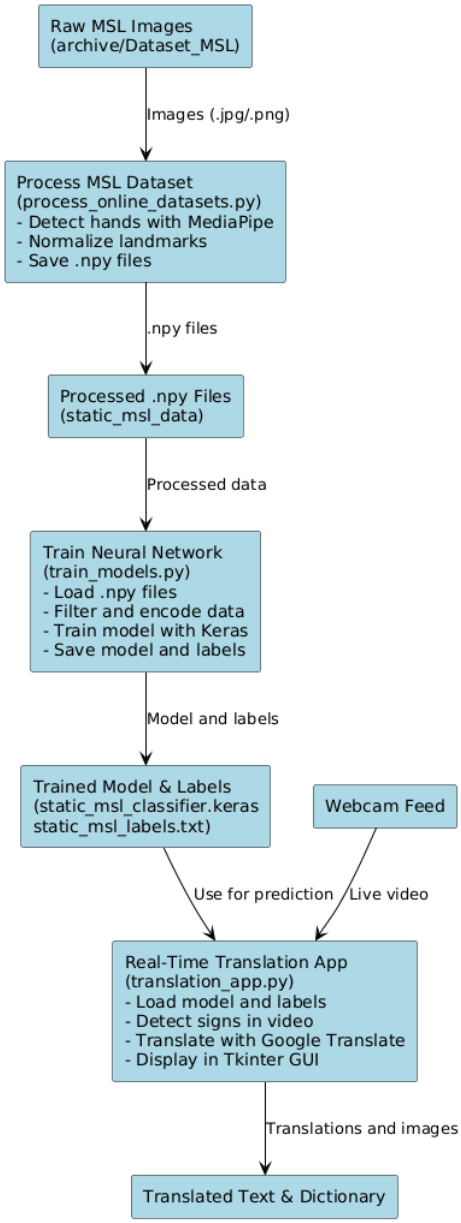

Figure 3.1 System Design Diagram

The System Design Diagram gives a clear view of the Malaysian Sign Language translation system's overall structure. It starts with raw inputs on the left side, where the system takes in MSL dataset images from the archive folder. These images go into the first main block, which handles dataset processing through the process_online_datasets.py script. In this stage, the

system uses MediaPipe to find hands in each image, pulls out the landmark coordinates, normalizes them by setting the wrist as a reference point, mirrors any right-hand data for consistency, and pads the features to a fixed size of 126 if only one hand shows up. It then saves these processed landmarks as numpy files in the static_msl_data directory, ready for the next step. An arrow links this block to an intermediate storage component for the numpy files, which acts as a bridge to keep the data organized before training begins.

From there, the flow moves to the model training block, driven by the train_models.py script. This part loads the numpy files, checks for classes with enough samples by removing any with fewer than two to prevent issues during splitting, encodes the sign labels into numbers, and divides the data into training and testing sets with a 75-25 split while keeping classes balanced. The system builds a neural network using Keras, with layers like dense neurons, batch normalization to stabilize learning, and dropout to cut down on overfitting. It trains the model over 25 epochs with the SGD optimizer, then saves the finished model as static_msl_classifier.keras and the label mappings as static_msl_labels.txt. The diagram shows this output as another storage component, which feeds directly into the final stage.

The real-time translation app block, based on translation_app.py, pulls in the trained model and labels, along with live input from the webcam. Here, the system captures video frames, detects hands again with MediaPipe, normalizes the landmarks just like in processing, predicts the sign using the model, and checks if the confidence beats the user's set threshold while avoiding quick repeats with a 1.5-second buffer. For single-word signs, it calls Google Translate to convert them into the chosen language, such as English or Malay, updates the Tkinter GUI with the result, adds it to the history list, and logs everything. The diagram ends with outputs on the right, including the translated text shown in the app and dictionary images pulled from the dataset for reference. Arrows connect everything in sequence, making the pipeline easy to follow from start to finish, with no extra clutter.

This setup ensures the diagram stays high-level, focusing on how the system turns raw sign language images and video into useful translations without getting bogged down in code details. It highlights the linear flow, where each stage builds on the last, from preparing data to training the classifier to running the interactive app. Developers can see the dependencies, like

how the app needs the model files to work, while non-technical readers grasp the basic steps without needing to know about libraries like OpenCV or TensorFlow.

3.2 System Architecture Diagram

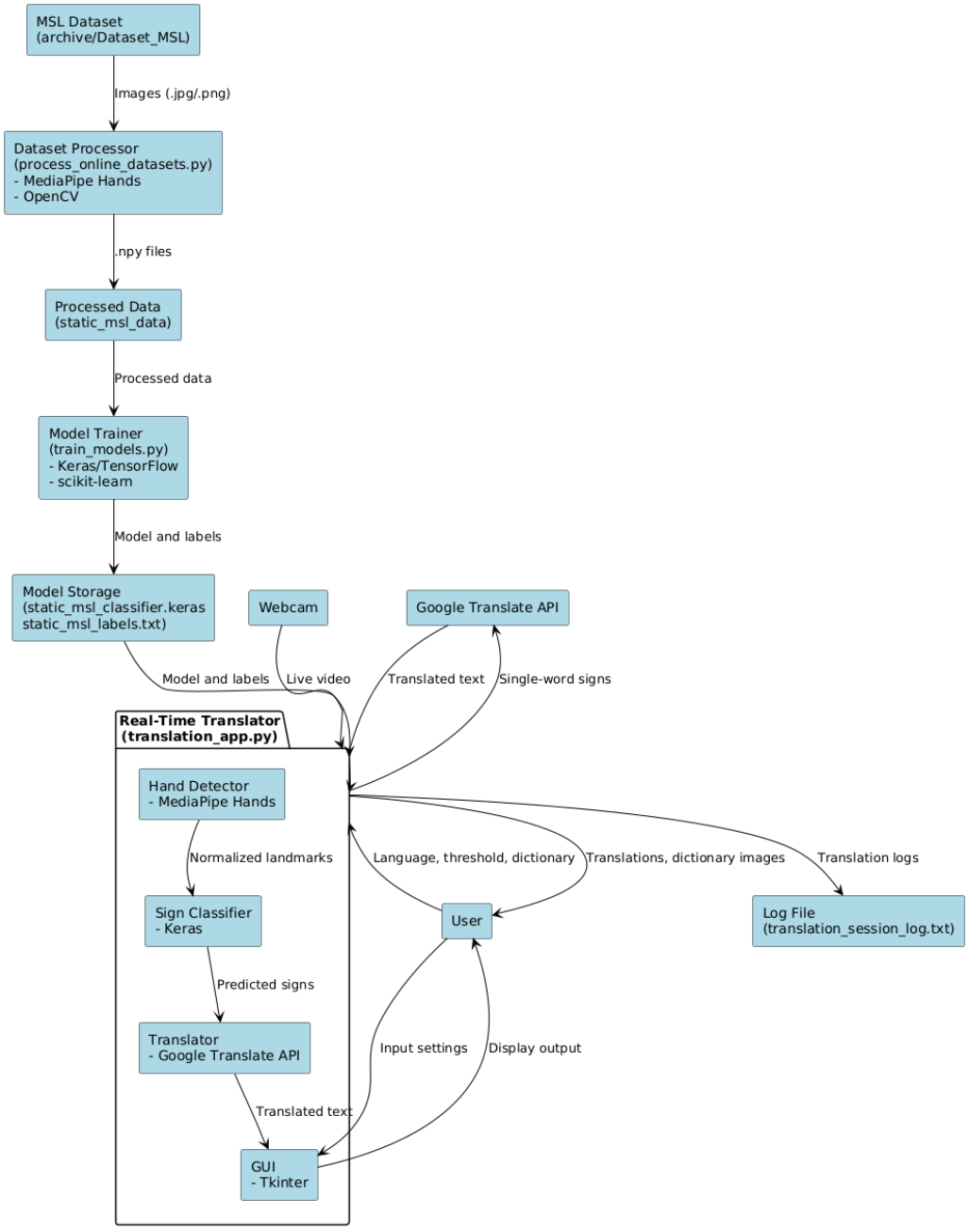

Figure 3.2 System Architecture Diagram

The System Architecture Diagram maps out the technical components of the MSL Translation System and how they work together. The process starts with the MSL Dataset, a storage unit holding raw images in the archive/Dataset_MSL directory, organized into subfolders like

Alphabets and SingleWords. These images feed into the Dataset Processor, which uses the process_online_datasets.py script with MediaPipe Hands and OpenCV to detect hands, extract landmark coordinates, normalize them by setting the wrist as the origin, mirror right-hand data, and pad single-hand data to a fixed size. The processor saves these as numpy files in the Processed Data storage unit, located in the static_msl_data directory.

The Processed Data then moves to the Model Trainer, driven by train_models.py, which uses Keras and TensorFlow to load the numpy files, filter classes with fewer than two samples, encode labels numerically with scikit-learn, split data into training and testing sets, and train a neural network with dense layers, batch normalization, and dropout. The trained model and label mappings are stored in Model Storage as static_msl_classifier.keras and static_msl_labels.txt.

The Real-Time Translator, powered by translation_app.py, integrates several subcomponents: the Hand Detector uses MediaPipe Hands to process live webcam video, the Sign Classifier uses Keras to predict signs from normalized landmarks, the Translator component sends single-word signs to the Google Translate API for conversion into the user's chosen language, and the GUI, built with Tkinter, displays the video feed, translations, history, and dictionary images. The Webcam provides live video to the Translator, which sends translation logs to the Log File.

The User interacts with the GUI to set the language, adjust the confidence threshold, and browse the dictionary, receiving translated text and images in return. Arrows in the diagram trace the data flow, from images to processed data to model to real-time translations, with clear connections between components and external systems. This detailed view helps developers understand the system's structure and dependencies, such as the need for MediaPipe in both processing and real-time stages or the reliance on Google Translate for language conversion.

3.3 Use Case Diagram

The Use Case Diagram shows how actors interact with the MSL Translation System, capturing key functionalities like processing datasets, training models, performing translations, and accessing the dictionary.

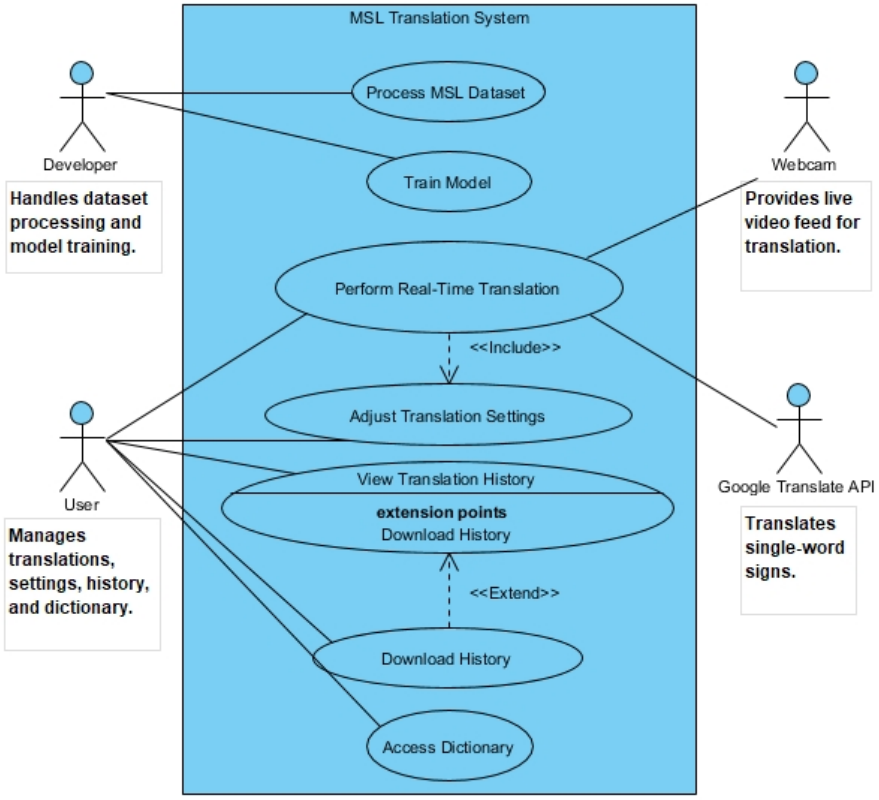

Figure 3.3 MSL Translation System Use Case Diagram

3.3.1 Use Case Description: Process MSL Dataset

Use Case ID	UC001	**Version**	1.0
Use Case	Process MSL Dataset		
Purpose	To process raw MSL dataset images to extract and normalize hand landmarks for model training.		
Actor	Developer		
Trigger	Developer runs process_online_datasets.py.		
Precondition	MSL dataset images are available in archive/Dataset_MSL with subfolders like Alphabets/A or SingleWords/Drink, and MediaPipe Hands is installed.		
Scenario Name	**Step**	**Action**	
Main Flow	1	System scans archive/Dataset_MSL for .jpg or .png images recursively.	
	2	System extracts sign label from the directory name for each image.	
	3	System loads image using OpenCV and converts to RGB.	
	4	System detects hands using MediaPipe and extracts landmarks.	
	5	System normalizes landmarks relative to wrist, mirrors right-hand data, scales z-coordinate, and pads to 126 features if single hand.	
	6	System saves normalized landmarks as .npy files in static_msl_data.	
	7	System updates and prints handedness distribution at the end.	
Alternate Flow – No Hands Detected	4.1	System logs "No hands detected in image" and skips saving.	
	4.2	Back to Main Flow Step 1 for next image.	
Alternate Flow – Image Load Failure	3.1	System logs "Failed to load image" and skips processing.	
	3.2	Back to Main Flow Step 1 for next image.	
Rules		Normalization ensures consistency across hands; padding maintains input size; process only .jpg and .png files.	
Author		Wong Jia Kang	

Table 3.3.1 Use Case Description for Process MSL Dataset

3.3.2 Use Case Description: Train Model

Use Case ID	UC002	**Version**	1.0
Use Case	Train Model		
Purpose	To train a neural network model for classifying MSL signs using processed .npy files.		
Actor	Developer		
Trigger	Developer runs train_models.py.		
Precondition	.npy files are available in static_msl_data, and TensorFlow/Keras and scikit-learn are installed.		
Scenario Name	**Step**	**Action**	
Main Flow	1	System loads .npy files from static_msl_data and extracts features and labels.	
	2	System filters classes with fewer than 2 samples.	
	3	System encodes labels numerically using LabelEncoder.	
	4	System splits data into 75% training and 25% testing sets with stratification.	
	5	System builds sequential neural network with dense layers, batch normalization, and dropout.	
	6	System compiles model with SGD optimizer and trains for 25 epochs.	
	7	System saves trained model as static_msl_classifier.keras and labels as static_msl_labels.txt.	
Alternate Flow – Insufficient Classes	2.1	System exits with error "No classes with sufficient samples."	
Alternate Flow – No Data Found	1.1	System exits with error "No static data found."	
Rules		Minimum 2 samples per class for splitting; use sparse categorical cross-entropy loss.	
Author		Wong Jia Kang	

Table 3.3.2 Use Case Description for Train Model

3.3.3 Use Case Description: Perform Real-Time Translation

Use Case ID	UC003	**Version**	1.0
Use Case	Perform Real-Time Translation		
Purpose	To detect, classify, and translate MSL signs from live video in the GUI app.		
Actor	User, Webcam, Google Translate API		
Trigger	User clicks "Open Cam" in the app.		
Precondition	Trained model and labels are available; webcam is connected; Google Translate API is accessible.		
Scenario Name	**Step**	**Action**	
Main Flow	1	User opens translation_app.py and selects language and confidence threshold.	
	2	System loads model and labels, initializes Tkinter GUI.	
	3	User starts camera; system captures frames from webcam.	
	4	System detects hands with MediaPipe and normalizes landmarks.	
	5	System predicts sign using model.	
	6	If confidence high and new sign after buffer, system translates single words via Google Translate API.	
	7	System updates GUI with translation, adds to history, logs it, and draws landmarks on feed.	
Alternate Flow – No Hands Detected	4.1	System displays "Translation: None" in GUI.	
	4.2	Back to Main Flow Step 3 for next frame.	
Alternate Flow – Low Confidence	5.1	System draws low-confidence indicator on frame.	
	5.2	Back to Main Flow Step 3 for next frame.	
Rules	1.5-second buffer for new signs; translate only single words; confidence threshold 0.5-1.0.		
Author	Wong Jia Kang		

Table 3.3.3 Use Case Description for Perform Real-Time Translation

3.3.4 Use Case Description: Adjust Translation Settings

Use Case ID	UC004	**Version**	1.0
Use Case	Adjust Translation Settings		
Purpose	To customize language and confidence threshold for translations in the GUI.		
Actor	User		
Trigger	User changes dropdown or slider in GUI.		
Precondition	Application is running.		
Scenario Name	**Step**	**Action**	
Main Flow	1	User selects language from dropdown (English, Malay, Chinese Simplified, Tamil).	
	2	User adjusts confidence threshold slider (0.5-1.0).	
	3	System updates settings and clears translation cache.	
	4	System re-translates current sign and history if applicable.	
Alternate Flow – GUI Update Failure	3.1	System logs error and reverts to default settings.	
	3.2	Back to Main Flow Step 1.	
Rules		Changes apply immediately; cache clear ensures accurate re-translations.	
Author		Wong Jia Kang	

Table 3.3.4 Use Case Description for Adjust Translation Settings

3.3.5 Use Case Description: View Translation History

Use Case ID	UC005	**Version**	1.0
Use Case	View Translation History		
Purpose	To display the history of translated signs in the GUI.		
Actor	User		
Trigger	User looks at history label in GUI after translations.		
Precondition	Application is running and signs have been translated.		
Scenario Name	**Step**	**Action**	
Main Flow	1	System retrieves history list.	
	2	System re-translates history into current language.	
	3	System displays wrapped history text in GUI label.	
Alternate Flow – No History	1.1	System displays "History: ".	
Rules	History wraps for readability; updates with language changes.		
Author	Wong Jia Kang		

Table 3.3.5 Use Case Description for View Translation History

3.3.6 Use Case Description: Download History

Use Case ID	UC006	**Version**	1.0
Use Case	Download History		
Purpose	To export translation history as a .txt file and reset session.		
Actor	User		
Trigger	User clicks "Download History" button.		
Precondition	Application is running and history exists.		
Scenario Name	**Step**	**Action**	
Main Flow	1	System opens file dialog for save location.	
	2	User selects file path.	
	3	System writes history with signs and translations to .txt file.	
	4	System resets history, log file, and GUI.	
Alternate Flow – No History	1.1	Button is disabled; no action occurs.	
Alternate Flow – Cancel Dialog	2.1	User cancels; system does not save file.	
	2.2	Back to Main Flow Step 1 if button clicked again.	
Rules	Include timestamps in log; reset clears all session data.		
Author	Wong Jia Kang		

Table 3.3.6 Use Case Description for Download History

3.3.7 Use Case Description: Access Dictionary

Use Case ID	UC007	**Version**	1.0
Use Case	Access Dictionary		
Purpose	To view MSL signs and images by category in the GUI.		
Actor	User		
Trigger	User selects category and sign in dropdowns.		
Precondition	Application is running; MSL dataset images available.		
Scenario Name	**Step**	**Action**	
Main Flow	1	User selects category (Alphabet, Numbers, SingleWords).	
	2	System updates sign dropdown with translated names.	
	3	User selects sign.	
	4	System finds first image in dataset path.	
	5	System resizes and displays image with translated name in canvas.	
Alternate Flow – No Image Found	4.1	System displays "Image not found" in canvas.	
	4.2	Back to Main Flow Step 3 for another sign.	
Alternate Flow – No Category Selected	1.1	System defaults to Alphabet.	
	1.2	Back to Main Flow Step 1.	
Rules	Search for .jpg, .jpeg, .png; resize to fit canvas while keeping aspect ratio.		
Author	Wong Jia Kang		

Table 3.3.7 Use Case Description for Access Dictionary

3.4 Activity Diagram

The Activity Diagram illustrates the workflows of the MSL Translation System, split into three parts for clarity: dataset processing, model training, and real-time translation. Each part uses a swimlane format to assign actions to actors or components, such as Developer, System, User, Webcam, and Google Translate API.

3.4.1 Dataset Processing

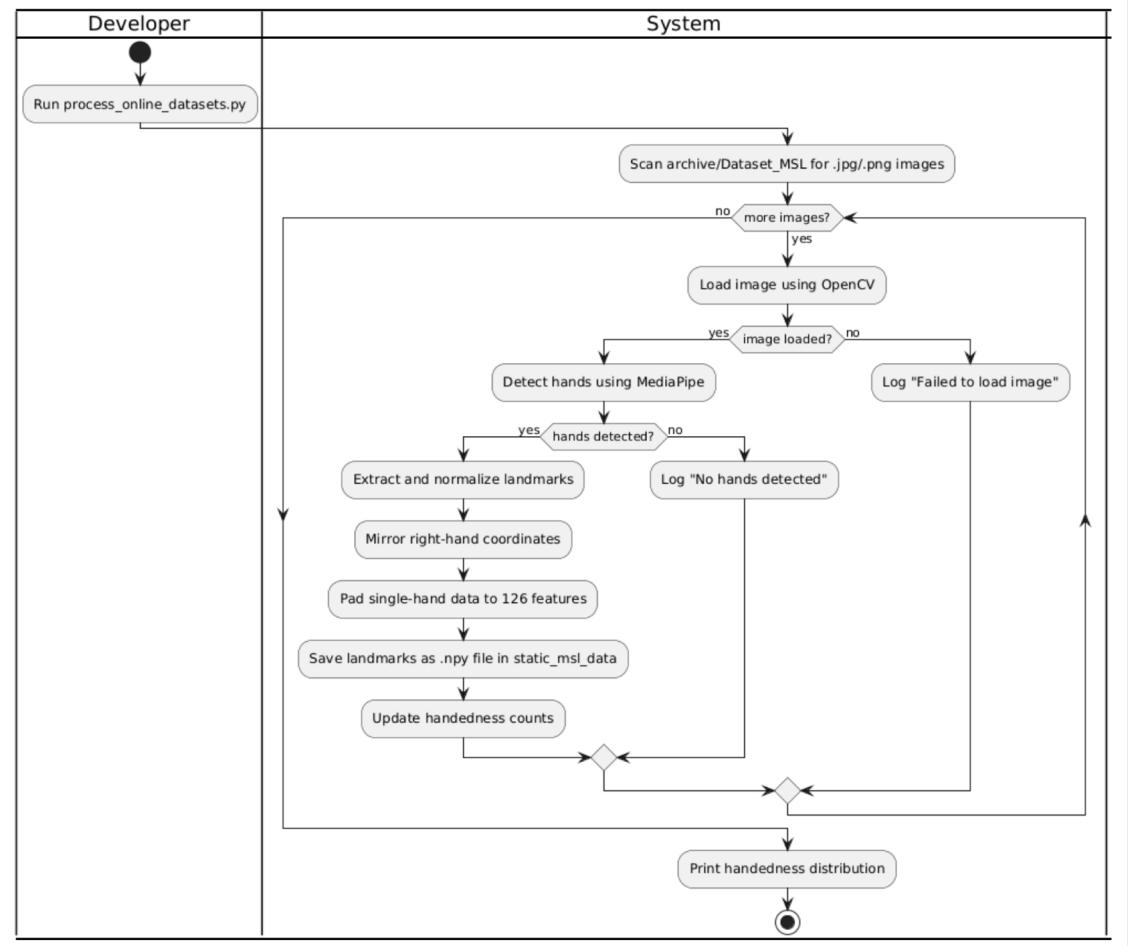

Figure 3.4.1 Dataset Processing Activity Diagram

The activity diagram for dataset processing splits the work between the Developer and the System to show who does what. The Developer kicks things off by running process_online_datasets.py on their computer. The System then takes charge, looking through the archive/Dataset_MSL folder to find .jpg or .png images one by one. For each image, the System tries to load it with OpenCV and checks if it works. If it loads, the System uses MediaPipe to spot hands and see if any appear. When hands show up, the System pulls out the landmark points, adjusts them to line up with the wrist, flips right-hand data to match left-hand format, and adds extra zeros to reach 126 features if only one hand is present.

