VISVESVARAYA TECHNOLOGICAL UNIVERSITY
BELAGAVI-590 018

A PROJECT REPORT ON

SIGN LANGUAGE TRANSLATOR

Submitted in partial fulfillment of the requirements for the award of the degree of

BACHELOR OF ENGINEERING IN

COMPUTER SCIENCE AND ENGINEERING

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CERTIFICATE

Certified that the project work entitled "**SIGN LANGUAGE TRANSLATOR**" carried out by **Mr. ABBAS SHAZIN**, USN **4PA22CS001**, **Mr. ABDUL KADER SUHAIR AFRAN**, USN **4PA22CS002**, **Mr. ABDULLA ANFAL**, USN **4PA22CS005**, **Mr. ABOOBAKKER MAZIL TANVEER**, USN **4PA22CS010**, bonafide students of **P.A. College of Engineering** in partial fulfilment for the award of bachelor of engineering in **Department of Computer Science & Engineering** of the Visvesvaraya Technological University, Belagavi, during the year **2025-2026**. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in the Report deposited in the departmental library. The project report has been approved as it satisfies the academic requirements in respect of Project work prescribed for the said degree.

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DECLARATION

We, the students of Sixth Semester B.E, in the Department of Computer Science and Engineering, **P.A. College of Engineering**, Mangalore declare that the project entitled "SIGN LANGUAGE TRANSLATOR" has been carried out by us and submitted in partial fulfilment of the course requirements for the award of degree in **Bachelor of Engineering in Computer Science and Engineering** of Visvesvaraya Technological University, Belagavi during the academic year 2025- 2026.The matter embodied in this report submitted has not been presented to any other University (or) Institution for the award of any Degree (or) Diploma.

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ABSTRACT

Communication barriers between the deaf and hard-of-hearing community and individuals unfamiliar with sign language continue to pose significant challenges in social and professional interactions. Sign language serves as a vital communication medium for individuals with hearing impairments, yet its limited understanding among the general population often leads to exclusion and misunderstanding. To address this issue, the proposed system introduces a real-time sign language translation model that converts hand gestures into textual output. This system aims to enhance accessibility and foster inclusive communication by enabling sign language users to convey their messages effectively to non-signers in day-to-day situations.

The proposed system employs a vision-based approach that captures hand gestures using a webcam and processes them in real time. The recognition pipeline is structured into multiple stages: image acquisition, pre-processing, feature extraction, and classification. Using OpenCV for image handling and MediaPipe for keypoint detection, the system identifies and tracks hand landmarks with high precision. These key features are then analyzed to determine the corresponding gesture, which is mapped to its textual equivalent. The frontend interface, developed using React, provides users with a smooth and interactive experience, displaying recognized text in real time for clear communication.

Designed for efficiency and accuracy, the system achieves robust performance even under varying lighting and background conditions. Its lightweight design ensures compatibility with consumer-grade hardware, allowing seamless execution without requiring high-end computational resources. By bridging the gap between sign language and textual communication, this project contributes to the development of inclusive technologies that empower the deaf and hard-of-hearing community, promoting greater understanding and accessibility in everyday communication.

TABLE OF CONTENTS

CONTENTS

CHAPTER 1

INTRODUCTION

1.1 Overview

Sign language plays a vital role in enabling communication for individuals with hearing and speech impairments. However, the lack of awareness and understanding of sign language among the general population often leads to communication barriers, limiting inclusion and accessibility. With the rapid advancements in artificial intelligence and computer vision, researchers are developing systems that can automatically recognize and interpret gestures. This project presents a real-time sign language translation system that uses MediaPipe and OpenCV to detect and classify hand gestures into corresponding text. The goal is to bridge the communication gap between sign language users and non-signers, thereby promoting inclusivity and enhancing human interaction.

1.2 Introduction

Sign language is an essential mode of communication for millions of individuals with hearing and speech impairments, enabling them to express thoughts, emotions, and ideas effectively. However, the lack of sign language knowledge among the general population continues to create a communication gap, often leading to social isolation and misunderstanding. Traditional methods of interpretation, such as human translators or pre-recorded gesture videos, are neither reliable nor scalable for real-time use. As the demand for inclusive and accessible technology grows, there is an increasing need for automated systems capable of interpreting sign language accurately and efficiently.