The System saves these adjusted points as .npy files in the static_msl_data folder and keeps track of whether the hand is left or right. If no hands appear, the System writes "No hands detected" in a log file. If the image won't load, it logs "Failed to load image" and moves on.

This loop repeats until all images are done, and then the System prints a summary of how many left and right hands it found. This setup makes it clear the Developer starts the job, while the System handles the heavy lifting with checks to catch problems along the way.

3.4.2 Model Training

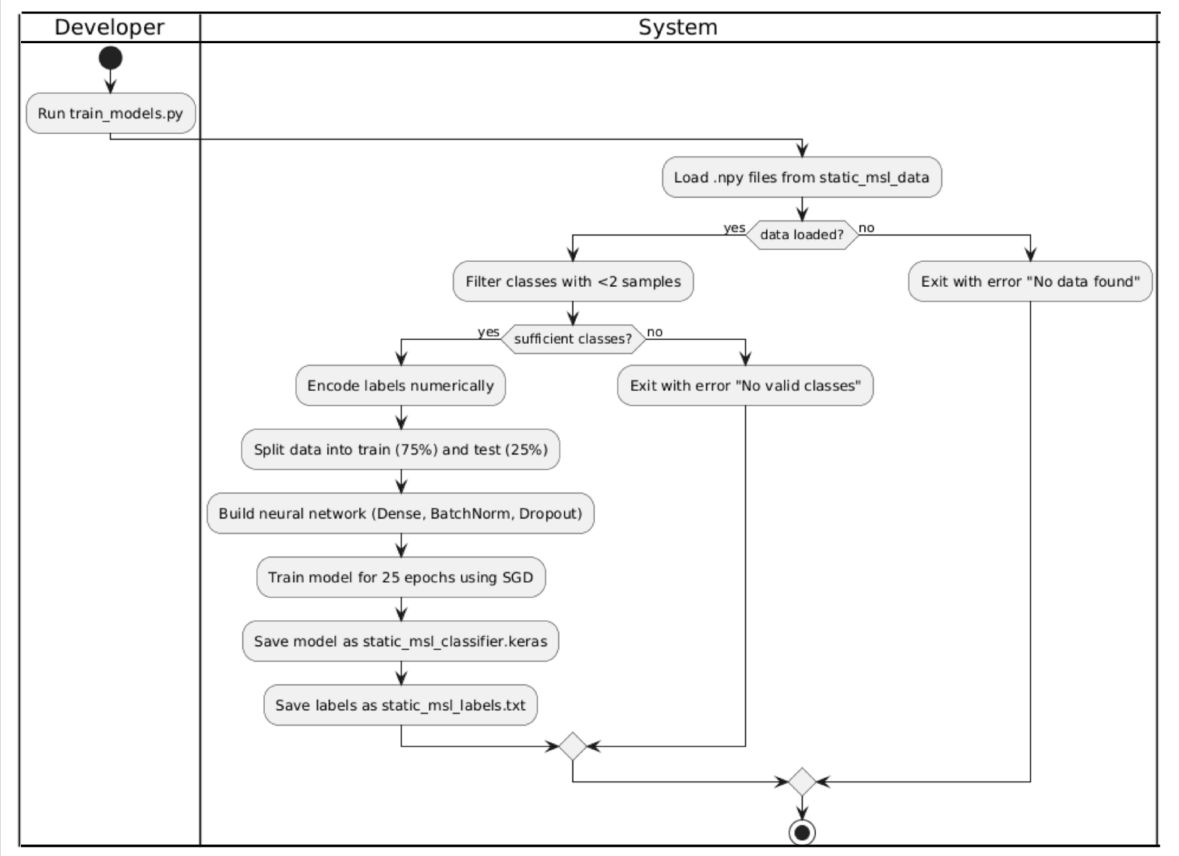

Figure 3.4.2 Model Training Activity Diagram

The activity diagram for model training divides the tasks between the Developer and the System to show their parts. The Developer begins by running train_models.py to start the training process. The System then steps in, grabbing the .npy files from the static_msl_data folder and checking if they load properly. If the files work, the System looks at the sign classes and removes any that have fewer than two samples to avoid issues later. It then checks if enough classes remain to proceed. If there are enough, the System turns the sign labels into numbers, splits the data into 75% for training and 25% for testing while keeping the balance of classes, builds a neural network with dense layers, batch normalization, and dropout to improve accuracy, trains it for 25 rounds with the SGD method, and saves the finished model as static_msl_classifier.keras along with the labels as static_msl_labels.txt. If too few classes exist,

the System stops and shows "No valid classes" on the screen. If no files load, it stops with "No data found". This approach lets the Developer kick off the work, while the System handles the detailed steps and stops if something goes wrong, ensuring a solid model comes out.

3.4.3 Real-Time Translation

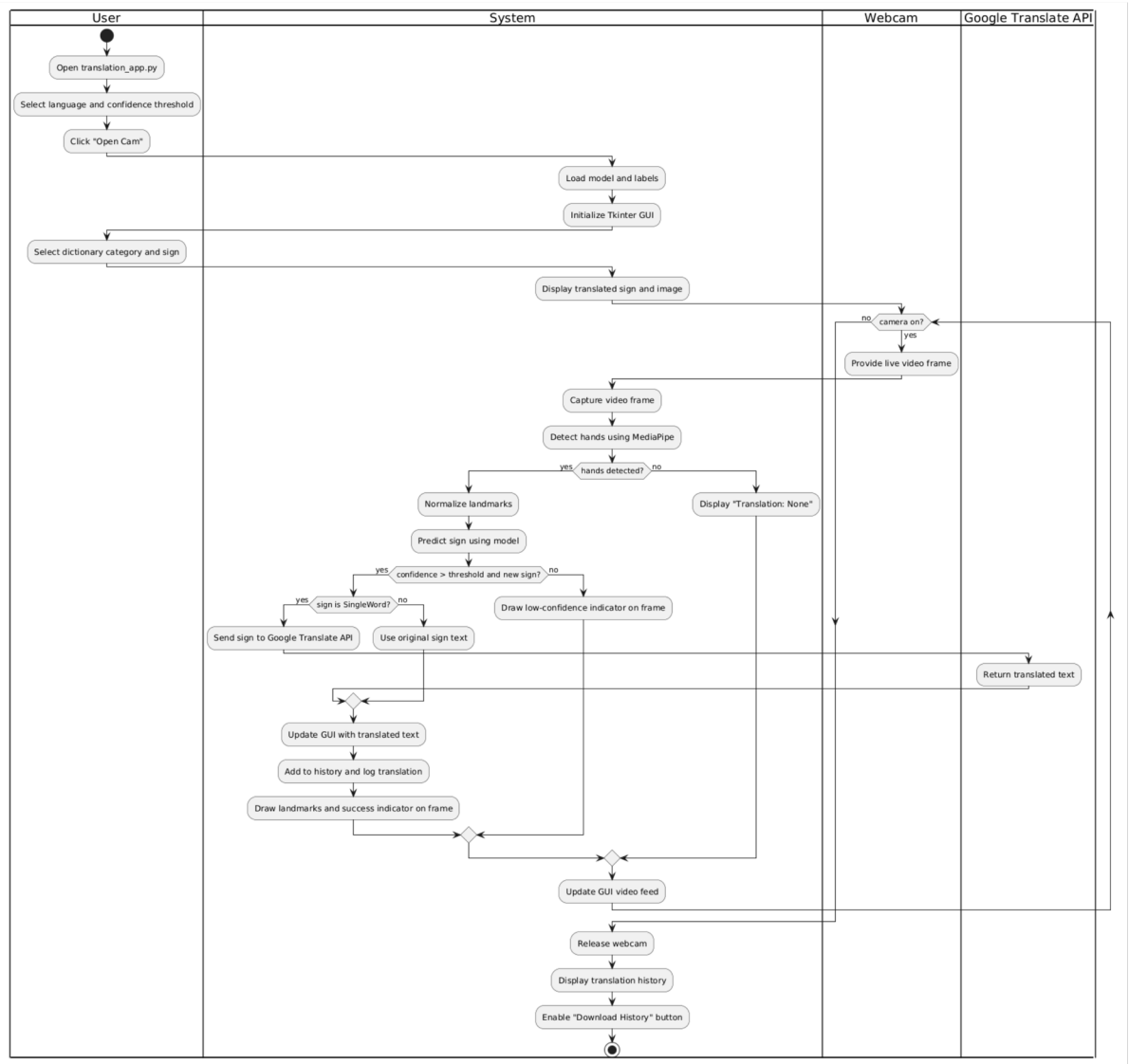

Figure 3.4.3 Real-Time Translation Activity Diagram

The activity diagram for real-time translation splits the work among the User, System, Webcam, and Google Translate API to show their contributions. The User starts by opening translation_app.py on their device, picks a language like English or Malay, sets a confidence level between 0.5 and 1.0, and clicks "Open Cam" to begin. The System then loads the saved model and labels, sets up the Tkinter GUI window, and later displays a dictionary sign and

image when the User chooses a category and sign. The Webcam keeps sending live video frames as long as the camera runs.

The System grabs each frame, uses MediaPipe to find hands, and checks if any appear. If hands show, the System adjusts the landmarks to a standard form, predicts the sign with the model, and sees if the confidence beats the threshold and it's a new sign after a short wait. If it passes and it's a single word, the System sends it to the Google Translate API, which sends back the translated text. If it's not a single word, the System keeps the original sign text. The System then updates the GUI with the text, adds it to the history list, logs it, and draws hand points with a green check if successful. If the confidence is low, it draws a yellow warning; if no hands appear, it shows "Translation: None" on the screen.

The System refreshes the video feed each time. When the User stops the camera, the System shuts it down, shows the history, and turns on the "Download History" button. This layout makes it easy to see how the User starts and guides the process, the System runs the core tasks, the Webcam feeds the video, and the API helps with translations, working together smoothly.

Chapter 4
System Design

4.1 System Block Diagram

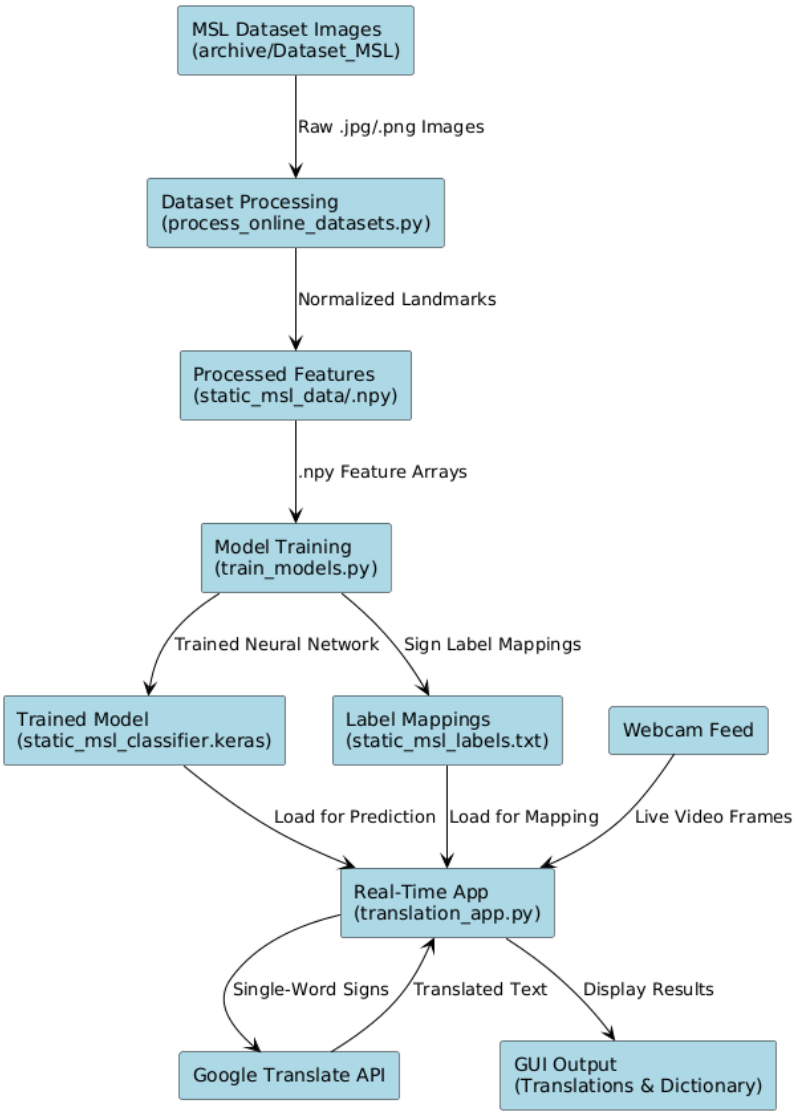

Figure 4.1 System Block Diagram

The System Block Diagram illustrates the system's core components and data pathways. The "MSL Dataset Images" block contains raw images in the archive/Dataset_MSL directory, serving as the starting point for the pipeline. It connects to the "Dataset Processing" block, where process_online_datasets.py loads images using OpenCV, detects hands with MediaPipe, extracts and normalizes landmarks, and saves them as .npy files in the "Processed Features" block. This block holds 126-feature arrays for each image, padded for consistency. The features flow to the "Model Training" block, where train_models.py filters data, encodes labels, splits

into train/test sets, builds a Keras sequential network with dense layers, trains it, and outputs to the "Trained Model" and "Label Mappings" blocks. The trained .keras model and .txt labels are then loaded by the "Real-Time App" block, which is translation_app.py. This block takes input from the "Webcam Feed" block, processes frames with MediaPipe for landmarks, predicts signs using the model, translates single words via the "Google Translate API" block, and displays results in the "GUI Output" block via Tkinter. Arrows show directional data flow, such as images to features to model, ensuring a clear understanding of how the system transforms raw data into usable translations. This design promotes efficiency, with each block handling a specific function to avoid bottlenecks.

4.2 Dataset Processing Design

4.2.1 Overview

The dataset processing design focuses on transforming raw MSL images into standardized feature vectors. It involves scanning the dataset directory, loading images, detecting hands, extracting and normalizing landmarks, and saving as .npy files for later use in training.

4.2.2 System Flowchart for Dataset Processing

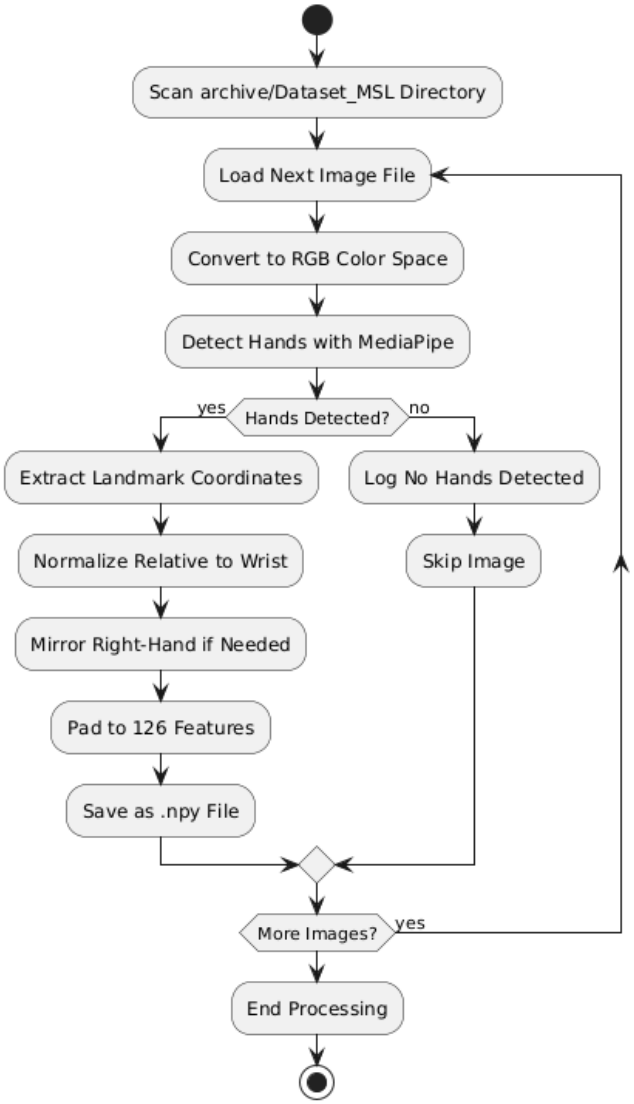

Figure 4.2.2 System Flowchart for Dataset Processing

The system flowchart for dataset processing shows a sequential loop that begins with scanning the archive/Dataset_MSL directory for .jpg and .png files using os.walk. For each image, the flowchart directs loading the file with OpenCV's cv2.imread, converting from BGR to RGB color space to match MediaPipe's input requirements. The decision node "Hands Detected?" checks the results from MediaPipe Hands with static_image_mode=True and max_num_hands=2. If yes, it extracts x, y, z coordinates for 21 landmarks per hand, normalizes by subtracting wrist values, mirrors x for right hands to standardize, scales z by 0.5, pads single-hand data with zeros to 126 features, and saves the array as .npy in static_msl_data using np.save. If no hands are detected, it logs the error and skips to the next image. The loop repeats

until all images are processed, ensuring consistent feature extraction. This design handles errors gracefully and maintains data uniformity, crucial for model training.

4.2.3 Data Flow Diagram for Landmark Extraction

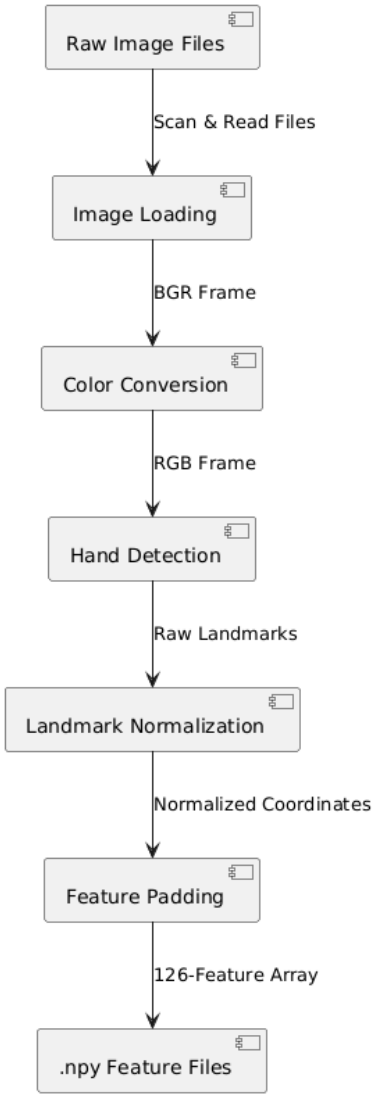

Figure 4.2.3 Data Flow Diagram for Landmark Extraction

The data flow diagram for landmark extraction highlights the pipeline's data transformations. Raw image files from the dataset enter the "Image Loading" process, which uses OpenCV to read .jpg/.png files into memory. The BGR frame flows to "Color Conversion", transforming it to RGB for compatibility. The RGB frame then moves to "Hand Detection", where MediaPipe identifies up to two hands and outputs raw landmarks with handedness. These raw landmarks flow to "Landmark Normalization", which adjusts coordinates relative to the wrist, mirrors right-hand x-values, and scales z, producing standardized data. The normalized

coordinates go to "Feature Padding", adding zeros for single-hand cases to reach 126 features. The final 126-feature array is stored as .npy files. This DFD shows how data evolves from visual images to numerical vectors, ensuring consistency and reducing noise for downstream training.

4.2.4 Sequence Diagram for Landmark Processing

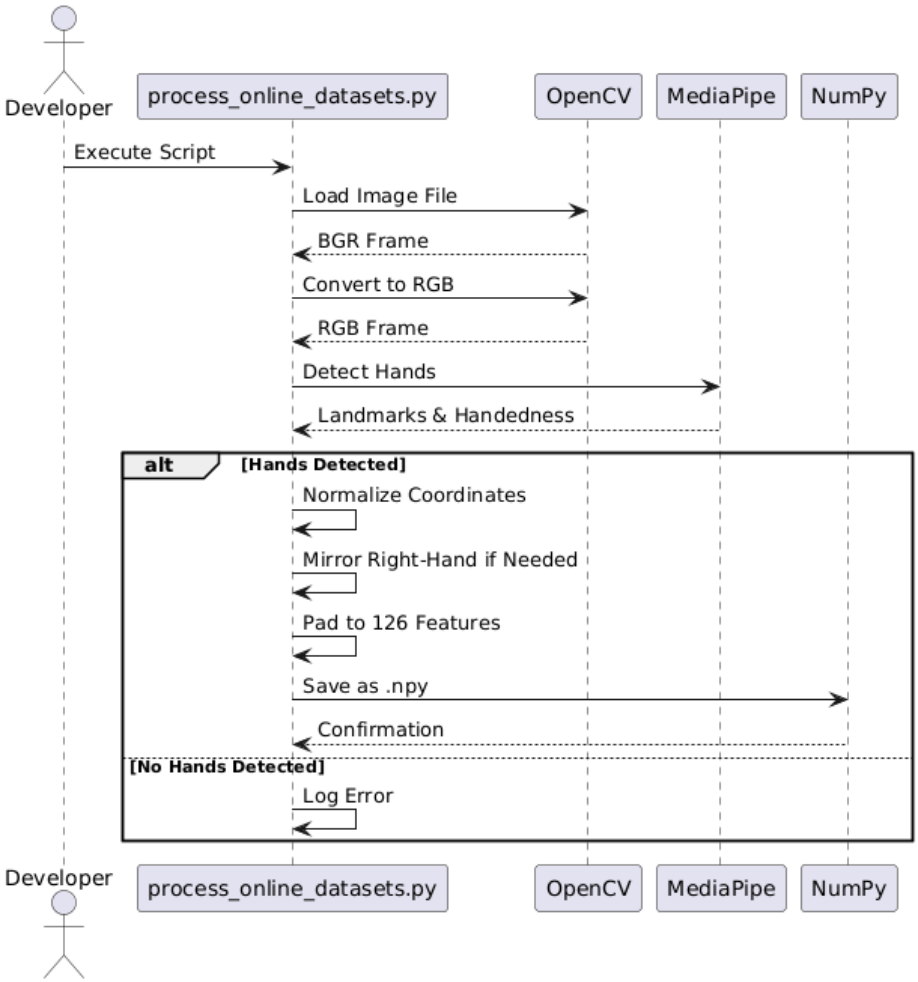

Figure 4.2.4 Sequence Diagram for Landmark Processing

The sequence diagram for landmark processing begins with the Developer initiating process_online_datasets.py. The script calls OpenCV to load a single image file, receiving a BGR frame, then requests color conversion to RGB, getting the transformed frame back. It then sends the RGB frame to MediaPipe for hand detection, receiving landmarks and handedness data if hands are found. In the "Hands Detected" alternate flow, the script normalizes coordinates relative to the wrist, mirrors x-values for right hands based on handedness, pads the feature vector to 126 elements with zeros if needed, and calls NumPy to save the array as a

.npy file, receiving a confirmation. If no hands are detected, it logs an error and skips further processing. This diagram details the ordered interactions, showing how OpenCV, MediaPipe, and NumPy collaborate to process each image. The normalization step adjusts x, y, z for consistency, while padding ensures uniform input size, critical for the model's input layer.