This study introduces a vision-based approach to gesture recognition using computer vision and deep learning techniques. The system utilizes MediaPipe and OpenCV to detect, track, and analyze hand landmarks, identifying gestures and translating them into textual output. By recognizing key hand movements and positions, the model effectively interprets sign language in real time, bridging the gap between signers and non-signers.

With rapid advancements in artificial intelligence and web technologies, it is now possible to create responsive and user-friendly systems that operate solely using a camera. MediaPipe, a

state-of-the-art framework developed by Google, offers robust hand landmark detection and tracking capabilities, making it ideal for real-time sign recognition. Combined with OpenCV for image processing and React for an interactive frontend, the proposed system provides a seamless platform for communication. The primary aim of this project is to develop a real-time sign language translation system that converts hand gestures into readable text. By leveraging computer vision and machine learning, the project aims to promote inclusivity, enhance communication accessibility, and empower individuals with hearing and speech impairments to interact freely in society.

1.3 Literature Survey

In 2025, **Sneha Sharma[1]** presented "Real-Time Sign Language Recognition Using MediaPipe and Deep Learning", a study focusing on improving accessibility for hearing-impaired individuals through intelligent computer vision. The proposed system utilized MediaPipe Hands for landmark detection and a Convolutional Neural Network (CNN) for gesture classification. MediaPipe extracted 21 key landmarks from hand movements, which were then processed into numerical feature vectors for training. The system achieved high accuracy in real-time gesture recognition while maintaining low latency. **Sneha Sharma[1]** emphasized the model's scalability, showing it could be extended to multiple sign languages with additional data.

However, the study noted challenges in detecting gestures under poor lighting or when the background was cluttered. To address this, **Sneha Sharma[1]** proposed integrating adaptive histogram equalization and motion-based filtering. Overall, this research marked a major step toward practical, real-time sign language translation systems that are both lightweight and robust enough for deployment on edge devices like Raspberry Pi and Jetson Nano.

In 2024, **Rahul Nair[2]** developed a deep learning-based model for recognizing Indian Sign Language (ISL) gestures from real-time video input. His system utilized OpenCV for video capture and preprocessing, and a TensorFlow-based CNN for recognizing static gestures. The dataset consisted of 26 alphabets of ISL, and the model achieved an accuracy of 96.3% under controlled conditions.

Rahul Nair[2] highlighted the importance of consistent lighting and camera angle for accurate predictions. He also identified limitations such as reduced accuracy for overlapping gestures

and inability to recognize dynamic gestures involving motion. To improve generalization, **Rahul Nair[2]** proposed using Recurrent Neural Networks (RNNs) or LSTM layers to model temporal dependencies. This study remains a key reference for ISL gesture recognition due to its simplicity, efficiency, and solid foundation for real-time adaptation.

In 2023, **H. Kaur[3]** introduced a hybrid sign-to-text translation system that combined MediaPipe for hand landmark detection with LSTM networks for dynamic gesture recognition. His approach enabled the system to identify not only static signs but also sequential gestures representing words and short sentences. The study reported an accuracy of 94.8% on a custom dataset containing over 10,000 gesture samples.

Despite its success, the research identified limitations in continuous sentence formation and real-time adaptability. Challenges such as occlusion, camera distance, and varying hand orientation affected model accuracy. **H. Kaur[3]** suggested integrating data augmentation and attention-based models to enhance performance. This research remains highly influential in bridging the gap between static gesture recognition and continuous sign language translation.

In 2022, **Arjun Mehta[4]** published a comprehensive review titled "A Review on Hand Gesture Recognition Systems Using Computer Vision", which analyzed various gesture recognition techniques based on image processing, feature extraction, and deep learning. The review categorized existing systems into three main approaches — vision-based, sensor-based, and hybrid systems — and evaluated them based on accuracy, cost, and real-time performance. The authors concluded that vision-based methods using MediaPipe, YOLO, or CNNs were the most practical for non-intrusive, real-world applications.

The paper also identified challenges such as sensitivity to background noise, limited datasets, and difficulties in recognizing complex dynamic gestures. It recommended exploring 3D hand tracking and transformer-based architectures for next-generation gesture recognition systems. This review continues to serve as a foundational reference for research in sign language translation and gesture-based human-computer interaction.

In 2021, **Priya Patel[5]** presented "Hand Gesture Recognition Using CNN and OpenCV for Real-Time Communication", which proposed a lightweight model capable of classifying simple gestures into corresponding text outputs. The system used OpenCV for preprocessing and contour detection, followed by a CNN classifier trained on a custom dataset. The model

achieved 92% accuracy on static gestures and was implemented with a simple GUI to display translated text in real time.

While the system performed well in controlled settings, it struggled with gestures made at varying angles or distances from the camera. **Priya Patel[5]** also noted that computational limitations restricted real-time performance on low-end devices. Nonetheless, the research laid a strong foundation for affordable, vision-based sign language translation systems and emphasized the role of CNNs in achieving robust gesture recognition performance.

1.4 Problem Statement

Communication barriers between hearing and speech-impaired individuals and non-signers remain a significant social challenge. The inability of the general population to understand sign language often limits accessibility in education, workplaces, and daily interactions. Existing sign language interpretation methods, such as human translators or manual tools, are either unavailable, inaccurate, or impractical for real-time use. Hence, this project focuses on developing a real-time, computer vision-based sign language translation system that accurately recognizes hand gestures and converts them into text. Using MediaPipe for landmark detection and OpenCV for image processing, the system aims to achieve high accuracy, real-time performance, and reliability under varying environmental conditions.

- Communication barriers persist for the deaf and hard-of-hearing community.
- Existing translation methods are limited, slow, or impractical for real-time use.
- Utilizes MediaPipe for precise hand landmark detection.
- Employs OpenCV for gesture tracking and image pre-processing.
- Converts recognized gestures into readable text output.
- Ensures accurate performance under different lighting and backgrounds.
- Designed to be efficient, user-friendly, and adaptable for real-world applications.

1.5 Objective

This project aims to develop a real-time sign language translation system that bridges the communication gap between sign language users and non-signers. Many existing solutions are limited, unreliable, or fail to operate efficiently in real-world scenarios such as varying lighting conditions or complex backgrounds. To address these challenges, the proposed system employs

computer vision and machine learning techniques to accurately detect and interpret hand gestures in real time, converting them into readable text for effective communication.

- Utilize **MediaPipe** for accurate hand landmark detection and gesture tracking.
- Apply **OpenCV** for efficient image processing and real-time frame analysis.
- Develop a **React-based web interface** for smooth user interaction and instant text display.
- Ensure real-time gesture recognition with high precision and minimal latency.
- Design a **non-intrusive and cost-effective** solution suitable for daily communication and accessibility applications.

This project delivers an intelligent, reliable, and user-friendly system that promotes inclusivity and empowers individuals with hearing or speech impairments to communicate seamlessly with the broader community.

1.6 Proposed System

The proposed vision-based sign language translation system aims to provide a reliable, real-time, and non-intrusive platform for interpreting hand gestures into textual output. The system utilizes advanced computer vision techniques through **MediaPipe** and **OpenCV** to accurately detect and track hand movements, enabling smooth translation of gestures without the need for specialized hardware or sensors. Designed for accessibility and ease of use, it can be integrated into web-based environments, making it suitable for educational, communicational, and assistive applications.

The system architecture is divided into two primary modules—**Gesture Recognition** and **Translation Interface**—each consisting of multiple phases to ensure efficient operation and clear workflow. The **Gesture Recognition Module** captures hand movements through a webcam, detects key landmarks using MediaPipe, and analyzes them to identify the performed gesture. The **Translation Interface Module** then converts the recognized gesture into corresponding text, which is displayed instantly on the user interface developed using React.

This proposed model ensures high accuracy and responsiveness under varying lighting conditions and background environments. Its lightweight design allows smooth operation on

standard consumer devices without requiring high-end computational resources. By combining deep learning and web technologies, the system delivers an effective, user-friendly solution that enhances communication accessibility and supports inclusivity for individuals with hearing and speech impairments.