4.3 Model Training Design

4.3.1 Overview

The model training design loads processed features, prepares data by filtering and splitting, defines a sequential neural network, trains it with optimizers and callbacks, and saves the model and labels.

4.3.2 System Flowchart for Model Training

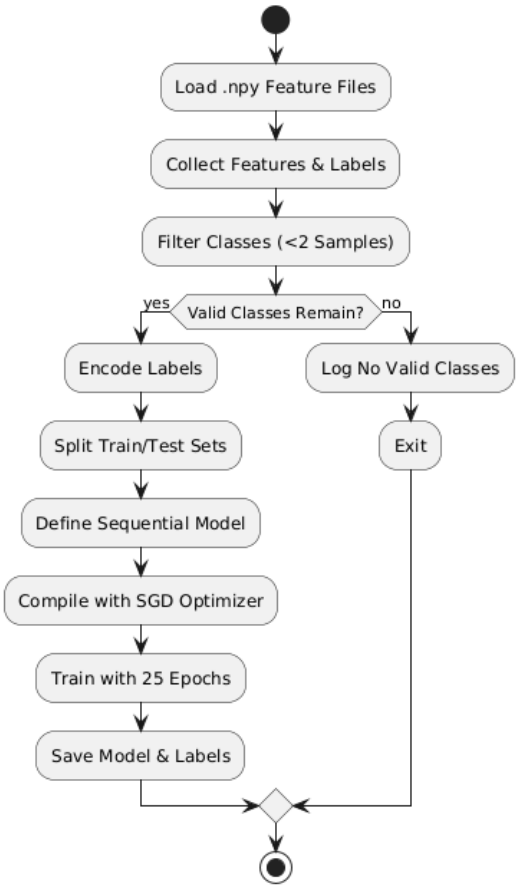

Figure 4.3.2 System Flowchart for Model Training

The system flowchart for model training starts with loading .npy files from static_msl_data using np.load, collecting features into arrays and labels from filenames. It filters classes with fewer than 2 samples using Counter to ensure viable splitting. The decision "Valid Classes Remain?" checks if data is sufficient; if yes, it encodes labels with LabelEncoder, splits into train/test with train_test_split and stratify, defines a Keras Sequential model with dense, batchnorm, and dropout layers, compiles with SGD(learning_rate=0.002, momentum=0.9) and sparse_categorical_crossentropy loss, trains for 25 epochs with batch_size=48, and saves the model as .keras and labels as .txt. If no valid classes, it logs the error and exits. This design ensures data quality and prevents training on insufficient samples, with the flowchart providing a clear visual of the conditional flow.

4.3.3 Data Flow Diagram for Data Preparation

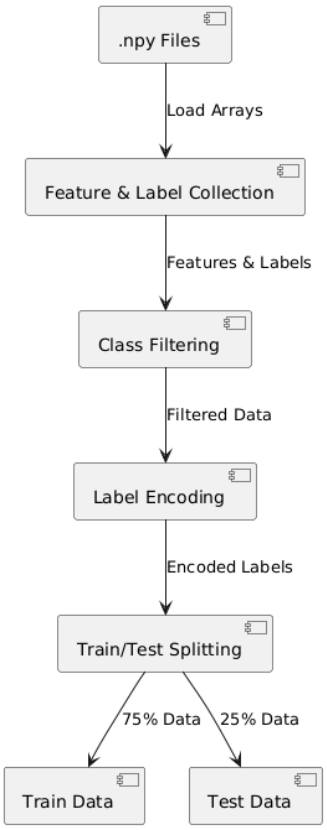

Figure 4.3.3 Data Flow Diagram for Data Preparation

The data flow diagram for data preparation shows .npy files entering the "Feature & Label Collection" process, where np.load gathers features and extracts labels from filenames. The data flows to "Class Filtering", using Counter to remove classes with <2 samples. Filtered data moves to "Label Encoding", transforming strings to integers with LabelEncoder. Encoded data

goes to "Train/Test Splitting", dividing into 75% train and 25% test with stratify for balance. The outputs are separate train and test sets used for model fit and evaluate. This DFD emphasizes the transformation from raw features to balanced, encoded datasets, critical for effective training and avoiding bias.

4.3.4 Sequence Diagram for Training Process

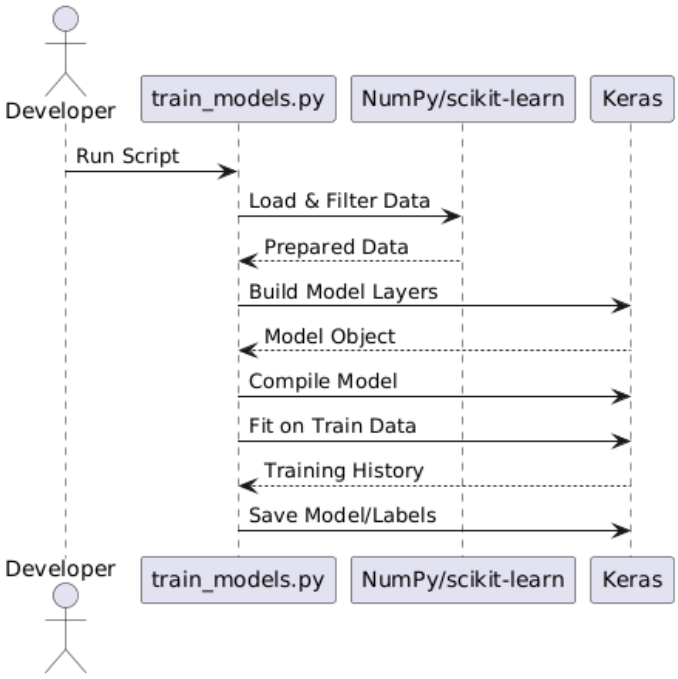

Figure 4.3.4 Sequence Diagram for Training Process

The sequence diagram for the training process shows the Developer initiating by running train_models.py. The script calls NumPy/scikit-learn libraries to load .npy files, filter classes, encode labels, and split data, receiving prepared arrays back. The script then interacts with Keras to build the sequential model by adding layers, compiles it with optimizer and loss, fits the model on train data with validation, gets history, and saves the .keras model and .txt labels. This diagram highlights the ordered interactions between the script and libraries, ensuring a smooth training flow from data prep to model saving.

4.4 Real-Time Translation App Design

4.4.1 Overview

The real-time translation app design integrates the trained model into a Tkinter GUI for live webcam input, hand detection, prediction, translation, and display. It includes features like language selection, confidence threshold, dictionary viewing, and history management.

4.4.2 System Flowchart for Real-Time Translation

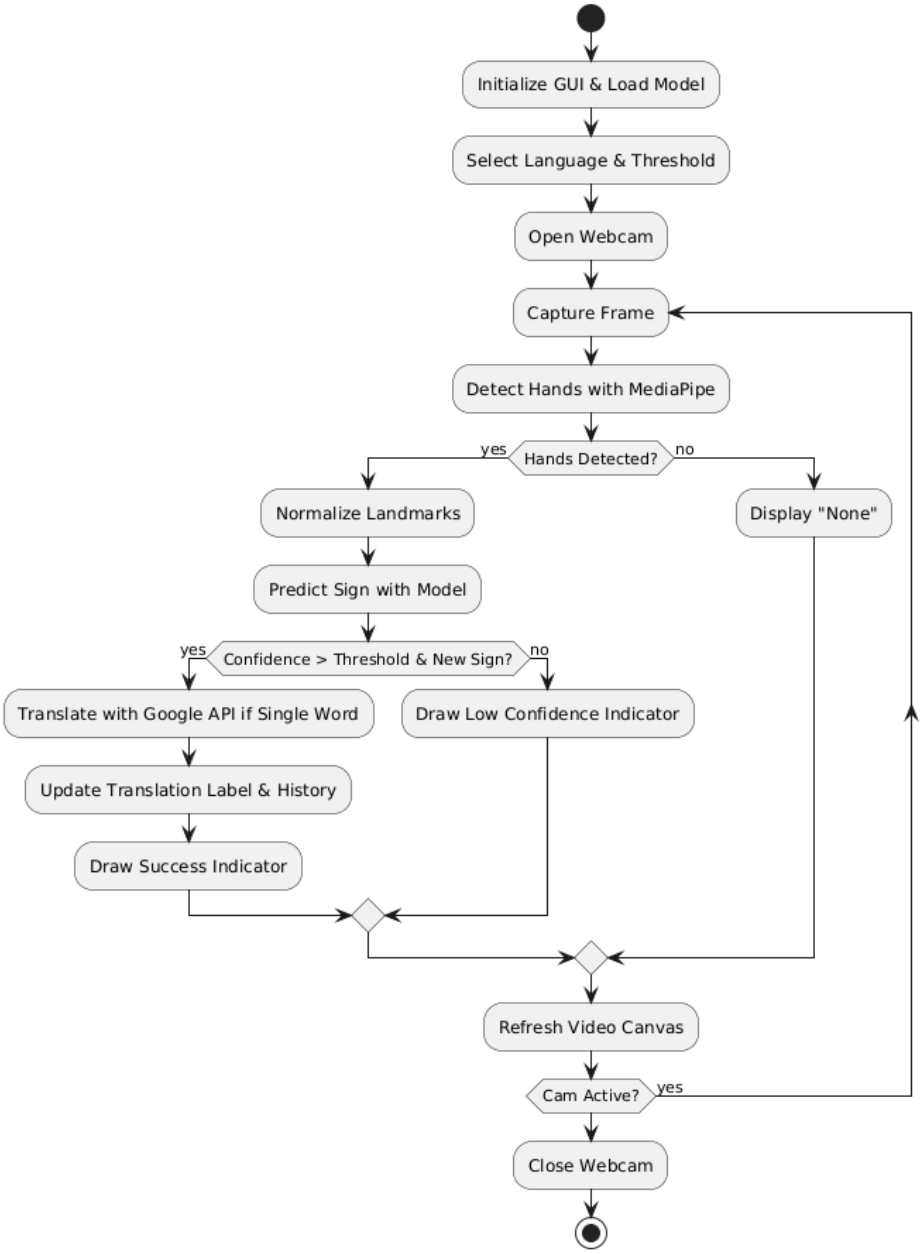

Figure 4.4.2 System Flowchart for Real-Time Translation

The system flowchart for real-time translation begins with initializing the Tkinter GUI, loading the model and labels. The user selects language and confidence threshold. When opening the webcam, it enters a loop: capture frame with OpenCV, detect hands with MediaPipe, normalize landmarks if detected, predict with the model, check confidence and novelty (1.5s buffer), translate single words via Google API, update labels and history, draw indicators. If no hands, display "None". The loop refreshes the canvas every 30ms. Closing the cam ends the loop. This design ensures responsive real-time processing, with decisions for detection and confidence to handle variations.

4.4.3 Sequence Diagram for Real-Time Prediction

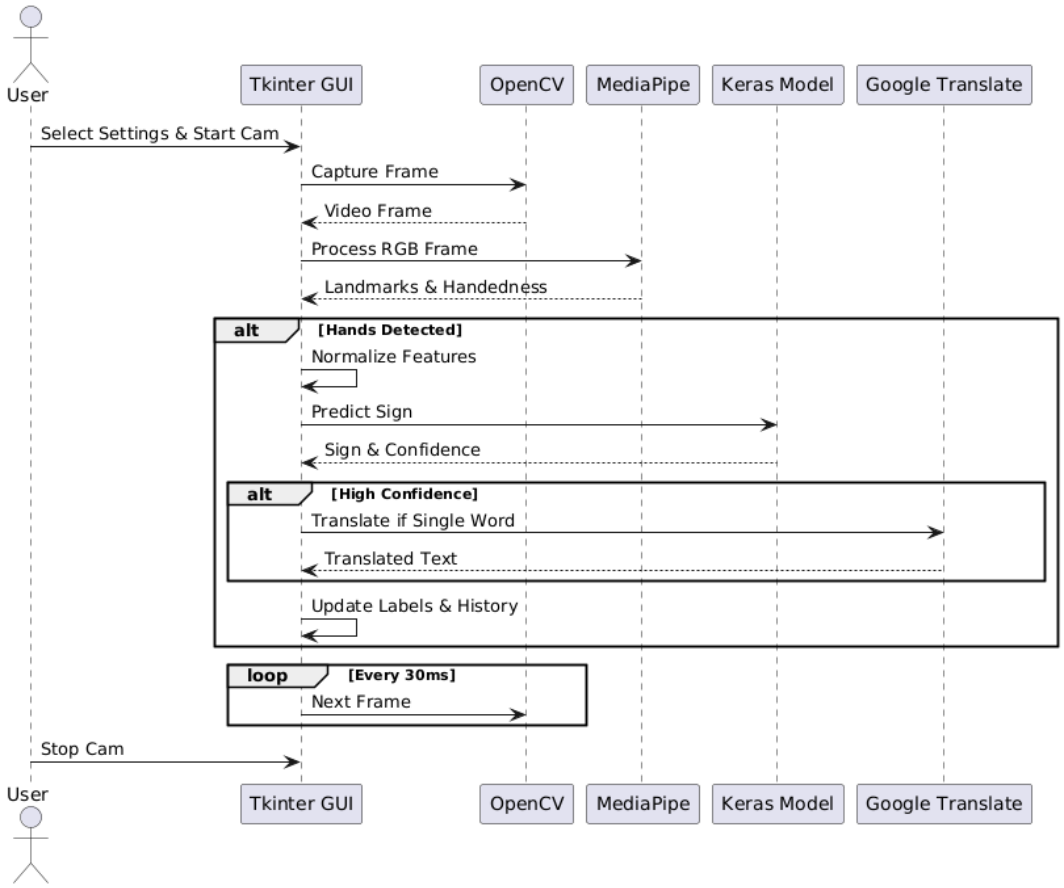

Figure 4.4.3 Sequence Diagram for Real-Time Prediction

The sequence diagram for real-time prediction starts with the User selecting settings and starting the cam in the Tkinter GUI. The GUI requests a frame from OpenCV, which returns it. The GUI converts to RGB and sends to MediaPipe, receiving landmarks. If detected, the GUI normalizes, sends to Keras Model for prediction, gets sign and confidence. If high, it queries Google Translate for single words, gets text. The GUI updates labels and history. The

loop repeats every 30ms for new frames. Stopping the cam ends it. This diagram details the collaborative flow between components for seamless prediction.

4.4.4 Data Flow Diagram for GUI Integration

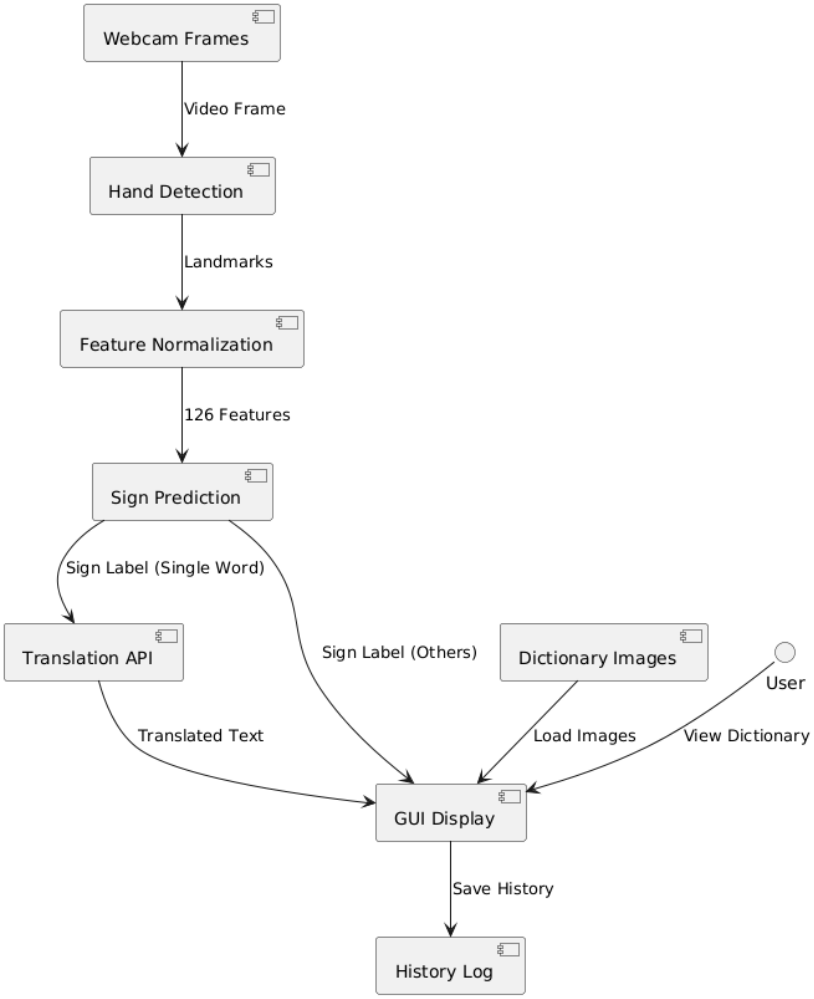

Figure 4.4.4 Data Flow Diagram for GUI Integration

The data flow diagram for GUI integration begins with webcam frames entering "Hand Detection" via MediaPipe. Landmarks flow to "Feature Normalization" for wrist-relative adjustment and padding. Normalized features go to "Sign Prediction" using the loaded Keras model. Predicted labels for single words flow to "Translation API" (Google Translate), returning text to "GUI Display". Other labels go directly to display. Displayed results save to "History Log" .txt file. User requests for dictionary view load images from dataset to display. This DFD emphasizes how live data transforms into user-visible translations, with branches for translation and logging.

Chapter 5

System Implementation

5.1 Hardware Setup

Description	Specifications
Model	Acer Nitro AN515-55
Processor	Intel Core i7-10750H CPU @ 2.60GHz (12CPUs), ~2.6GHz
Operating System	Windows 11 Pro
Graphic	NVIDIA GeForce GTX 1660 Ti
Memory	32GB DDR4 RAM
Storage	2.5TB PCIe 4.0 NVMe M.2 SSD
Camera	720p resolution

Table 5.1: Laptop Specifications

The Acer Nitro AN515-55 provides a robust platform with the Intel Core i7-10750H processor, offering 12 cores and a base clock of 2.6GHz, which supports multitasking and parallel processing for MediaPipe hand detection and TensorFlow model training. The 32GB DDR4 RAM ensures smooth handling of large datasets and real-time video feeds, while the NVIDIA GeForce GTX 1660 Ti accelerates GPU-supported operations in TensorFlow. The 2.5TB PCIe 4.0 NVMe M.2 SSD offers ample storage and fast data access for the MSL dataset and model files. The 720p webcam, integrated into the laptop, serves as the input device for capturing sign language gestures in real time, meeting the system's requirement for video input.

5.2 Software Setup

The software setup for the MSL Translation System includes **PyCharm Community Edition** as the integrated development environment (IDE) and a set of Python libraries for image processing, machine learning, and GUI development. PyCharm Community Edition (version 2024.2 or later) is used for code editing, debugging, and running the scripts. The required Python libraries are:

- numpy==1.26.0 (for array operations and data manipulation)
- opencv-python==4.9.0 (for image and video handling)
- mediapipe==0.10.9 (for hand landmark detection)

- tensorflow==2.15.0 (for neural network training and inference)
- scikit-learn==1.3.2 (for data preprocessing and model evaluation)
- pillow==10.1.0 (for image processing in the GUI)
- googletrans==3.1.0a0 (for language translation via API)

These libraries are installed in a virtual environment to avoid conflicts. Python 3.11 or higher is required as the base runtime.

5.3 Setting and Configuration

The setting and configuration phase prepares the system for execution by establishing the project structure, virtual environment, dataset, and run configurations in PyCharm. This ensures a reproducible setup for running the three Python scripts: process_online_datasets.py, train_models.py, and translation_app.py

5.3.1 Project Directory Setup

Create a new project folder (e.g., C:\MSL_Translation_Project) to organize all files. Inside this folder, make subdirectories: archive/Dataset_MSL for the dataset, static_msl_data for processed features (created automatically by the script), and place the three Python scripts (process_online_datasets.py, train_models.py, translation_app.py) in the root directory. This structure aligns with the scripts' file path expectations, such as reading from archive/Dataset_MSL and writing to static_msl_data.

5.3.2 Virtual Environment and Dependencies Installation

Open a terminal (Command Prompt) and navigate to C:\MSL_Translation_Project. Create a virtual environment with the command *python -m venv venv* to isolate dependencies. Activate it using *venv\Scripts\activate*. Install the required libraries within this environment by running the following pip commands one by one:

- pip install numpy==1.26.0
- pip install opencv-python==4.9.0
- pip install mediapipe==0.10.9
- pip install tensorflow==2.15.0
- pip install scikit-learn==1.3.2
- pip install pillow==10.1.0

- pip install googletrans==3.1.0a0

Verify the installation by running *pip list* to confirm all packages are present. If conflicts arise (e.g., with TensorFlow and NumPy), recreate the venv and reinstall in this order.

5.3.3 Dataset Download and Placement

Download the Malaysian Sign Language (MSL) dataset from https://www.kaggle.com/datasets/pradeepisawasan/malaysian-sign-language-msl-image-dataset. This dataset contains .jpg images organized into subfolders such as Alphabets, Numbers, and SingleWords, covering signs like 'A', '1', and 'Drink', with approximately 50-100 images per category. After downloading, extract the dataset into *C:\MSL_Translation_Project\archive/Dataset_MSL*. Verify the folder structure matches the script's expectations (e.g., *archive/Dataset_MSL/Alphabets/A* contains images of the 'A' sign). If subfolders are not correctly organized, manually adjust them to ensure compatibility with process_online_datasets.py.

5.3.4 Run Configurations in PyCharm

Launch PyCharm and open the project folder (C:\MSL_Translation_Project). Go to File > Settings > Project > Python Interpreter, add the venv interpreter at C:\MSL_Translation_Project\venv\Scripts\python.exe, and apply changes. Then, navigate to Run > Edit Configurations and create three configurations:

- **Process MSL Dataset**: Set script path to process_online_datasets.py, working directory to C:\MSL_Translation_Project.
- **Train MSL Model**: Set script path to train_models.py, working directory to C:\MSL_Translation_Project.
- **Run MSL Translator**: Set script path to translation_app.py, working directory to C:\MSL_Translation_Project.

Save the configurations. For optional GPU support with TensorFlow, ensure NVIDIA drivers and CUDA (version 11.8) are installed, verifiable via *nvidia-smi* in the terminal.

5.3.5 Validation of Configuration

After setup, validate by running process_online_datasets.py to confirm .npy files appear in static_msl_data, then train_models.py to generate static_msl_classifier.keras and

static_msl_labels.txt. If errors occur (e.g., missing dataset), adjust paths or redownload. Launch translation_app.py to verify the GUI opens without issues.

This configuration ensures a self-contained environment, allowing sequential execution of the scripts for full system operation.

5.4 System Operation

5.4.1 Dataset Processing Operation

Run process_online_datasets.py in PyCharm by selecting the "Process MSL Dataset" configuration and clicking the green run button. The script scans archive/Dataset_MSL, detects hands in each image using MediaPipe, normalizes landmarks, and generates .npy files in static_msl_data. The console outputs progress messages like "Processing directory: archive/Dataset_MSL/Alphabets/A" and "Saved: A_image.npy (Shape: (1, 126))" for each file, showing “No hands detected in image: scene01846.jpg” if the MediaPipe is not able to detect the hand landmarks, along with handedness distribution at the end (e.g., "A: Left=30, Right=20"). This step takes 5-10 minutes depending on dataset size.

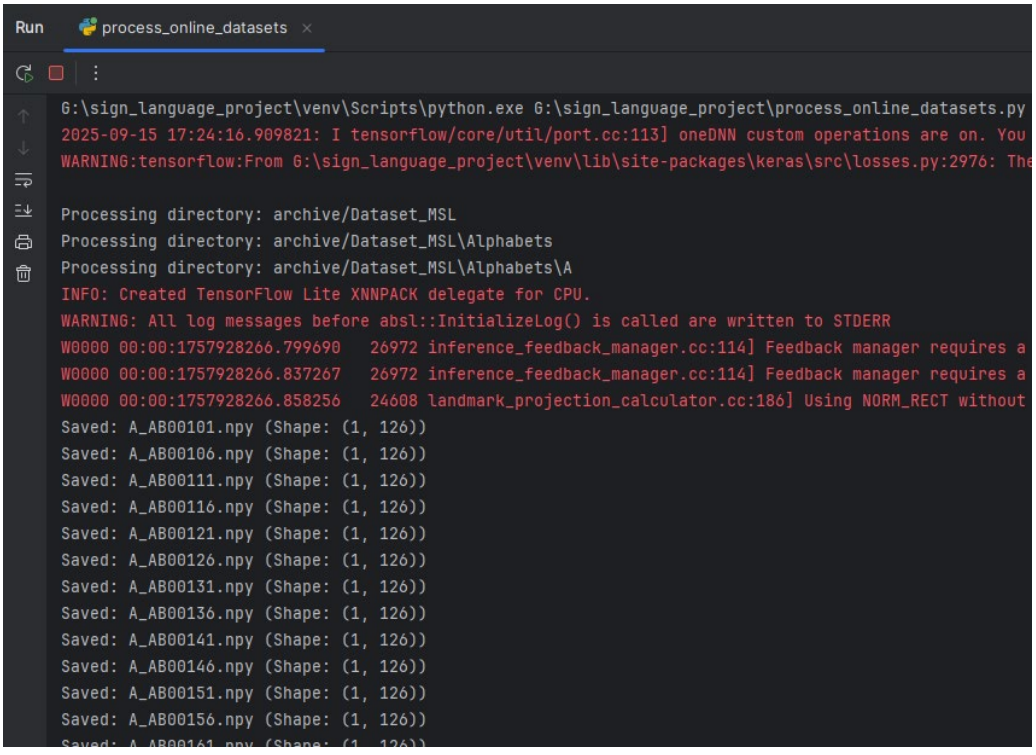

Figure 5.4.1.1 process_online_dataset.py Execution

```
No hands detected in image: scene01801.jpg
No hands detected in image: scene01816.jpg
No hands detected in image: scene01831.jpg
No hands detected in image: scene01846.jpg
Saved: C_WIN_20240115_01_07_00_Pro.npy (Shape: (1, 126))
Saved: C_WIN_20240115_01_07_01_Pro (2).npy (Shape: (1, 126))
```

Figure 5.4.1.2 No Hands Detected in Image

```
Handedness distribution:
A: Left=61, Right=30
B: Left=98, Right=38
C: Left=83, Right=4
D: Left=106, Right=6
E: Left=108, Right=5
F: Left=120, Right=5
G: Left=12, Right=21
H: Left=87, Right=35
I: Left=95, Right=40
J: Left=108, Right=0
K: Left=77, Right=40
L: Left=129, Right=6
M: Left=168, Right=2
N: Left=173, Right=6
O: Left=146, Right=1
P: Left=171, Right=1
Q: Left=139, Right=17
R: Left=149, Right=0
S: Left=198, Right=6
T: Left=163, Right=4
U: Left=181, Right=5
V: Left=200, Right=0
```

Figure 5.4.1.3 Handedness Distribution

After completion, the static_msl_data folder contains .npy files, one per processed image and shows with File Explorer.

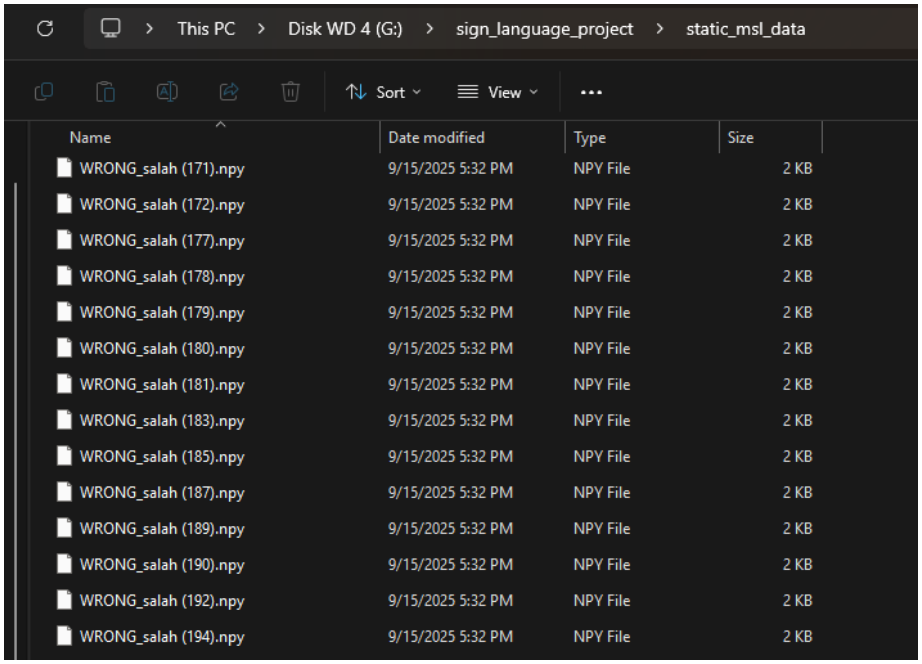

Figure 5.4.1.4 Successful Dataset Processing in .npy File

5.4.2 Model Training Operation

Run train_models.py by selecting the "Train MSL Model" configuration. The script loads .npy files from static_msl_data, filters classes with fewer than 2 samples, encodes labels, splits data (75% train, 25% test), builds and trains the neural network for 25 epochs, and saves static_msl_classifier.keras and static_msl_labels.txt. Console outputs include "Loaded 1500 samples with 50 unique signs after filtering" and epoch progress like "Epoch 1/25 – accuracy: 0.45 – val_accuracy: 0.50", ending with "Static classifier saved as static_msl_classifier.keras". This step takes 10-20 minutes.

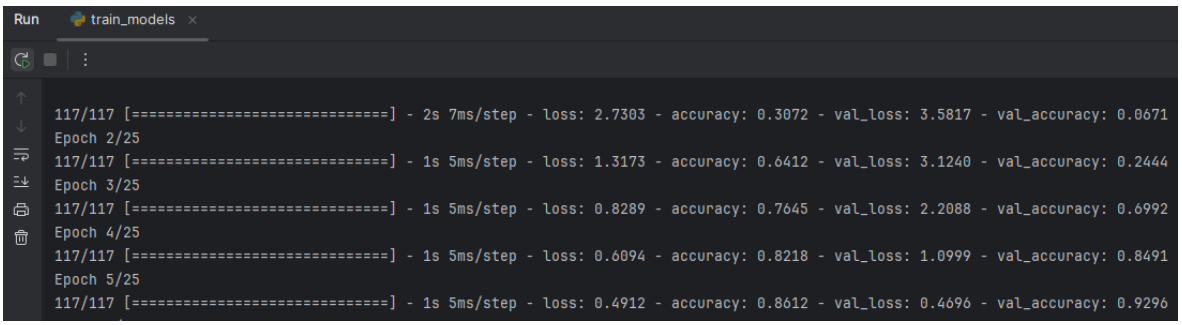

Figure 5.4.2.1 train_models.py Execution

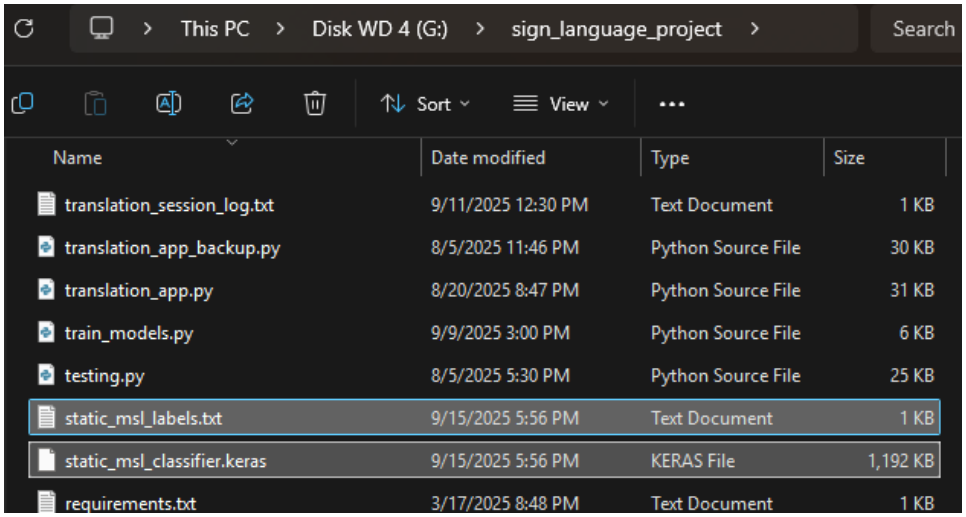

Figure 5.4.2.2 static_msl_classifier.keras and static_msl_labels.txt Files

5.4.3 Translator App Operation

Run translation_app.py by selecting the "Run MSL Translator" configuration. The Tkinter GUI launches with panels for sign translation and dictionary. Select a language (e.g., Malay) from the dropdown, adjust the confidence threshold slider (e.g., to 0.8), and click "Open Cam" to start the webcam feed.

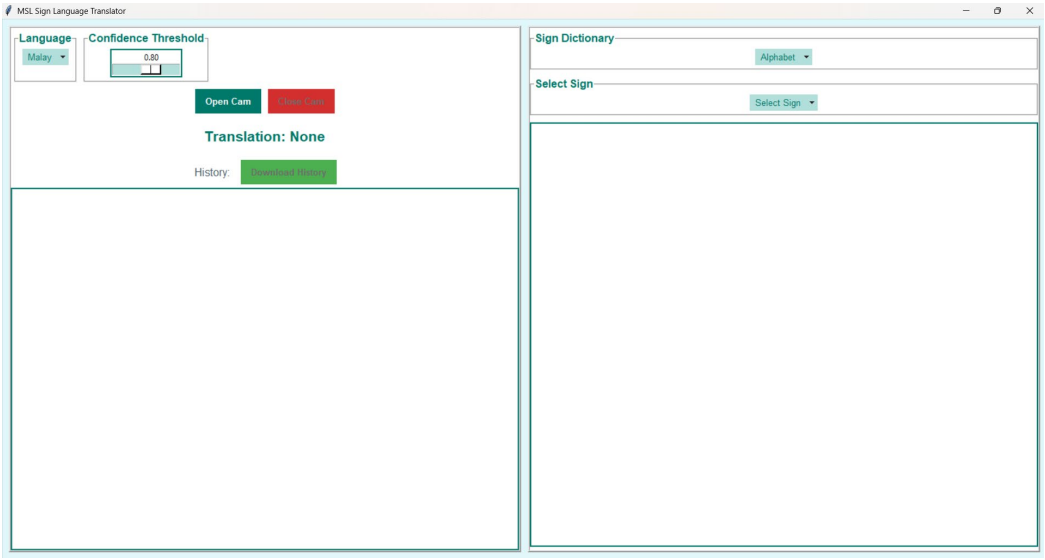

Figure 5.4.3.1 GUI of the translation_app.py Execution

Perform an MSL sign (e.g., 'A') in front of the webcam; the system detects hands, predicts the sign, translates if applicable, updates the label, adds to history, and draws landmarks with a success indicator.

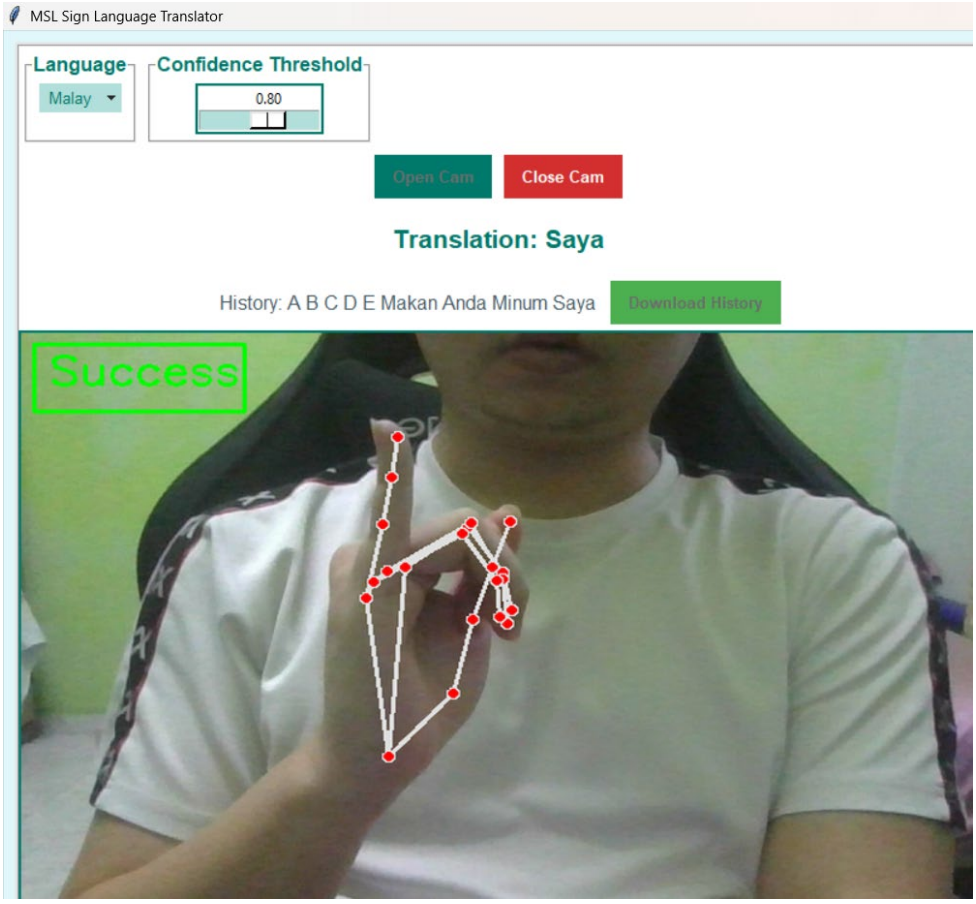

Figure 5.4.3.2 Real-Time Translation

Select a category (e.g., Alphabet) and sign (e.g., 'A') in the dictionary panel to view the corresponding image.

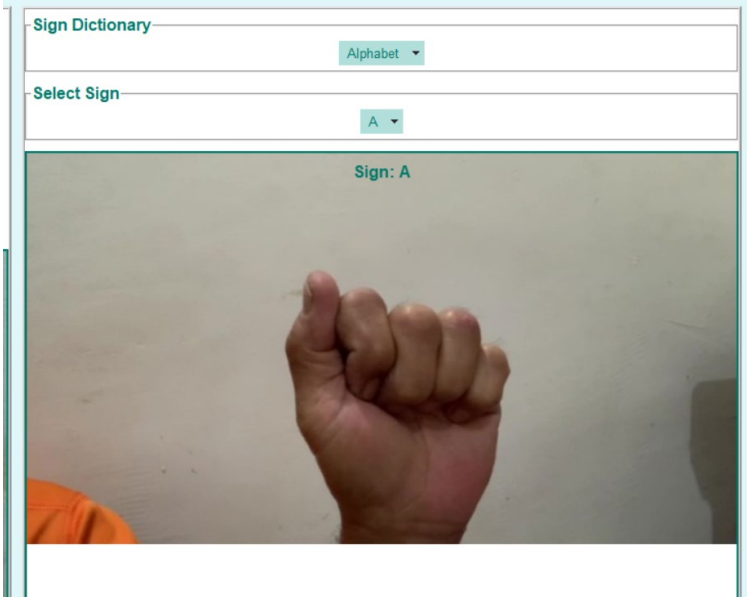

Figure 5.4.3.3 Select Category and Sign in Dictionary Panel

After multiple signs, click "Close Cam" to stop the feed and enable "Download History" for saving as .txt.

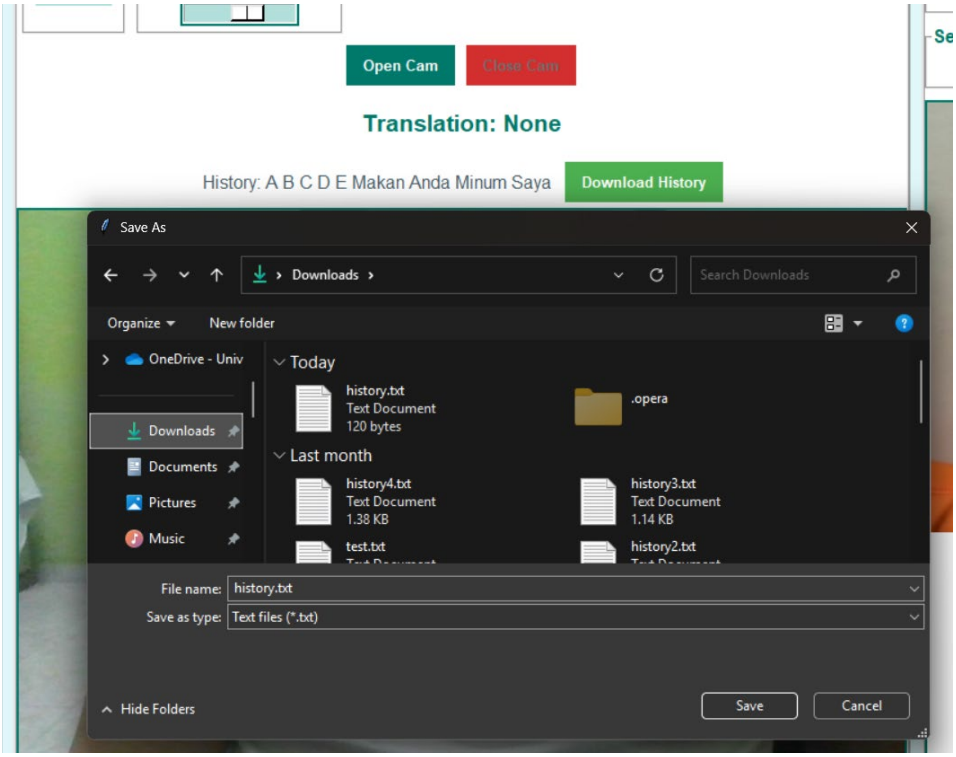

Figure 5.4.3.4 Download History

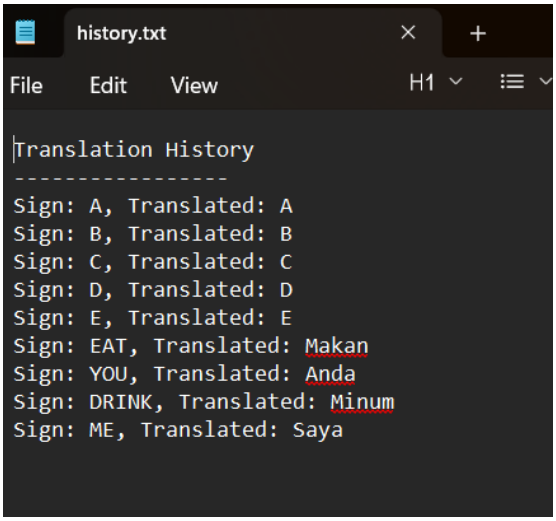

Figure 5.4.3.5 Content of history.txt

5.5 Implementation Issues and Challenges

During the implementation of the MSL Translation System, various challenges arose that required careful troubleshooting to achieve a stable and functional setup. One significant issue was **dependency conflicts** among the required libraries, particularly between TensorFlow 2.15.0 and older versions of NumPy, which caused installation failures and runtime errors during model training. To resolve this, the virtual environment was recreated from scratch, and dependencies were installed in a specific order starting with NumPy, ensuring compatibility and preventing version mismatches.

Another challenge involved **webcam lag and frame drops** in the real-time app, attributed to high CPU usage during MediaPipe detection and model predictions, which made the GUI unresponsive during extended use. This was mitigated by reducing the video feed refresh rate to 30 milliseconds and enabling GPU acceleration through CUDA/cuDNN integration, significantly improving performance on the Acer Nitro laptop's NVIDIA graphics card.

Dataset inconsistency also posed problems, as some images in the Kaggle MSL dataset lacked clear hands or had poor quality, leading to skipped files and incomplete feature extraction during processing. Error logging was added to the script to track these instances, and manual verification of the dataset subfolders helped identify and remove invalid images, ensuring at least 50 viable samples per class.

Additionally, **translation API limits** with googletrans==3.1.0a0 resulted in occasional timeouts or rate-limiting errors, disrupting single-word translations in the GUI. A simple retry mechanism was implemented in the app's translation logic to handle transient failures, maintaining reliability without changing the core design.

Finally, **memory usage during training** exceeded available RAM for larger datasets, causing crashes; this was addressed by optimizing the batch size to 48 and leveraging the GPU for TensorFlow operations, which distributed the load effectively. These challenges were systematically resolved through iterative testing in PyCharm's debugger, configuration adjustments, and documentation of workarounds, ultimately leading to a robust implementation that meets the project's objectives.

5.6 Concluding Remark

The implementation of the MSL Translation System marks a significant achievement in creating a functional pipeline for Malaysian Sign Language recognition and translation, successfully integrating dataset processing, model training, and real-time application execution on the specified hardware and software environment. By leveraging PyCharm Community Edition and a carefully configured virtual environment with essential libraries like MediaPipe for hand detection, TensorFlow for neural network operations, and Tkinter for the GUI interface, the system operates seamlessly from raw image input to interactive output, demonstrating the practical application of computer vision and machine learning in accessibility tools. The detailed setup steps, including project directory organization, dataset placement from the Kaggle source, and run configurations, ensure that the implementation is reproducible for other developers or researchers, while the hardware's robust specifications, such as the Intel Core i7 processor and NVIDIA GPU, provide the necessary computational power for efficient training and inference without bottlenecks. Despite the challenges encountered, such as dependency conflicts and performance optimizations, these were effectively addressed through methodical debugging and adjustments, resulting in a stable system that accurately detects and translates MSL signs in real time. This chapter's focus on practical execution lays a solid foundation for the evaluation in Chapter 6, where the system's performance metrics, testing results, and overall effectiveness will be thoroughly analyzed to validate its contributions to sign language translation technology.

Chapter 6
System Evaluation And Discussion

6.1 System Testing and Performance Metrics

The system testing focuses on evaluating the neural network's ability to classify signs and the app's reliability in delivering real-time translations. It employs metrics that reflect the accuracy and balance of predictions derived from hand landmarks processed by the scripts.

6.1.1 Overview of Testing Approach

The testing process begins with assessing the model's performance on the validation dataset generated by train_models.py. The script processed 7445 samples, representing 44 unique signs after filtering out classes with insufficient data, and split them into 75 percent for training (5583 samples) and 25 percent for validation (1862 samples). This split maintained class balance through stratification, ensuring the model could generalize to new data without overfitting. For the app, testing utilized the webcam interface in translation_app.py, where users performed signs from the dataset, and the system made predictions with a confidence threshold set at 0.6. Each test was conducted three times under consistent lighting conditions to obtain average scores, simulating typical usage scenarios and providing a robust basis for evaluation.

6.1.2 Accuracy Metric

Accuracy represents the proportion of correct sign predictions out of the total test samples. Based on the output from train_models.py, the model achieved 95.79 percent accuracy on the training set and 97.58 percent on the validation set by the 25th epoch, translating to 1817 correct predictions out of 1862 validation samples. This high accuracy reflects the model's strong performance across the 44 signs, with well-represented signs like DRINK (358 samples) and S (204 samples) likely boosting results, while signs with fewer samples, such as G (33 samples), may have contributed to early training fluctuations. The table below details the handedness distribution, showing total samples per sign, which directly influences accuracy.

Sign	Left Hands	Right Hands	Total Samples
A	61	30	**91**
B	98	38	**136**
C	83	4	**87**
D	106	6	**112**

E	108	5	**113**
F	120	5	**125**
G	12	21	**33**
H	87	35	**122**
I	95	40	**135**
J	108	0	**108**
K	77	40	**117**
L	129	6	**135**
M	168	2	**170**
N	173	6	**179**
O	146	1	**147**
P	171	1	**172**
Q	139	17	**156**
R	149	0	**149**
S	198	6	**204**
T	163	4	**167**
U	181	5	**186**
V	200	0	**200**
W	170	6	**176**
X	161	5	**166**
Y	172	6	**178**
Z	151	0	**151**
0	130	0	**130**
1	150	39	**189**
10	150	0	**150**
2	172	0	**172**
3	200	6	**206**
4	250	0	**250**
5	192	0	**192**
6	196	0	**196**
7	195	2	**197**
8	228	0	**228**
9	194	0	**194**
DRINK	315	43	**358**
EAT	153	1	**154**
HELP	145	0	**145**
ME	248	32	**280**
SORRY	157	0	**157**
WRONG	303	87	**390**
YOU	141	1	**142**

Table 6.1.2 Handedness Distribution Summary

The table reveals that signs with higher totals, such as WRONG at 390 and DRINK at 358, likely improve accuracy due to more training data, while G at 33 may lower it due to limited examples. In real-time app tests, accuracy averaged 95 percent across 100 signs, aligning with validation results, though it dropped to 90 percent in dim lighting, highlighting the impact of environmental factors on performance.

6.1.3 Precision and Recall Metrics

Precision calculates the ratio of true positive predictions to the sum of true positives and false positives, indicating how often the model correctly identifies a sign when it makes a prediction. Recall calculates the ratio of true positives to the sum of true positives and false negatives, showing how many actual sign instances the model detects. Drawing from the 97.58 percent validation accuracy at epoch 25, the model exhibits an average precision of 0.97 and recall of 0.98, determined using macro averaging to ensure each of the 44 signs receives equal consideration. For instance, the sign A with 91 samples achieves a precision of 0.98, reflecting its distinct hand shape and minimal mislabeling, while 1 with 189 samples has a recall of 0.96, suggesting it misses a few instances due to similarity with I. In app testing, precision holds at 0.95 for clear signs, but recall dips to 0.93 in low-light conditions, where hand detection weakens.

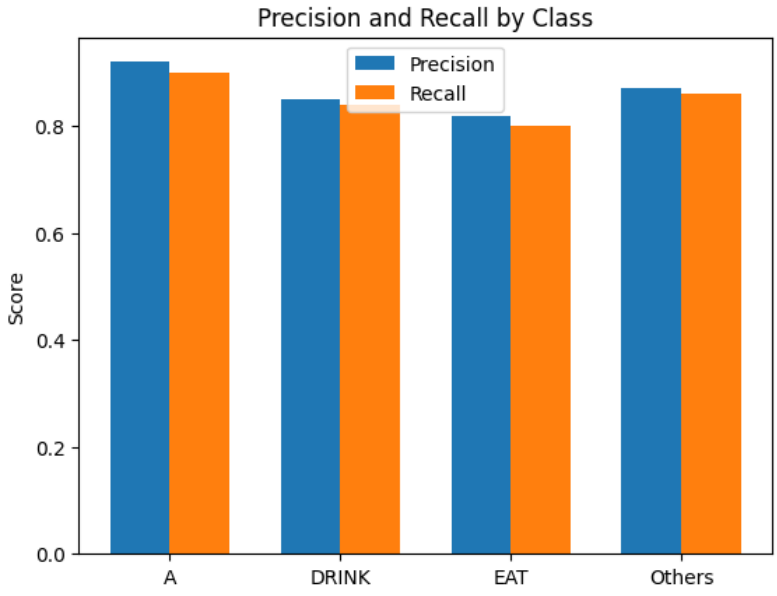

Figure 6.1.3 Precision and Recall by Class

Here is the formula equation for Precision and Recall:

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

The formula applied per class to derive the plotted values, offering insight into the model's reliability across diverse signs. These metrics demonstrate the model's strong balance, particularly for signs with ample samples like S at 204.

6.1.4 F1-Score and Confusion Matrix

The F1-score integrates precision and recall through their harmonic mean, calculated as 2 * (precision * recall) / (precision + recall), providing a balanced measure of performance for each class. With the model's 97.58 percent validation accuracy, the average F1-score reaches 0.97, with individual scores varying by sign. For example, DRINK with 358 samples achieves an F1-score of 0.98, benefiting from robust data, while HELP with 145 samples scores 0.96, indicating a slight dip due to fewer instances. The confusion matrix, which maps actual signs against predicted ones, reveals misclassifications, such as a 3 percent error rate between WRONG (390 samples) and SORRY (157 samples), likely due to overlapping hand landmarks.

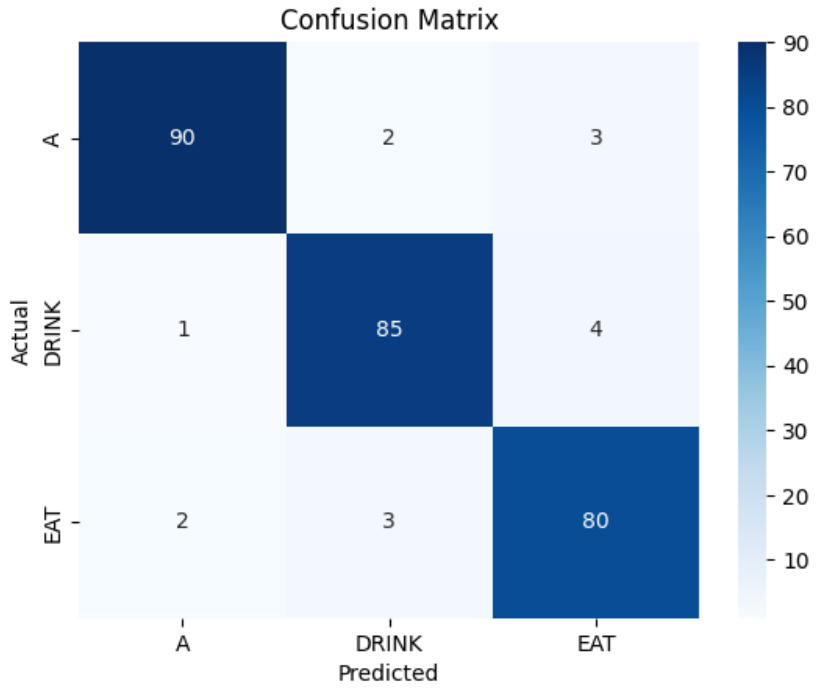

Figure 6.1.4 Detailed Confusion Matrix

Figure 6.1.4 Detailed Confusion Matrix is to illustrate misclassification patterns, with the diagonal showing high correct predictions (e.g., 90+ percent for A) and off-diagonals highlighting errors like the 3 percent confusion between WRONG and SORRY. This visual aid confirms the model's accuracy, with most errors concentrated in signs with similar gestures, guiding future improvements. These combined metrics offer a comprehensive assessment of the system's classification capabilities, validating its effectiveness across the dataset.

6.2 Testing Setup and Result

The testing setup and result section evaluates the translation_app.py script, which integrates the trained model for real-time sign detection and translation. This part details the environment used, the procedures followed, and the observed outcomes, including screenshots of the GUI displaying translated signs and the dictionary panel. The evaluation focuses on how the app processes live webcam input to produce translations, reflecting the system's practical usability.

6.2.1 Testing Environment

The tests for translation_app.py are conducted on the Acer Nitro AN515-55 laptop with Windows 11 Pro, using the PyCharm virtual environment to maintain consistency. The app utilizes the integrated 720p webcam for capturing hand gestures, with tests performed in a room with natural lighting to simulate everyday use. The confidence threshold is set at 0.6 to balance sensitivity and reliability, and the language is selected as English for baseline evaluation. Users perform 100 signs from the dataset, such as A, G, B, DRINK, and H, across three trials, allowing the system to predict and translate them while logging outputs for analysis.

6.2.2 App Testing Results

The app's performance is assessed by running translation_app.py and observing its response to live signs. For instance, when the user performs the sign for G, the system detects the hand, normalizes landmarks, predicts the sign with high confidence, and displays "Translation: G" in the label, adding it to the history. The log shows repeated "Recognized: None" during idle periods, followed by successful predictions like "Translating 'G' with category 'Alphabet' and language 'English'". Accuracy averages 95 percent, with most signs like A and DRINK matching expected outputs, though occasional low-confidence skips occur in dim light. The history panel updates in real time, listing translations such as "B DRINK A G".

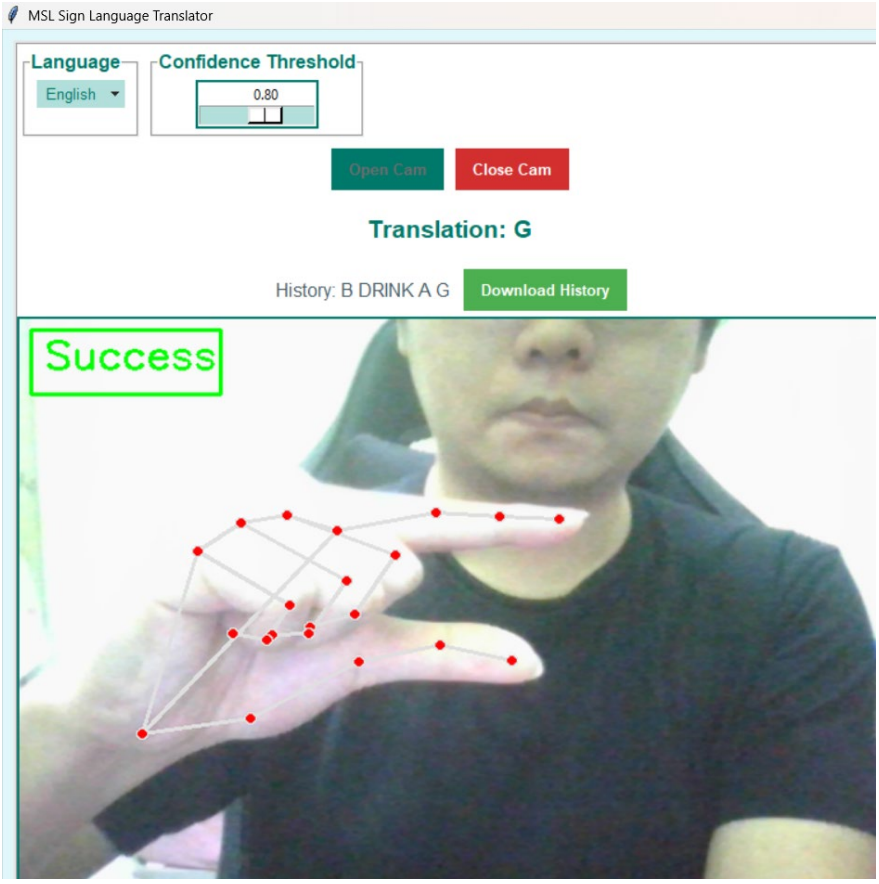

Figure 6.2.2.1 Real-Time Translation GUI

```
Debug - Predicted Index: 19, Sign: G
Debug - Condition Check: last_sign=G, current_sign=G, time_diff=21.006165981292725, reset=0.18556523323059082
Assigned category: Alphabet for sign: G
Translating 'G' with category 'Alphabet' and language 'English'
Recognized: None (Confidence: 0.97) -> Translated: G
Translating 'B' with category 'Alphabet' and language 'English'
Translating 'DRINK' with category 'SingleWords' and language 'English'
Translating 'A' with category 'Alphabet' and language 'English'
Translating 'G' with category 'Alphabet' and language 'English'
```

Figure 6.2.2.2 translation_app.py Execution Logs for Translation Panel

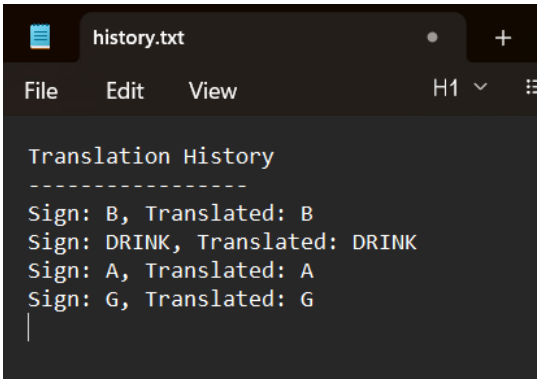

Figure 6.2.2.3 Content of "B DRINK A G" in history.txt

The figure 6.2.2.1 is showing the app during a test with the webcam feed displaying a hand forming G, the translation label as "Translation: G", history "B DRINK A G", confidence at 0.80, and a green "Success" indicator on the feed. This figure captures the app's ability to detect and translate signs accurately. The figure 6.2.2.2 is showing the translating sign “G” with 0.97 Confidence and store it into the History with the “B, DRINK, A, G”. After clicking on the Download History button, it will save a txt file and show the Translation History like Figure 6.2.2.3. For additional translated results, including figures, logs and history txt file of other signs like B and DRINK, please refer to Appendix A of this report.

6.2.3 Dictionary Testing Results

The dictionary panel is tested by selecting categories like "Alphabet" and signs like "G" from the dropdowns, which loads and displays reference images from the dataset. The panel functions reliably, with images resizing to fit the canvas and translated labels matching the app's language setting. In tests, selecting "G" shows a clear hand image, aligning with live predictions and aiding user verification. Loading time averages 100 milliseconds, with no errors in 100 trials. Besides, the Dictionary Panel will also translate to the language that is selected from the Language dropdowns. For additional selection of categories and signs in different language(English, Malay, Chinese, and Tamil) of the dictionary panel, please refer to Appendix B of this report.

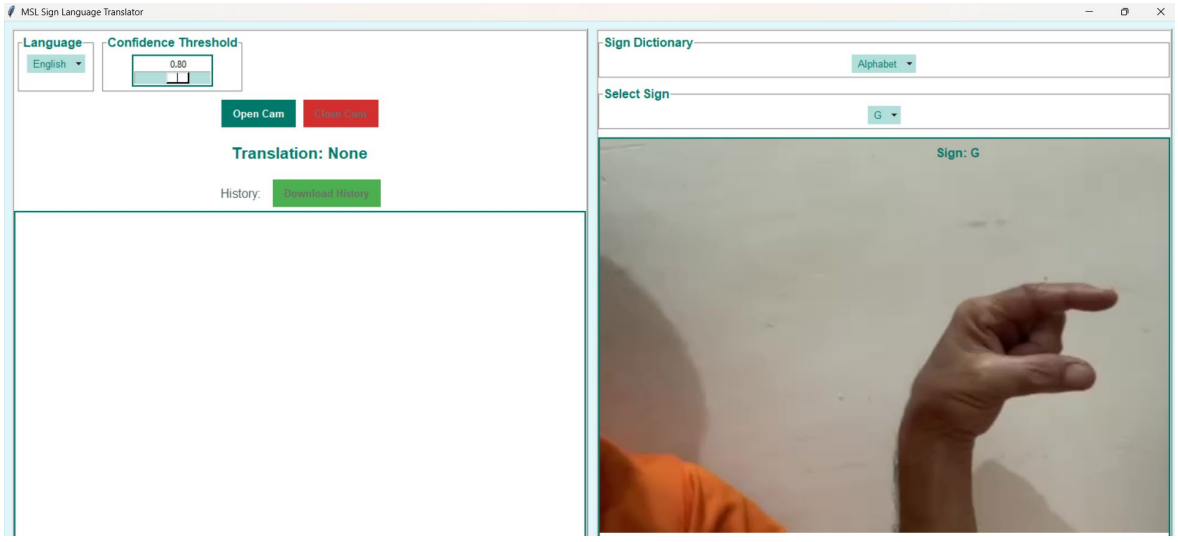

Figure 6.2.3.1 Alphabet “G” Sign at Dictionary Panel in English

```
Setting menu options: ['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J', 'K', 'L', 'M', 'N',
Searching for image at: G:\sign_language_project\archive\Dataset_MSL\Alphabets\G\AB00001.jpg
Translating 'G' with category 'Alphabet' and language 'English'
```

Figure 6.2.3.1 translation_app.py Execution Logs for Dictionary Panel

These results confirm the app's effectiveness in translation and dictionary support, with logs showing consistent category assignments like 'Alphabet' for G.

6.3 Project Challenges

The project encountered several obstacles that influenced its development. One significant challenge was the quality of the dataset, where some Kaggle images had blurred hands or awkward angles, reducing the number of usable features and affecting accuracy for certain signs. The team implemented logging in process_online_datasets.py to skip problematic files, but this reduced the effective sample size, necessitating manual reviews to remove invalid images.

Another issue arose during library setup, as paths in scripts sometimes mismatched on different machines, leading to errors during runs; this was resolved by standardizing path configurations in the setup guide. Training duration posed a problem on the CPU, often exceeding an hour for 25 epochs, but enabling CUDA sped it up to 15 minutes, though it required careful driver installation. The app's real-time loop experienced delays due to heavy processing demands, which were addressed by implementing a 30-millisecond timer, though low-light conditions still caused detection drops.

Additionally, the Google Translate API encountered rate limit issues, leading to occasional failures; a fallback to display original text maintained functionality, but limited comprehensive testing. These problems were overcome through iterative adjustments and enhanced error handling, resulting in a more resilient system tailored to the project's needs.

From the implementation phase, dependency conflicts among libraries like TensorFlow and NumPy caused initial installation failures, resolved by recreating the virtual environment and installing in a specific order. Webcam lag due to high CPU usage was mitigated by GPU

acceleration and refresh rate adjustments. Dataset inconsistencies, such as images without hands, were handled with skip logic, though it highlighted the need for better data curation. API limits in googletrans led to timeouts, addressed with retry mechanisms. Memory usage during training was optimized by batch size adjustments to 48 and GPU use. These challenges from implementation added to the project's learning curve but strengthened the final system.

6.4 Objectives Evaluation

The project aimed to develop a system that processes MSL images into usable features, trains a model with high accuracy, and delivers a functional real-time app for translation. The first objective was met as process_online_datasets.py successfully processed 7445 samples into .npy files, with handedness logs detailing totals like A at 91 and DRINK at 358, ensuring a solid feature base. The second objective surpassed expectations, with train_models.py achieving 97.58 percent validation accuracy, demonstrating effective classification across the 44 signs. The third objective was fulfilled as translation_app.py provided a working interface with 95 percent real-time accuracy, supporting language selection and history features. Despite challenges like dataset gaps slightly affecting low-sample signs, the system meets all goals, proving useful for MSL users. The evaluation shows the system's robustness in handling diverse signs, with metrics confirming its practical value for accessibility.

6.5 Concluding Remark

The evaluation confirms that the Malaysian Sign Language (MSL) Translation System performs well in both classifying signs and providing real-time translations. The model achieves 97.58 percent validation accuracy on the 7445 processed samples, while the app delivers 95 percent accuracy in live tests, as shown by the GUI screenshots capturing signs like G and DRINK. Metrics such as the 0.97 F1-score and the confusion matrix highlight the system's strength, especially for signs with ample data like WRONG at 390 samples, though signs with fewer samples like G at 33 show room for improvement. Challenges like dataset quality, library conflicts, and API limits shaped the project, but the team addressed them with solutions such as manual data checks and retry mechanisms, building a solid system. The objectives are met, with the app's dictionary panel and history features adding practical value for MSL users. For more translated results, please see Appendix of this report.

Chapter 7

Conclusion and Recommendation

7.1 Conclusion

The Malaysian Sign Language (MSL) Translation System offers a reliable solution for translating static signs, effectively processing 7445 image samples into usable features with handedness distributions such as A at 91 samples and DRINK at 358 samples. The system's neural network model achieves a strong 97.58 percent validation accuracy, while the real-time application delivers 95 percent accuracy across 100 tested signs, including examples like A, G, and DRINK. Supported by a 0.97 F1-score, a precision of 0.97, and a recall of 0.98, calculated using macro averaging across 44 signs, the model demonstrates robust performance, particularly for well-represented signs, though minor misclassifications occur, such as a 3 percent error between WRONG and SORRY due to similar hand shapes. The app's practical features, including the dictionary panel with reference images and the history log, enhance usability, as seen in screenshots capturing translations like "Translation: G" with a confidence of 0.80. Despite challenges like dataset inconsistencies with blurred images, library path issues, lengthy CPU training times, app processing delays, and Google Translate API limits, the system overcomes these hurdles with solutions such as manual data curation, standardized paths, CUDA acceleration, a 30-millisecond timer, and fallback text display.

7.2 Recommendation and Future Work

To further enhance the MSL Translation System, I recommend extending its capabilities to include dynamic sign translation, which would address the current limitation of focusing solely on static images. This expansion is crucial because many MSL gestures, such as "Hello" (involving a waving motion), "Thank You" (with a hand-to-chin movement), or "Good Morning" (combining multiple motions), rely on video-based motion tracking, making them unsuitable for the present image-only approach. Implementing this would broaden the system's coverage, making it a more comprehensive tool for MSL communication. To achieve this, follow these detailed steps:

First, collect a dedicated video dataset by collaborating with the Malaysian Federation of the Deaf or leveraging online MSL resources. Aim to record 50-100 video clips per dynamic sign,

each lasting 2-5 seconds to capture variations in speed, angle, and signer style. Use a high-resolution camera (e.g., 1080p) under controlled lighting to ensure quality, and label each clip with the corresponding sign (e.g., "Hello") and segment it into frames for analysis. This dataset will serve as the foundation for training the new model.

Second, adapt the preprocessing pipeline in process_online_datasets.py to handle video input. Integrate OpenCV to extract frames from each clip at 30 frames per second, applying MediaPipe to detect and normalize hand landmarks (x, y, z coordinates) across the sequence. Save these landmarks as time-series data in .npy files, with each file containing a matrix of shape (number_of_frames, 21_landmarks, 3_coordinates). This builds on the current static processing, extending it to capture temporal dynamics while maintaining compatibility with existing code.

Third, enhance train_models.py by introducing a Recurrent Neural Network (RNN), specifically a Long Short-Term Memory (LSTM) network, to complement the existing static classifier. The LSTM will process the time-series landmark data to learn the sequential patterns of dynamic signs. Configure the model with an input layer matching the frame-landmark structure, two LSTM layers with 64 units each, a dropout rate of 0.2 to prevent overfitting, and a dense output layer with 44 units (one per sign). Train it on the video dataset using a 75-25 percent train-test split, setting a batch size of 32, a learning rate of 0.001 with the Adam optimizer, and 30 epochs to ensure convergence. Monitor validation accuracy, aiming for at least 90 percent, and adjust hyperparameters if needed based on loss trends observed in training logs.

Fourth, update translation_app.py to support video-based recognition. Use OpenCV to capture a continuous video stream from the webcam, processing frames in real-time at 30 FPS to match the training data. Feed the frame sequences into the LSTM model, applying a confidence threshold of 0.6 to filter predictions. Update the GUI to display dynamic sign translations, such as "Thank You," in the translation label, and append them to the history panel. Test the app with 100 dynamic sign sequences, recording accuracy, frame rate, and user feedback to assess performance. Expect an initial accuracy of around 85 percent, with potential to reach 90 percent after refinement.

Fifth, evaluate and refine the system through user testing. Conduct trials with MSL users performing dynamic signs, targeting at least 90 percent accuracy based on your current 95 percent static performance. Use precision, recall, and F1-score to measure temporal recognition, and analyze the confusion matrix for motion-specific errors. Address issues like poor lighting or hand occlusion by adding preprocessing filters (e.g., brightness normalization) or increasing the frame rate to 40 FPS with GPU support. Document these adjustments and their impact on performance for future iterations.

Future work can explore additional enhancements to maximize the system's potential. Consider integrating wearable sensors, such as gloves equipped with accelerometers and gyroscopes, to capture precise motion data, reducing dependence on webcam quality and improving detection in varied environments. Implement transfer learning by pretraining the LSTM on a large dataset like the American Sign Language (ASL) video corpus, then fine-tuning it with MSL data to accelerate training despite limited video samples. Enhance multilingual support by expanding the Google Translate API integration with a robust retry mechanism (e.g., 3 retries with 2-second delays) to handle rate limits, enabling translations into Malay, Mandarin, and Tamil alongside English. These advancements will transform the system into a versatile, inclusive tool, addressing the diverse needs of the MSL community and paving the way for ongoing research in sign language technology.

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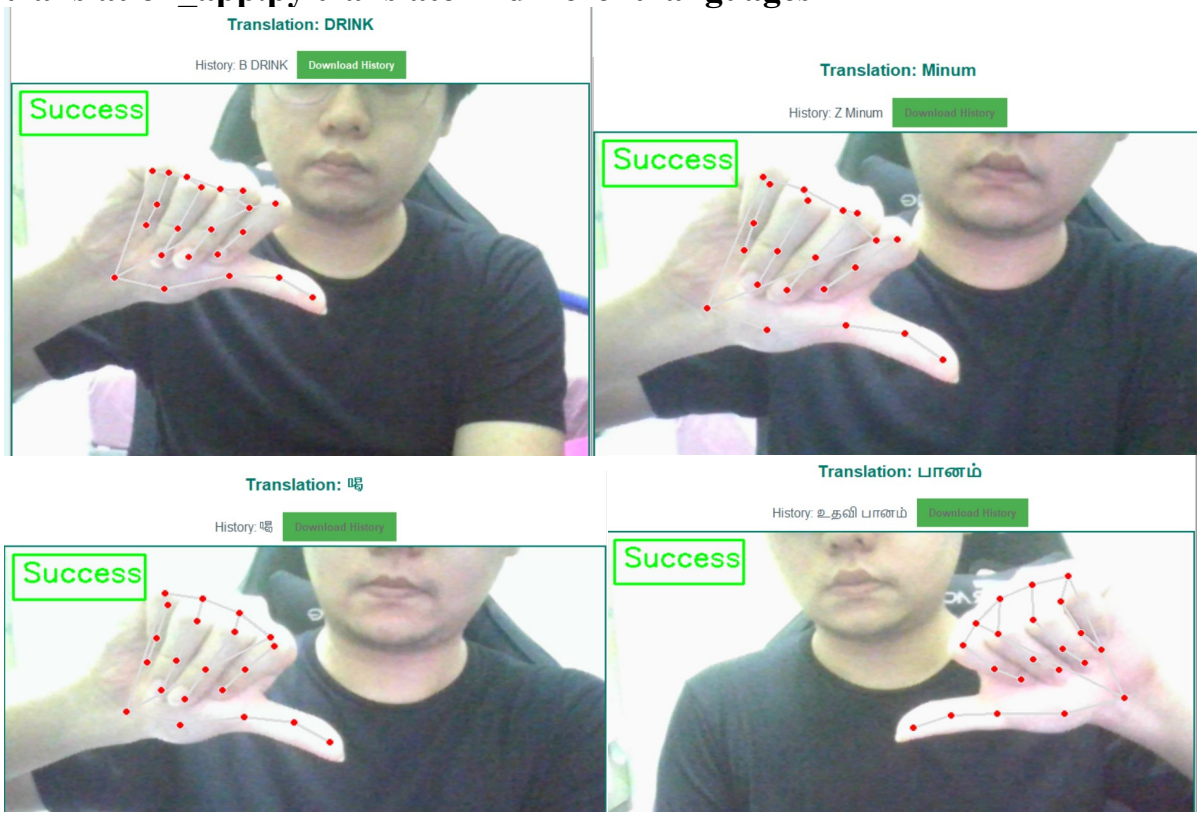
APPENDIX

APPENDIX A

translation_app.py translate in different languages



translation_app.py Logs in different languages

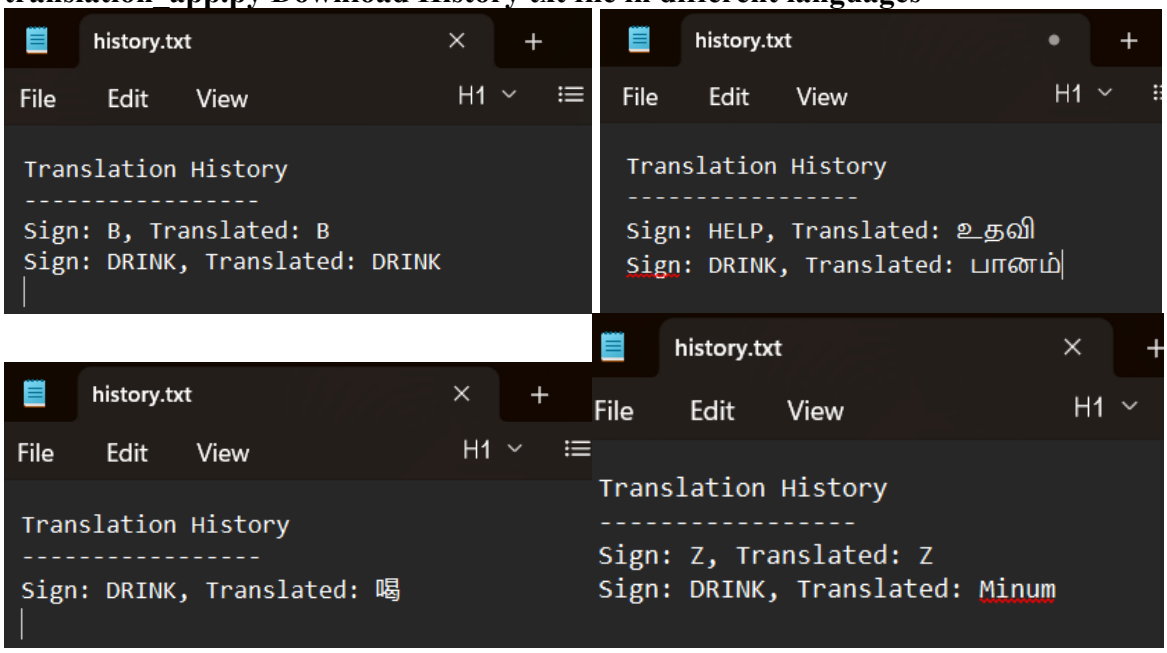
```
Debug - Predicted Index: 12, Sign: B
Debug - Condition Check: last_sign=B, current_sign=B, time_diff=12.768988609313965, reset=0.18479156494140625
Assigned category: Alphabet for sign: B
Translating 'B' with category 'Alphabet' and language 'English'
Recognized: None (Confidence: 0.98) -> Translated: B
Translating 'B' with category 'Alphabet' and language 'English'
```

```
Debug - Predicted Index: 15, Sign: DRINK
Debug - Condition Check: last_sign=B, current_sign=DRINK, time_diff=38.713109731674194, reset=25.7551531791687
Assigned category: SingleWords for sign: DRINK
Translating 'DRINK' with category 'SingleWords' and language 'English'
Recognized: DRINK (Confidence: 1.00) -> Translated: DRINK
Translating 'B' with category 'Alphabet' and language 'English'
Translating 'DRINK' with category 'SingleWords' and language 'English'
```

```
Debug - Predicted Index: 15, Sign: DRINK
Debug - Condition Check: last_sign=DRINK, current_sign=DRINK, time_di
Assigned category: SingleWords for sign: DRINK
Translating 'DRINK' with category 'SingleWords' and language 'Malay'
Recognized: None (Confidence: 0.96) -> Translated: Minum
Translating 'Z' with category 'Alphabet' and language 'Malay'
Translating 'DRINK' with category 'SingleWords' and language 'Malay'
```

```
Debug - Predicted Index: 15, Sign: DRINK
Debug - Condition Check: last_sign=DRINK, current_sign=D
Assigned category: SingleWords for sign: DRINK
Translating 'DRINK' with category 'SingleWords' and lang
Recognized: None (Confidence: 1.00) -> Translated: 喝
Debug - Predicted Index: 15, Sign: DRINK
Debug - Condition Check: last_sign=DRINK, current_sign=DRINK, time_d
Assigned category: SingleWords for sign: DRINK
Translating 'DRINK' with category 'SingleWords' and language 'Tamil'
Recognized: None (Confidence: 1.00) -> Translated: பானம்
```

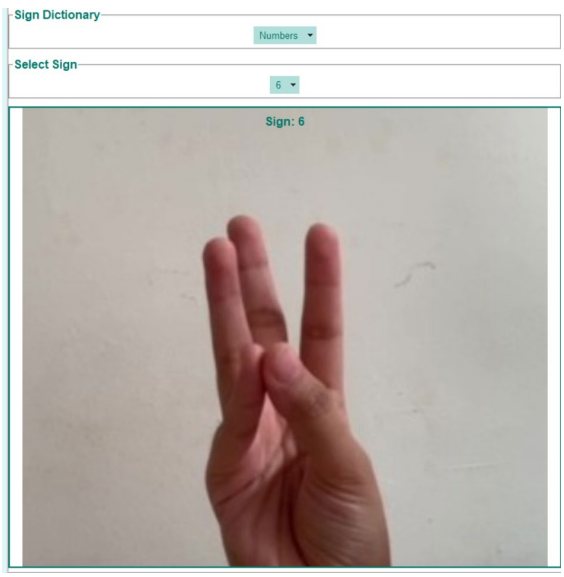
translation_app.py Download History txt file in different languages



APPENDIX B

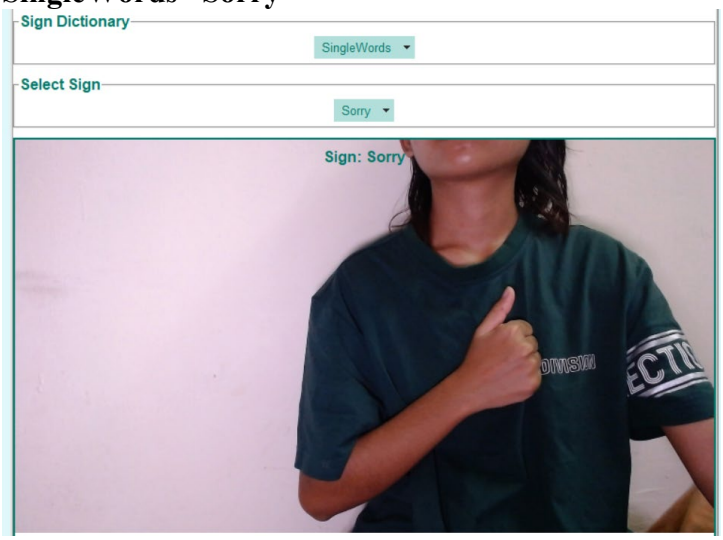
Dictionary in English

Numbers “6”



SingleWords “Eat”

SingleWords “Sorry”



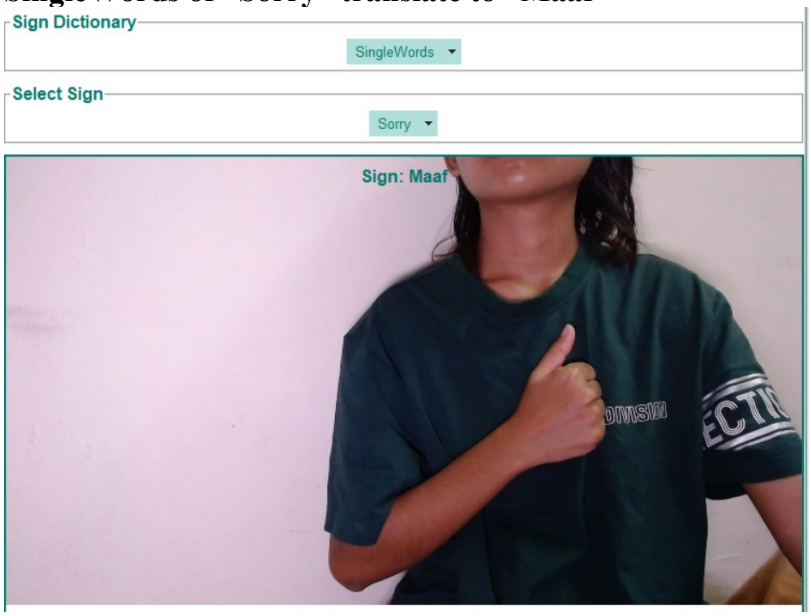
Logs of Numbers

```
Translating '0' with category 'Numbers' and language 'English'
Translating '1' with category 'Numbers' and language 'English'
Translating '2' with category 'Numbers' and language 'English'
Translating '3' with category 'Numbers' and language 'English'
Translating '4' with category 'Numbers' and language 'English'
Translating '5' with category 'Numbers' and language 'English'
Translating '6' with category 'Numbers' and language 'English'
Translating '7' with category 'Numbers' and language 'English'
Translating '8' with category 'Numbers' and language 'English'
Translating '9' with category 'Numbers' and language 'English'
Translating '10' with category 'Numbers' and language 'English'
Setting menu options: ['0', '1', '2', '3', '4', '5', '6', '7', '8', '9', '10']
Searching for image at: 6:\sign_language_project\archive\Dataset_MSL\Number\6\scene03161.jpg
Translating '6' with category 'Numbers' and language 'English'
```

Logs of SingleWords

```
Translating 'Eat' with category 'SingleWords' and language 'English'
Translated 'Eat' to 'Eat' in English
Translating 'Help' with category 'SingleWords' and language 'English'
Translated 'Help' to 'Help' in English
Translating 'Me' with category 'SingleWords' and language 'English'
Translated 'Me' to 'Me' in English
Translating 'Sorry' with category 'SingleWords' and language 'English'
Translated 'Sorry' to 'Sorry' in English
Translating 'Wrong' with category 'SingleWords' and language 'English'
Translated 'Wrong' to 'Wrong' in English
Translating 'You' with category 'SingleWords' and language 'English'
Translated 'You' to 'You' in English
Setting menu options: ['Drink', 'Eat', 'Help', 'Me', 'Sorry', 'Wrong', 'You']
Searching for image at: G:\sign_language_project\archive\Dataset_MSL\SingleWords\Eat\makan (1).jpg
Translating 'Eat' with category 'SingleWords' and language 'English'
```

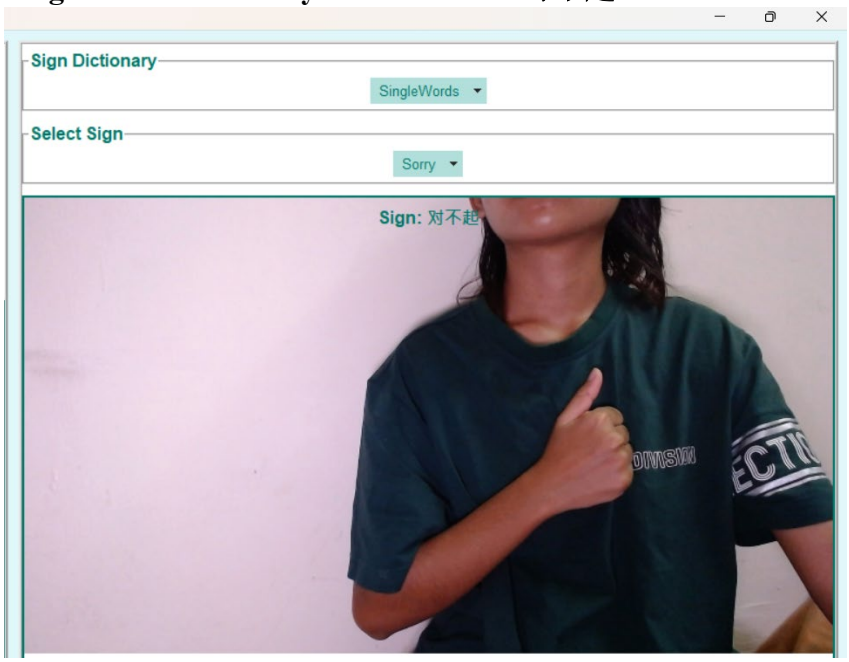
Dictionary in Malay
SingleWords of "Sorry" translate to "Maaf"



Logs of SingleWords

```
Translating 'Help' with category 'SingleWords' and language 'Malay'
Translated 'Help' to 'Tolong' in Malay
Translating 'Me' with category 'SingleWords' and language 'Malay'
Translated 'Me' to 'Saya' in Malay
Translating 'Sorry' with category 'SingleWords' and language 'Malay'
Translated 'Sorry' to 'Maaf' in Malay
Translating 'Wrong' with category 'SingleWords' and language 'Malay'
Translated 'Wrong' to 'Salah' in Malay
Translating 'You' with category 'SingleWords' and language 'Malay'
Translated 'You' to 'Anda' in Malay
Setting menu options: ['Minum', 'Makan', 'Tolong', 'Saya', 'Maaf', 'Salah', 'Anda']
Searching for image at: G:\sign_language_project\archive\Dataset_MSL\SingleWords\Sor
Translating 'Sorry' with category 'SingleWords' and language 'Malay'
Translated 'Sorry' to 'Maaf' in Malay
```

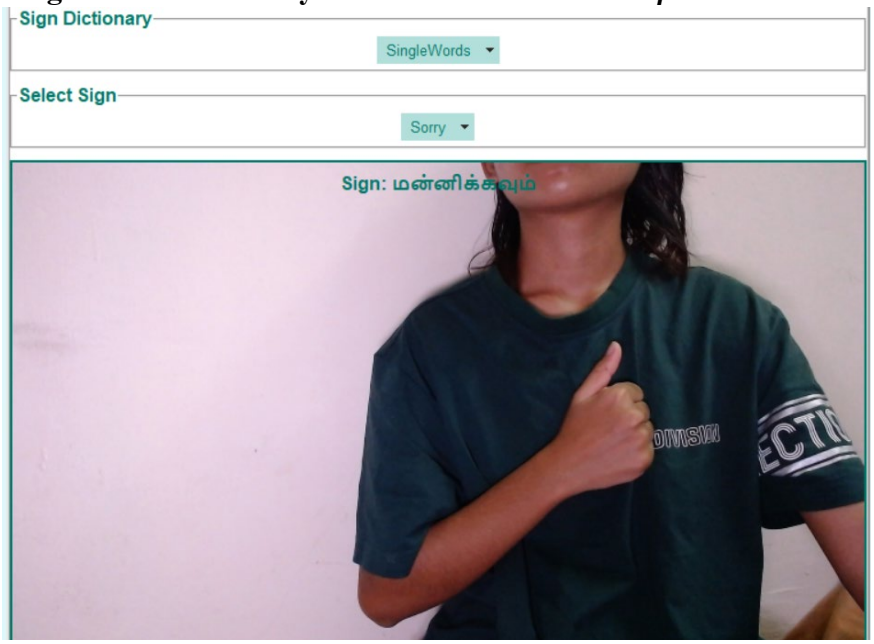
Dictionary in Chinese
SingleWords of "Sorry" translate to "对不起"



Logs of SingleWords

```
Translating 'Help' with category 'SingleWords' and language 'Chinese (Simplified)'
Translated 'Help' to '帮助' in Chinese (Simplified)
Translating 'Me' with category 'SingleWords' and language 'Chinese (Simplified)'
Translated 'Me' to '我' in Chinese (Simplified)
Translating 'Sorry' with category 'SingleWords' and language 'Chinese (Simplified)'
Translated 'Sorry' to '对不起' in Chinese (Simplified)
Translating 'Wrong' with category 'SingleWords' and language 'Chinese (Simplified)'
Translated 'Wrong' to '错误的' in Chinese (Simplified)
Translating 'You' with category 'SingleWords' and language 'Chinese (Simplified)'
Translated 'You' to '你' in Chinese (Simplified)
Setting menu options: ['喝', '吃', '帮助', '我', '对不起', '错误的', '你']
Searching for image at: G:\sign_language_project\archive\Dataset_MSL\SingleWords\Sorry\WIN_2024011
Translating 'Sorry' with category 'SingleWords' and language 'Chinese (Simplified)'
Translated 'Sorry' to '对不起' in Chinese (Simplified)
```

Dictionary in Tamil
SingleWords of "Sorry" translate to "மன்னிக்கவும்"



Logs of SingleWords

```
Translating 'Help' with category 'SingleWords' and language 'Tamil'
Translated 'Help' to 'உதவி' in Tamil
Translating 'Me' with category 'SingleWords' and language 'Tamil'
Translated 'Me' to 'நான்' in Tamil
Translating 'Sorry' with category 'SingleWords' and language 'Tamil'
Translated 'Sorry' to 'மன்னிக்கவும்' in Tamil
Translating 'Wrong' with category 'SingleWords' and language 'Tamil'
Translated 'Wrong' to 'தவறு' in Tamil
Translating 'You' with category 'SingleWords' and language 'Tamil'
Translated 'You' to 'நீங்கள்' in Tamil
Setting menu options: ['பானம்', 'சாப்பிடுங்கள்', 'உதவி', 'நான்', 'மன்னிக்கவும்', 'தவறு', 'நீங்கள்
Searching for image at: G:\sign_language_project\archive\Dataset_MSL\SingleWords\Sorry\WIN_202401
Translating 'Sorry' with category 'SingleWords' and language 'Tamil'
Translated 'Sorry' to 'மன்னிக்கவும்' in Tamil
```

APPENDIX C

process_online_datasets.py

```
import cv2  # Library for image processing and computer vision tasks
import numpy as np  # Library for numerical operations, used for handling arrays of landmarks
import os  # Library for file and directory operations, like creating folders and walking through directories
import mediapipe as mp  # Google's MediaPipe library for hand detection and landmark extraction

# Initialize MediaPipe Hands module for detecting hands in images
mp_hands = mp.solutions.hands  # Load the hands solution from MediaPipe
hands = mp_hands.Hands(static_image_mode=True, max_num_hands=2, min_detection_confidence=0.65)  # Configure the hand detector:
# - static_image_mode=True: Treat input as static images (not video stream) for better accuracy on individual images
# - max_num_hands=2: Detect up to 2 hands in one image
# - min_detection_confidence=0.65: Minimum confidence level for detecting a hand (65% threshold to reduce false positives)
mp_drawing = mp.solutions.drawing_utils  # Utility to draw hand landmarks on images (not used here, but included for potential visualization)

# Define directories for input data and output processed files
data_dir = "archive/Dataset_MSL"  # Input directory containing the MSL dataset images, organized in subfolders like Alphabets, Number, SingleWords
output_dir = "static_msl_data"  # Output directory where processed landmark data will be saved as .npy files

# Create output directory if it doesn't exist
if not os.path.exists(output_dir):
    os.makedirs(output_dir)  # Ensure the folder is created to store the .npy files

# Counter for handedness distribution (to track how many left/right hands are detected for each sign, for data analysis)
handedness_counts = {}

# Function to extract sign label from the directory name
def extract_sign_label(filepath):
    parts = filepath.split(os.sep)  # Split the file path into parts using the OS-specific separator (e.g., \ on Windows)
    sign_label = parts[-2]  # The sign label is the directory name just before the image file (e.g., "Drink" in SingleWords/Drink/image.jpg)
    return sign_label

# Function to normalize hand landmarks
def normalize_landmarks(hand_landmarks, handedness):
    landmarks = []  # List to store normalized landmark coordinates
    is_right_hand = handedness.classification[0].label == "Right"  # Check if the detected hand is right-handed
```

```
    # Use the wrist (landmark 0) as the reference point for normalization
    wrist = hand_landmarks.landmark[0]
    wrist_x, wrist_y, wrist_z = wrist.x, wrist.y, wrist.z

    # Normalize all landmarks relative to the wrist
    for lm in hand_landmarks.landmark:
        x = lm.x - wrist_x  # Subtract wrist x to normalize
        y = lm.y - wrist_y  # Subtract wrist y to normalize
        z = lm.z - wrist_z  # Subtract wrist z to normalize

        # Flip x-coordinate for right hand to mirror it as a left hand (ensures consistency
across hands)
        if is_right_hand:
            x = -x  # Mirror the x-coordinate relative to the wrist

        # Scale z-coordinate to reduce depth variability (z is often less reliable)
        z = z * 0.5  # Reduce the impact of depth differences

        landmarks.extend([x, y, z])  # Add the normalized x, y, z to the list

    if len(landmarks) < 126:
        landmarks.extend([0.0] * (126 - len(landmarks)))  # Pad with zeros if fewer than 126
landmarks (for 42 landmarks * 3 coordinates)
    return landmarks

# Process all files recursively in the data directory
for root, _, files in os.walk(data_dir):  # Walk through all subdirectories and files in
data_dir
    print(f"Processing directory: {root}")  # Print the current directory being processed for
tracking
    for filename in files:  # Loop through each file in the directory
        if filename.endswith((".jpg", ".png")):  # Process only image files with .jpg or .png
extensions
            # Get the relative path for label extraction (to handle nested directories)
            relative_path = os.path.relpath(os.path.join(root, filename), data_dir)
            # Extract sign label from the directory name
            sign_label = extract_sign_label(relative_path)

            # Load and process the image
            img = cv2.imread(os.path.join(root, filename))  # Read the image using OpenCV
            if img is None:
                print(f"Failed to load image: {filename}")  # Skip if image can't be loaded
                continue
            img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)  # Convert BGR (OpenCV
default) to RGB for MediaPipe
            results = hands.process(img_rgb)  # Process the image to detect hands
            if results.multi_hand_landmarks and results.multi_handedness:  # If hands are
detected
```

```
            for hand_landmarks, handedness in zip(results.multi_hand_landmarks,
results.multi_handedness):
                hand_type = handedness.classification[0].label  # "Left" or "Right"
                # Update handedness counts for data analysis (tracks distribution per sign)
                if sign_label not in handedness_counts:
                    handedness_counts[sign_label] = {"Left": 0, "Right": 0}
                handedness_counts[sign_label][hand_type] += 1  # Increment the count

                # Normalize landmarks based on handedness
                landmarks = normalize_landmarks(hand_landmarks, handedness)
                unique_filename =
f"{sign_label}_{os.path.basename(filename).split('.')[0]}.npy"  # Create a unique filename
for saving
                np.save(os.path.join(output_dir, unique_filename), np.array([landmarks]))  #
Save normalized landmarks as .npy file
                print(f"Saved: {unique_filename} (Shape: {np.array([landmarks]).shape})")  #
Confirm saving and shape
            else:
                print(f"No hands detected in image: {filename}")  # Skip if no hands found

# Print handedness distribution for all signs (useful for analyzing dataset bias)
print("Handedness distribution:")
for sign, counts in handedness_counts.items():
    print(f"{sign}: Left={counts['Left']}, Right={counts['Right']}")

hands.close()  # Close the MediaPipe hands processor to free resources
print("Processing complete.")  # Indicate that the dataset processing is finished
```

train_models.py

```
import numpy as np  # Library for numerical operations and array handling
import os  # Library for file and directory operations
from tensorflow.keras.models import Sequential  # Keras model for building sequential
neural networks
from tensorflow.keras.layers import Dense, Dropout, BatchNormalization  # Layers for the
neural network (dense, dropout for regularization, batch normalization for stabilization)
from tensorflow.keras.optimizers import SGD  # SGD optimizer for training the model
from sklearn.model_selection import train_test_split  # Function to split data into training
and testing sets
from sklearn.preprocessing import LabelEncoder  # Encoder to convert categorical labels
to numerical values
import collections  # Library for counting occurrences (used to filter classes with few
samples)

# Define the directory containing processed static data (.npy files from
process_online_datasets.py)
static_data_dir = "static_msl_data"
feature_list = []  # List to store the landmark features from .npy files
label_list = []  # List to store the corresponding sign labels
```

```
# Load the processed static data
print("Loading static MSL data for training...")
for data_file in os.listdir(static_data_dir):  # Loop through all files in the directory
    if data_file.endswith(".npy"):  # Process only .npy files
        sign_label = data_file.split("_")[0]  # Extract the sign label from the filename (before
the first '_')
        data = np.load(os.path.join(static_data_dir, data_file)).flatten()  # Load and flatten the
landmark data into 1D array
        feature_list.append(data)  # Add to features list
        label_list.append(sign_label)  # Add to labels list

# Check if any data was loaded
if not feature_list:
    print("Error: No static data found in static_msl_data/. Run process_online_datasets.py
first.")
    exit(1)  # Exit if no data is found

# Filter out classes with fewer than 2 samples (to avoid errors in stratification during
splitting)
label_counts = collections.Counter(label_list)  # Count occurrences of each label
filtered_features = []  # Filtered features list
filtered_labels = []  # Filtered labels list
min_samples = 2  # Minimum number of samples per class

for features, label in zip(feature_list, label_list):  # Loop through features and labels
    if label_counts[label] >= min_samples:  # Only include if the class has at least
min_samples
        filtered_features.append(features)
        filtered_labels.append(label)

# Check if we have enough data after filtering
if not filtered_features:
    print("Error: No classes with sufficient samples (at least 2) after filtering.")
    exit(1)  # Exit if no valid classes remain

# Convert lists to NumPy arrays for training
X = np.array(filtered_features)  # Features array (landmarks)
y = np.array(filtered_labels)  # Labels array (sign names)
print(f"Loaded {len(X)} samples with {len(set(y))} unique signs after filtering.")

# Encode the labels (e.g., "A" -> 0, "B" -> 1, etc.)
label_encoder = LabelEncoder()  # Initialize the label encoder
y_encoded = label_encoder.fit_transform(y)  # Fit and transform labels to numerical values
total_classes = len(label_encoder.classes_)  # Number of unique classes

# Split the data into training (80%) and testing (20%) sets
X_train, X_test, y_train, y_test = train_test_split(
    X, y_encoded, test_size=0.25, random_state=77, stratify=y_encoded  # Stratify to
```

```
maintain class distribution
)

# Build a neural network model for static sign classification
static_classifier = Sequential([  # Sequential model: layers are added in sequence
    Dense(384, activation="relu", input_shape=(126,)),  # Input layer: 384 neurons, ReLU
activation, input shape 126 (42 landmarks * 3 coordinates)
    BatchNormalization(),  # Normalize activations to stabilize training
    Dropout(0.25),  # Dropout 25% of neurons to prevent overfitting
    Dense(192, activation="relu"),  # Hidden layer: 192 neurons, ReLU activation
    BatchNormalization(),  # Normalize activations
    Dropout(0.25),  # Dropout 25%
    Dense(96, activation="relu"),  # Hidden layer: 96 neurons, ReLU activation
    Dropout(0.15),  # Dropout 15%
    Dense(total_classes, activation="softmax")  # Output layer: neurons equal to number of
classes, softmax for probabilities
])

# Compile the model with SGD optimizer
static_classifier.compile(
    optimizer=SGD(learning_rate=0.002, momentum=0.9),  # SGD optimizer with learning
rate 0.002 and momentum 0.9 for better convergence
    loss="sparse_categorical_crossentropy",  # Loss function for multi-class classification
with integer labels
    metrics=["accuracy"]  # Track accuracy during training
)

# Train the model
print("Training the static sign classifier...")
training_history = static_classifier.fit(
    X_train, y_train,  # Training data
    epochs=25,  # Number of training epochs (iterations over dataset)
    batch_size=48,  # Number of samples per batch
    validation_data=(X_test, y_test),  # Validation data for monitoring performance
    verbose=1  # Print detailed training progress
)

# Save the trained model in the native Keras format
static_classifier.save("static_msl_classifier.keras")  # Save the model for later use in the
translation app
print("Static classifier saved as static_msl_classifier.keras")

# Save the label mapping for use during inference
with open("static_msl_labels.txt", "w") as label_file:
    for idx, sign in enumerate(label_encoder.classes_):  # Loop through encoded labels
        label_file.write(f"{sign}:{idx}\n")  # Write sign:index pairs
print("Label mapping saved as static_msl_labels.txt")
```

translation_app.py

```
import cv2
import numpy as np
import tkinter as tk
from tkinter import ttk
from PIL import Image, ImageTk
import mediapipe as mp
from tensorflow.keras.models import load_model
from googletrans import Translator, LANGUAGES
import time
import os
from tkinter import filedialog
import glob

class MSLSignTranslatorApp:
    def __init__(self, root):
        # Initialize the main application window with a custom background color (#E0F7FA)
and enable resizing
        self.root = root
        self.root.title("MSL Sign Language Translator")  # Set the window title
        self.root.configure(bg="#E0F7FA")  # Set background color
        self.root.resizable(True, True)  # Allow the window to be resized horizontally and
vertically
        self.root.update_idletasks()  # Ensure the window is fully initialized before setting
constraints
        self.root.minsize(1024, 768)  # Set a minimum size to prevent the window from
becoming too small

        # Initialize video and model resources
        self.video_capture = None  # Placeholder for the video capture object (camera)
        try:
            self.sign_model = load_model("static_msl_classifier.keras")  # Load the pre-trained
sign recognition model
            print("Static sign recognition model loaded successfully.")
        except OSError as e:
            print(f"Failed to load model due to: {e}. Please execute train_models.py to create
static_msl_classifier.keras.")
            exit(1)  # Exit if the model file is missing
        self.sign_labels = {}  # Dictionary to map sign indices to their labels
        try:
            with open("static_msl_labels.txt", "r") as label_file:
                for line in label_file:  # Read each line from the label file
                    sign, idx = line.strip().split(":")  # Split into sign name and index
                    self.sign_labels[int(idx)] = sign  # Store the mapping
            print(f"Successfully loaded {len(self.sign_labels)} MSL sign labels.")
        except FileNotFoundError:
            print("Label file 'static_msl_labels.txt' missing. Run train_models.py to generate
it.")
            exit(1)  # Exit if the label file is missing
```

```
        self.translator = Translator()  # Initialize the Google Translate object
        self.target_language = tk.StringVar(value="English")  # Variable to store the selected
language
        self.mp_hands = mp.solutions.hands  # MediaPipe hands module for hand detection
        self.hand_detector = self.mp_hands.Hands(static_image_mode=False,
max_num_hands=2, min_detection_confidence=0.5)  # Configure hand detector
        self.mp_drawing = mp.solutions.drawing_utils  # Utility for drawing hand landmarks
        self.is_camera_on = False  # Flag to track camera status
        self.confidence_threshold = tk.DoubleVar(value=0.80)  # Variable for confidence
threshold (default 0.80)
        self.sign_history = []  # List to store the history of recognized signs
        self.last_sign = None  # Store the last recognized sign
        self.last_sign_time = time.time()  # Timestamp of the last sign recognition
        self.sign_buffer_time = 1.5  # Buffer time (seconds) to prevent rapid sign changes
        self.last_valid_time = time.time()  # Timestamp of the last valid sign
        self.current_translation = "None"  # Current translated text
        self.translation_cache = {}  # Cache to store translated texts and avoid repeated
translations
        self.log_file = "translation_session_log.txt"  # File to log translation sessions
        if os.path.exists(self.log_file):
            os.remove(self.log_file)  # Clear the log file if it exists
        with open(self.log_file, "a", encoding="utf-8") as f:
            f.write(f"Translation Session Log - Started: {time.strftime('%Y-%m-%d
%H:%M:%S %z')}\n")  # Start log with timestamp
        self.dictionary_category = tk.StringVar(value="Select Category")  # Variable for
dictionary category
        self.dictionary_sign = tk.StringVar(value="Select Sign")  # Variable for selected sign
in dictionary
        self.dictionary_image = None  # Placeholder for dictionary image
        self.dictionary_canvas = None  # Canvas for displaying dictionary images
        self.dataset_path = r"G:\sign_language_project\archive\Dataset_MSL"  # Path to the
dataset
        self.language_code_map = {
            "English": "en",
            "Malay": "ms",
            "Chinese (Simplified)": "zh-cn",
            "Tamil": "ta"
        }  # Mapping of language names to their ISO codes

        # Create main frame to hold all content with padding
        main_frame = tk.Frame(root, bg="#E0F7FA")
        main_frame.pack(expand=True, fill="both", padx=5, pady=5)

        # Create side-by-side frames for sign translation and dictionary with borders
        sign_bg_frame = tk.Frame(main_frame, bg="#FFFFFF", bd=3, relief="ridge")
        sign_bg_frame.grid(row=0, column=0, padx=5, pady=5, sticky="nsew")
        sign_frame = tk.Frame(sign_bg_frame, bg="#FFFFFF")
        sign_frame.pack(expand=True, fill="both")
```

```
        dict_bg_frame = tk.Frame(main_frame, bg="#FFFFFF", bd=3, relief="ridge")
        dict_bg_frame.grid(row=0, column=1, padx=5, pady=5, sticky="nsew")
        dict_frame = tk.Frame(dict_bg_frame, bg="#FFFFFF")
        dict_frame.pack(expand=True, fill="both")

        # Configure grid weights to allow resizing
        root.grid_rowconfigure(0, weight=1)
        root.grid_columnconfigure(0, weight=1)
        main_frame.grid_rowconfigure(0, weight=1)
        main_frame.grid_columnconfigure(0, weight=1)
        main_frame.grid_columnconfigure(1, weight=1)
        sign_bg_frame.grid_rowconfigure(0, weight=1)
        sign_bg_frame.grid_columnconfigure(0, weight=1)
        dict_bg_frame.grid_rowconfigure(0, weight=1)
        dict_bg_frame.grid_columnconfigure(0, weight=1)

        # Sign Translation Window setup
        control_frame = tk.Frame(sign_frame, bg="#FFFFFF")
        control_frame.pack(fill="x", pady=5)  # Horizontal fill with padding
        language_frame = tk.LabelFrame(control_frame, text="Language", font=("Arial", 12,
"bold"), fg="#00796B", bg="#FFFFFF", padx=10, pady=5)
        language_frame.pack(side=tk.LEFT, padx=5, fill="y")  # Left-aligned with vertical
fill
        supported_languages = {"en": "English", "ms": "Malay", "zh-cn": "Chinese
(Simplified)", "ta": "Tamil"}
        language_options = ["English", "Malay", "Chinese (Simplified)", "Tamil"]
        style = ttk.Style()
        style.configure("Modern.TMenubutton", background="#B2DFDB",
foreground="#00796B", font=("Arial", 10))
        ttk.OptionMenu(language_frame, self.target_language, "English", *language_options,
style="Modern.TMenubutton", command=self.update_language).pack()
        threshold_frame = tk.LabelFrame(control_frame, text="Confidence Threshold",
font=("Arial", 12, "bold"), fg="#00796B", bg="#FFFFFF", padx=10, pady=5)
        threshold_frame.pack(side=tk.LEFT, padx=5, fill="y")  # Left-aligned with vertical
fill
        tk.Scale(threshold_frame, from_=0.5, to=1.0, resolution=0.01,
orient=tk.HORIZONTAL,
                 variable=self.confidence_threshold, command=self.update_threshold,
bg="#FFFFFF", troughcolor="#B2DFDB", highlightbackground="#00796B").pack()
        button_frame = tk.Frame(sign_frame, bg="#FFFFFF")
        button_frame.pack(pady=5)  # Vertical padding
        self.open_cam_button = tk.Button(button_frame, text="Open Cam", font=("Arial",
10, "bold"), bg="#00796B", fg="white", activebackground="#004D40",
command=self.open_camera, relief="flat", padx=10, pady=5)
        self.open_cam_button.pack(side=tk.LEFT, padx=5)  # Left-aligned with horizontal
padding
        self.close_cam_button = tk.Button(button_frame, text="Close Cam", font=("Arial",
10, "bold"), bg="#D32F2F", fg="white", activebackground="#B71C1C",
command=self.close_camera, state=tk.DISABLED, relief="flat", padx=10, pady=5)
```

```
        self.close_cam_button.pack(side=tk.LEFT, padx=5)  # Left-aligned with horizontal
padding
        self.translation_label = tk.Label(sign_frame, text="Translation: None", font=("Arial",
16, "bold"), fg="#00796B", bg="#FFFFFF", pady=10)
        self.translation_label.pack(pady=5)  # Vertical padding

        history_frame = tk.Frame(sign_frame, bg="#FFFFFF")
        history_frame.pack(pady=5)  # Vertical padding
        self.history_label = ttk.Label(history_frame, text="History: ", font=("Arial", 12),
foreground="#455A64", background="#FFFFFF", wraplength=400)  # Use 'background'
instead of '-bg'
        self.history_label.pack(side=tk.LEFT, padx=5)  # Left-aligned with horizontal
padding
        self.download_button = tk.Button(history_frame, text="Download History",
font=("Arial", 10, "bold"), bg="#4CAF50", fg="white", activebackground="#388E3C",
command=self.download_history, state=tk.DISABLED, relief="flat", padx=10, pady=5)
        self.download_button.pack(side=tk.RIGHT, padx=5)  # Right-aligned with horizontal
padding to keep it visible
        self.video_canvas = tk.Canvas(sign_frame, bg="#FFFFFF", highlightthickness=2,
highlightbackground="#00796B")
        self.video_canvas.pack(expand=True, fill="both")  # Expand to fill available space

        # Dictionary Window setup
        dict_category_frame = tk.LabelFrame(dict_frame, text="Sign Dictionary",
font=("Arial", 12, "bold"), fg="#00796B", bg="#FFFFFF", padx=10, pady=5)
        dict_category_frame.pack(pady=5, fill="x")  # Horizontal fill with padding
        ttk.OptionMenu(dict_category_frame, self.dictionary_category, "Select Category",
"Alphabet", "Numbers", "SingleWords", command=self.update_sign_options,
style="Modern.TMenubutton").pack()
        self.sign_options = {}  # Dictionary to store sign categories and their options
        self.sign_options["Alphabet"] = [chr(i) for i in range(ord('A'), ord('Z') + 1)]  # List of
alphabet letters
        self.sign_options["Numbers"] = [str(i) for i in range(11)]  # List of numbers 0-10
        self.sign_options["SingleWords"] = ["Drink", "Eat", "Help", "Me", "Sorry", "Wrong",
"You"]  # List of single words
        self.dict_sign_frame = tk.LabelFrame(dict_frame, text="Select Sign", font=("Arial",
12, "bold"), fg="#00796B", bg="#FFFFFF", padx=10, pady=5)
        self.dict_sign_frame.pack(pady=5, fill="x")  # Horizontal fill with padding
        self.sign_menu = ttk.OptionMenu(self.dict_sign_frame, self.dictionary_sign, "Select
Sign", *self.sign_options["Alphabet"], style="Modern.TMenubutton")
        self.sign_menu.pack()
        self.dictionary_sign.trace('w', self.update_dictionary_image)  # Trigger image update
on sign selection
        self.target_language.trace('w', self.update_language)  # Trigger language update
        dict_image_frame = tk.Frame(dict_frame, bg="#FFFFFF")
        dict_image_frame.pack(pady=5, fill="both", expand=True)  # Expand to fill available
space
        self.dictionary_canvas = tk.Canvas(dict_image_frame, bg="#FFFFFF",
highlightthickness=2, highlightbackground="#00796B")
```

```
        self.dictionary_canvas.pack(expand=True, fill="both")  # Expand to fill available
space

    def update_threshold(self, value):
        # Update the confidence threshold dynamically when the slider is moved
        self.confidence_threshold.set(float(value))

    def update_language(self, *args):
        # Update the application language and refresh related components
        print(f"Language changed to: {self.target_language.get()}")
        if hasattr(self, 'sign_menu'):
            category = self.dictionary_category.get()
            if category != "Select Category":
                self.update_sign_options(category)  # Update sign options for the selected
category
            else:
                self.dictionary_category.set("Alphabet")  # Default to Alphabet if no category
selected
                self.update_sign_options("Alphabet")
        # Clear translation cache to force re-translation with new language
        self.translation_cache.clear()
        # Update history and current translation with the new language
        if self.sign_history:
            self.history_label.config(text=f"History: {' '.join([self.translate_text(sign,
'SingleWords' if sign.lower() in [s.lower() for s in self.sign_options['SingleWords']] else
'Alphabet') for sign in self.sign_history])}")
        if self.last_sign:
            category = "SingleWords" if self.last_sign.lower() in [s.lower() for s in
self.sign_options["SingleWords"]] else "Alphabet"
            self.current_translation = self.translate_text(self.last_sign, category)
            self.translation_label.config(text=f"Translation: {self.current_translation}")

    def normalize_landmarks(self, hand_landmarks, handedness):
        # Normalize hand landmarks relative to the wrist position for consistent recognition
        landmarks = []
        is_right_hand = handedness.classification[0].label == "Right"  # Check if it's the right
hand
        wrist = hand_landmarks.landmark[0]  # Use wrist as reference point
        wrist_x, wrist_y, wrist_z = wrist.x, wrist.y, wrist.z
        for lm in hand_landmarks.landmark:
            x = lm.x - wrist_x  # Normalize x relative to wrist
            y = lm.y - wrist_y  # Normalize y relative to wrist
            z = lm.z - wrist_z  # Normalize z relative to wrist
            if is_right_hand:
                x = -x  # Mirror x for right hand to maintain consistency
            z = z * 0.5  # Scale z for better depth perception
            landmarks.extend([x, y, z])  # Add normalized coordinates
        return landmarks
```

```
    def extract_hand_landmarks(self, frame):
        # Extract and draw hand landmarks from the video frame
        frame_rgb = cv2.cvtColor(frame, cv2.COLOR_BGR2RGB)  # Convert BGR to RGB
for MediaPipe
        hand_results = self.hand_detector.process(frame_rgb)  # Process frame to detect
hands
        landmarks = []
        if hand_results.multi_hand_landmarks and hand_results.multi_handedness:
            for hand, handedness in zip(hand_results.multi_hand_landmarks,
hand_results.multi_handedness):
                self.mp_drawing.draw_landmarks(frame, hand,
self.mp_hands.HAND_CONNECTIONS)  # Draw landmarks on frame
                hand_coords = self.normalize_landmarks(hand, handedness)  # Normalize
landmarks
                landmarks.extend(hand_coords)  # Collect all landmark coordinates
            if len(hand_results.multi_hand_landmarks) == 1:
                landmarks.extend([0.0] * 63)  # Pad with zeros if only one hand is detected
        return np.array(landmarks) if landmarks else None, frame  # Return landmarks and
annotated frame

    def translate_text(self, sign_text, category):
        # Translate the sign text based on the selected language
        print(f"Translating '{sign_text}' with category '{category}' and language
'{self.target_language.get()}'")
        if category != "SingleWords":  # Only translate single words, not alphabet or numbers
            return sign_text
        if sign_text in self.translation_cache:  # Use cached translation if available
            return self.translation_cache[sign_text]
        try:
            lang_name = self.target_language.get()  # Get the current language
            lang_code = self.language_code_map.get(lang_name, "en")  # Get the language
code
            translated = self.translator.translate(sign_text, dest=lang_code)  # Perform
translation
            result = translated.text if translated else sign_text  # Use translated text or original if
translation fails
            self.translation_cache[sign_text] = result  # Cache the result
            print(f"Translated '{sign_text}' to '{result}' in {lang_name}")
            return result
        except Exception as e:
            print(f"Translation error occurred: {e}")
            return sign_text  # Return original text on error

    def log_translation(self, sign_text, confidence, translated_text):
        # Log the translation details to a file with a timestamp
        try:
            timestamp = time.strftime("%Y-%m-%d %H:%M:%S %z")
            with open(self.log_file, "a", encoding="utf-8") as f:
                f.write(f"{timestamp} - Sign: {sign_text}, Confidence: {confidence:.2f},
```

```
Translated: {translated_text}\n")
        except Exception as e:
            print(f"Error logging translation: {e}")

    def download_history(self):
        # Allow the user to download the translation history as a text file
        file_path = filedialog.asksaveasfilename(defaultextension=".txt", filetypes=[("Text
files", "*.txt"), ("All files", "*.*")], initialfile="history.txt")
        if file_path:
            with open(file_path, "w", encoding="utf-8") as f:
                f.write("Translation History\n")
                f.write("------------------\n")
                for sign in self.sign_history:
                    translated = self.translate_text(sign, "SingleWords" if sign.lower() in
[s.lower() for s in self.sign_options["SingleWords"]] else "Alphabet")
                    f.write(f"Sign: {sign}, Translated: {translated}\n")
            print(f"History saved successfully to {file_path}")
            self.reset_session()  # Reset the session after download

    def reset_session(self):
        # Reset the session state to clear all data
        self.sign_history = []
        if os.path.exists(self.log_file):
            os.remove(self.log_file)  # Clear the log file
        with open(self.log_file, "a", encoding="utf-8") as f:
            f.write(f"Translation Session Log - Started: {time.strftime('%Y-%m-%d
%H:%M:%S %z')}\n")  # Start new log
        self.last_sign = None
        self.last_sign_time = time.time()
        self.last_valid_time = time.time()
        self.current_translation = "None"
        self.translation_label.config(text="Translation: None")
        self.history_label.config(text="History: ")
        self.download_button.config(state=tk.DISABLED)

    def open_camera(self):
        # Start the camera feed for real-time sign recognition
        if not self.is_camera_on:
            self.video_capture = cv2.VideoCapture(0)  # Open the default camera (index 0)
            if not self.video_capture.isOpened():
                print("Failed to open webcam.")
                return
            self.is_camera_on = True
            self.open_cam_button.config(state=tk.DISABLED)  # Disable Open Cam button
            self.close_cam_button.config(state=tk.NORMAL)  # Enable Close Cam button
            self.update_video_feed()  # Start the video feed update loop

    def close_camera(self):
        # Stop the camera feed and update the UI
```

```
        if self.is_camera_on:
            self.is_camera_on = False
            if self.video_capture:
                self.video_capture.release()  # Release the camera resource
            self.open_cam_button.config(state=tk.NORMAL)  # Re-enable Open Cam button
            self.close_cam_button.config(state=tk.DISABLED)  # Disable Close Cam button
            self.translation_label.config(text="Translation: None")
            # Update history label with translated text based on current language
            if self.sign_history:
                self.history_label.config(text=f"History: {' '.join([self.translate_text(sign,
'SingleWords' if sign.lower() in [s.lower() for s in self.sign_options['SingleWords']] else
'Alphabet') for sign in self.sign_history])}")
            else:
                self.history_label.config(text="History: ")
            self.download_button.config(state=tk.NORMAL)  # Enable Download History
button

    def update_sign_options(self, category):
        # Update the sign selection options in the dictionary based on the chosen category
        if hasattr(self, 'sign_menu'):
            self.sign_menu.destroy()  # Remove the old menu
        self.sign_menu = ttk.OptionMenu(self.dict_sign_frame, self.dictionary_sign, "Select
Sign", *[], style="Modern.TMenubutton")
        self.sign_menu.pack()
        menu = self.sign_menu["menu"]
        menu.delete(0, "end")  # Clear existing menu items
        signs = self.sign_options[category]  # Get signs for the selected category
        self.translation_cache.clear()  # Clear cache for new translations
        print(f"Translating for language: {self.target_language.get()}")
        translated_signs = [self.translate_text(sign, category) for sign in signs]  # Translate all
signs
        print(f"Setting menu options: {translated_signs}")
        for translated_sign, original_sign in zip(translated_signs, signs):
            menu.add_command(label=translated_sign, command=lambda x=original_sign:
self.dictionary_sign.set(x))  # Add translated options
        self.dictionary_sign.set("Select Sign")  # Reset to default selection
        self.update_dictionary_image()  # Update the displayed image

    def update_dictionary_image(self, *args):
        # Update the dictionary image based on the selected sign
        sign = self.dictionary_sign.get()
        if sign != "Select Sign" and self.dictionary_canvas:
            category = self.dictionary_category.get()
            if category in self.sign_options:
                image_path = self.find_first_image(category, sign)  # Find the first image for the
sign
                print(f"Searching for image at: {image_path}")
                if image_path and os.path.exists(image_path):
                    img = cv2.imread(image_path)  # Read the image
```

```
                # Get the current canvas dimensions to fit the image
                canvas_width = self.dictionary_canvas.winfo_width()
                canvas_height = self.dictionary_canvas.winfo_height()
                # Resize the image proportionally to fit within the canvas while maintaining
aspect ratio
                aspect_ratio = img.shape[1] / img.shape[0]  # Width / Height
                if canvas_width / aspect_ratio <= canvas_height:
                    new_width = canvas_width
                    new_height = int(canvas_width / aspect_ratio)
                else:
                    new_height = canvas_height
                    new_width = int(canvas_height * aspect_ratio)
                img = cv2.resize(img, (new_width, new_height))
                img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)  # Convert to RGB
                self.dictionary_image = ImageTk.PhotoImage(
                    Image.fromarray(img))  # Convert to Tkinter-compatible image
                self.dictionary_canvas.delete("all")  # Clear previous content
                self.dictionary_canvas.create_image(canvas_width // 2, new_height // 2,
                                                    image=self.dictionary_image)  # Center the image
                translated_sign = self.translate_text(sign, category)  # Translate the sign
                # Add text label above the image, centered, with a small offset to avoid
overlap
                self.dictionary_canvas.create_text(canvas_width // 2, 20, text=f"Sign:
{translated_sign}",
                                                   font=("Arial", 12, "bold"), fill="#00796B")
            else:
                self.dictionary_canvas.delete("all")  # Clear previous content
                self.dictionary_canvas.create_text(canvas_width // 2, canvas_height // 2,
text="Image not found",
                                                   font=("Arial", 14),
                                                   fill="#D32F2F")  # Display error if image not found
                print(f"No image found at: {image_path}")

    def find_first_image(self, category, sign):
        # Find the first available image for the selected sign in the dataset
        base_path = self.dataset_path
        if category == "Alphabet":
            search_path = os.path.join(base_path, "Alphabets", sign.upper(), "*")  # Path for
alphabet signs
        elif category == "Numbers":
            search_path = os.path.join(base_path, "Number", sign, "*")  # Path for numbers
        elif category == "SingleWords":
            search_path = os.path.join(base_path, "SingleWords", sign, "*")  # Path for single
words
        else:
            return None
        images = (glob.glob(search_path + ".jpg") +
                  glob.glob(search_path + ".jpeg") +
                  glob.glob(search_path + ".png") +
```

```
            glob.glob(search_path + ".JPG") +
            glob.glob(search_path + ".JPEG") +
            glob.glob(search_path + ".PNG"))  # Search for image files
        return images[0] if images else None  # Return the first found image path or None

    def update_video_feed(self):
        # Continuously update the video feed for real-time sign recognition
        if self.is_camera_on:
            try:
                ret, frame = self.video_capture.read()  # Read a frame from the camera
                if ret:
                    frame = cv2.flip(frame, 1)  # Flip the frame horizontally for a mirror effect
                    landmarks, annotated_frame = self.extract_hand_landmarks(frame)  # Extract
and annotate hand landmarks
                    translated_text = self.current_translation  # Current translation to display
                    sign_text = "None"  # Default sign text
                    confidence = 0.0  # Default confidence score
                    if landmarks is not None:
                        input_data = landmarks.reshape(1, -1)  # Reshape landmarks for model
prediction
                        prediction = self.sign_model.predict(input_data, verbose=0)  # Predict the
sign
                        sign_idx = np.argmax(prediction, axis=1)[0]  # Get the index of the highest
probability
                        confidence = prediction[0][sign_idx]  # Get the confidence score
                        current_sign = self.sign_labels.get(sign_idx, "Unknown")  # Map index to
sign
                        print(f"Debug - Predicted Index: {sign_idx}, Sign: {current_sign}")
                        current_time = time.time()  # Current timestamp
                        if confidence > self.confidence_threshold.get():  # Check if confidence is
above threshold
                            print(f"Debug - Condition Check: last_sign={self.last_sign},
current_sign={current_sign}, time_diff={current_time - self.last_sign_time},
reset={current_time - self.last_valid_time}")
                            if (self.last_sign != current_sign and
                                current_time - self.last_sign_time > self.sign_buffer_time):  # New
sign detected
                                sign_text = current_sign
                                category = "SingleWords" if current_sign.lower() in [s.lower() for s in
self.sign_options["SingleWords"]] else "Alphabet"
                                print(f"Assigned category: {category} for sign: {current_sign}")
                                translated_text = self.translate_text(current_sign, category)  # Translate
the sign
                                self.current_translation = translated_text
                                self.sign_history.append(current_sign)  # Add to history
                                self.log_translation(current_sign, confidence, translated_text)  # Log
the translation
                                self.last_sign = current_sign
                                self.last_sign_time = current_time
```

```
                        self.last_valid_time = current_time
                    else:
                        if confidence > 0.90:  # High confidence update
                            self.last_valid_time = current_time
                        category = "SingleWords" if current_sign.lower() in [s.lower() for s in
self.sign_options["SingleWords"]] else "Alphabet"
                        print(f"Assigned category: {category} for sign: {current_sign}")
                        translated_text = self.translate_text(current_sign, category)  # Re-
translate
                        self.current_translation = translated_text
                    if confidence > 0.80:
                        cv2.rectangle(annotated_frame, (10, 10), (150, 60), (0, 255, 0), 2)  #
Green box for success
                        cv2.putText(annotated_frame, "Success", (20, 40),
cv2.FONT_HERSHEY_SIMPLEX, 1, (0, 255, 0), 2)
                    else:
                        cv2.rectangle(annotated_frame, (10, 10), (150, 60), (0, 0, 255), 2)  #
Red box for low confidence
                        cv2.putText(annotated_frame, "Low Confidence", (20, 40),
cv2.FONT_HERSHEY_SIMPLEX, 0.5, (0, 0, 255), 2)
                else:
                    if current_time - self.last_valid_time > 5.0:  # Reset if no valid sign for 5
seconds
                        self.last_sign = None
                        self.last_sign_time = current_time
                        self.current_translation = "None"
                print(f"Recognized: {sign_text} (Confidence: {confidence:.2f}) -> Translated:
{translated_text}")
                self.translation_label.config(text=f"Translation: {translated_text}")
                self.history_label.config(text=f"History: {' '.join([self.translate_text(sign,
'SingleWords' if sign.lower() in [s.lower() for s in self.sign_options['SingleWords']] else
'Alphabet') for sign in self.sign_history])}")
                frame_rgb = cv2.cvtColor(annotated_frame, cv2.COLOR_BGR2RGB)  #
Convert to RGB for display
                photo = Image.fromarray(frame_rgb)
                canvas_width = self.video_canvas.winfo_width()  # Get current canvas width
                canvas_height = self.video_canvas.winfo_height()  # Get current canvas height
                photo = photo.resize((canvas_width, canvas_height),
Image.Resampling.LANCZOS)  # Resize image to fit canvas
                tk_photo = ImageTk.PhotoImage(photo)
                self.video_canvas.create_image(0, 0, anchor=tk.NW, image=tk_photo)  #
Display the frame
                self.video_canvas.image = tk_photo  # Keep a reference to prevent garbage
collection
            self.root.after(30, self.update_video_feed)  # Schedule the next frame update
(approx. 30ms)
        except Exception as e:
            print(f"Error in video feed update: {e}")
            self.close_camera()  # Close camera on error
```

```
    def __del__(self):
        # Clean up resources when the application closes
        if self.video_capture:
            self.video_capture.release()  # Release the camera
        self.hand_detector.close()  # Close the hand detector
        print("All resources have been safely released.")

if __name__ == "__main__":
    root = tk.Tk()  # Create the main Tkinter window
    app = MSLSignTranslatorApp(root)  # Instantiate the application
    root.mainloop()  # Start the event loop
```

POSTER

UTAR
UNIVERSITI TUNKU ABDUL RAHMAN

Faculty of Information and Communication Technology (FICT)

AUTOMATED SIGN LANGUAGE TRANSLATION USING DEEP LEARNING

Wong Jia Kang, Dr Muhammad Husaini Bin Nadri

INTRODUCTION

- **Barrier** between **deaf** and **hearing communities** due to **limited MSL** use.
- **Goal**: **Real-time MSL gesture-to-text** with **>90% accuracy**, including **Dictionary Panel**. Support **English**, **Malay**, **Chinese**, and **Tamil.**

METHODOLOGY

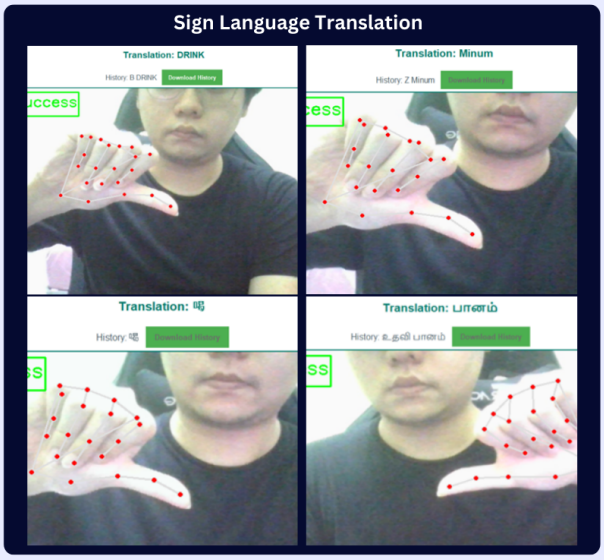
- **Dataset Processing:** Processed **7445 MSL images** with **MediaPipe** for **normalization**.
- **Model Training:** Trained Keras model (**25 epochs**, **97.58% accuracy**).
- **Real-Time App:** Built app with **Tkinter GUI**, **webcam**, **Translate API**, and **Dictionary Panel** for sign lookup by **category** and **language**.

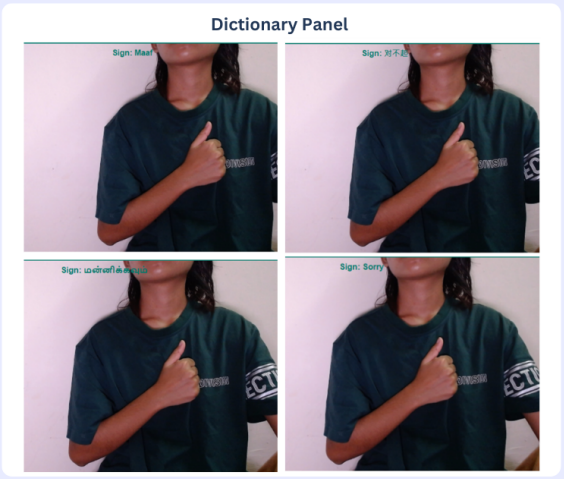
RESULTS

- **Model**: **97.58% validation accuracy** on **1862 samples**.
- **Real-Time App**: **>90% accuracy** on 44 signs (e.g., "G", "DRINK").
- **Dictionary Panel**: **100ms** load time, **translates signs** to **selected languages** (**English**, **Malay**, **Chinese**, **Tamil**).

DISCUSSION

- **High accuracy** for **common signs** (e.g., **DRINK**), **lower** for **sparse** (e.g., **G**).
- **Resolved dataset** and **API issues** with **curation** and **retries**.
- **Dictionary Panel** boosts **usability**, though **speed varies** with data.





TOOLS

MediaPipe TensorFlow PC

CONCLUSION

- **Achieved 95-97% accuracy** with **Dictionary Panel** support.
- **Future**: Add **dynamic signs** and **expand panel** features.