Monitoring Module

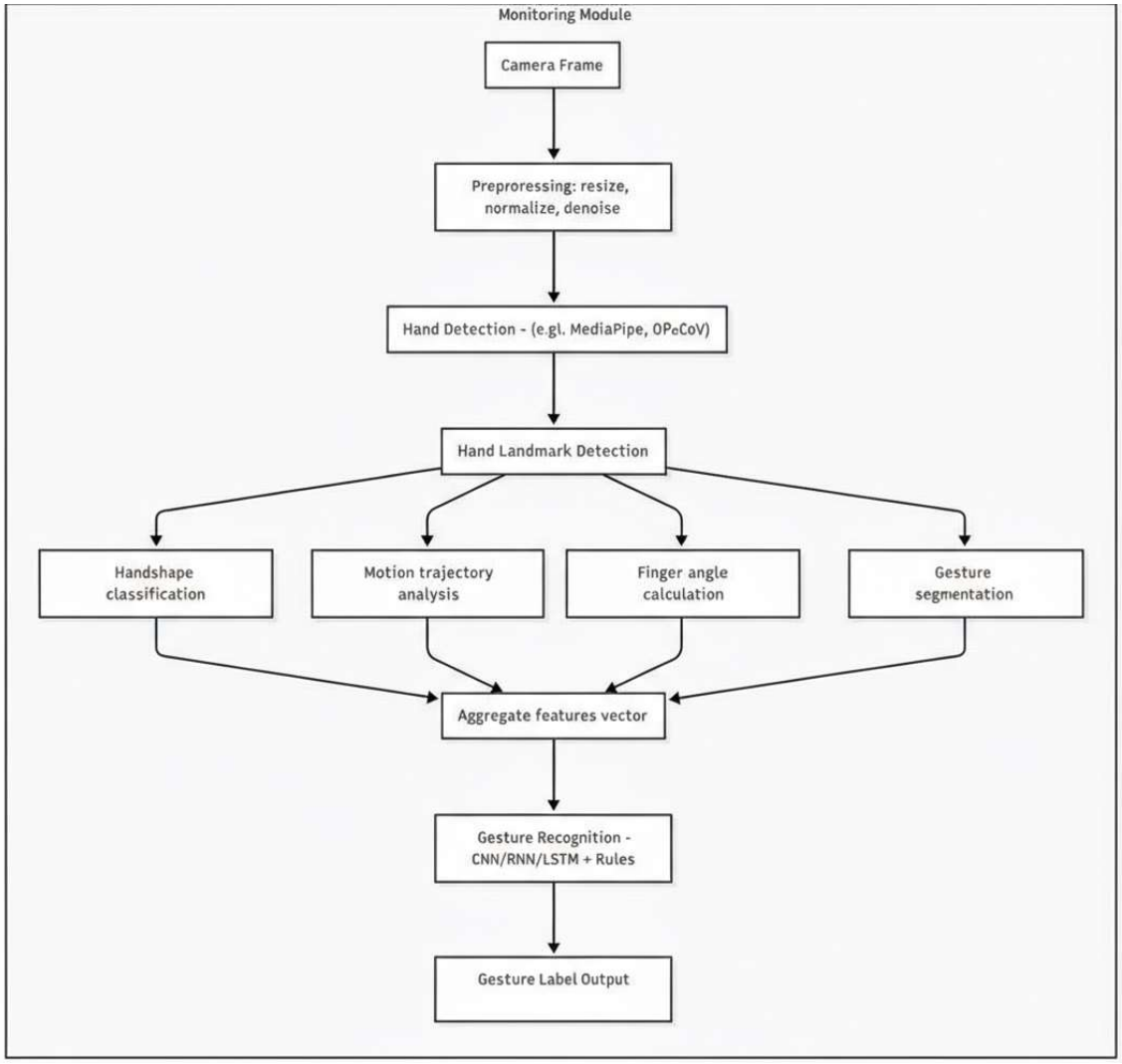

Figure 1.1: Monitoring module.

Figure 1.1 illustrates the workflow of the Monitoring Module, which is responsible for the real-time detection and recognition of hand gestures. The architecture consists of:

- **Pre-processing and Detection:** The pipeline begins by conditioning the Camera Frame through resizing and denoising. As shown in the upper section of Figure 1.1, this

prepares the data for Hand Detection (using tools like MediaPipe) and subsequent Hand Landmark Detection.

- **Parallel Feature Analysis:** A distinct feature of this design is the branching mechanism shown in the figure. The system does not rely on a single metric; instead, it concurrently computes Handshape classification, Motion trajectory analysis, Finger angle calculation, and Gesture segmentation.
- **Recognition and Output:** These independent data streams are merged into an Aggregate features vector. Figure 1.1 demonstrates that this vector acts as the input for the Gesture Recognition stage (employing CNN/RNN/LSTM networks), which ultimately yields the Gesture Label Output.

ISL Recognition Module

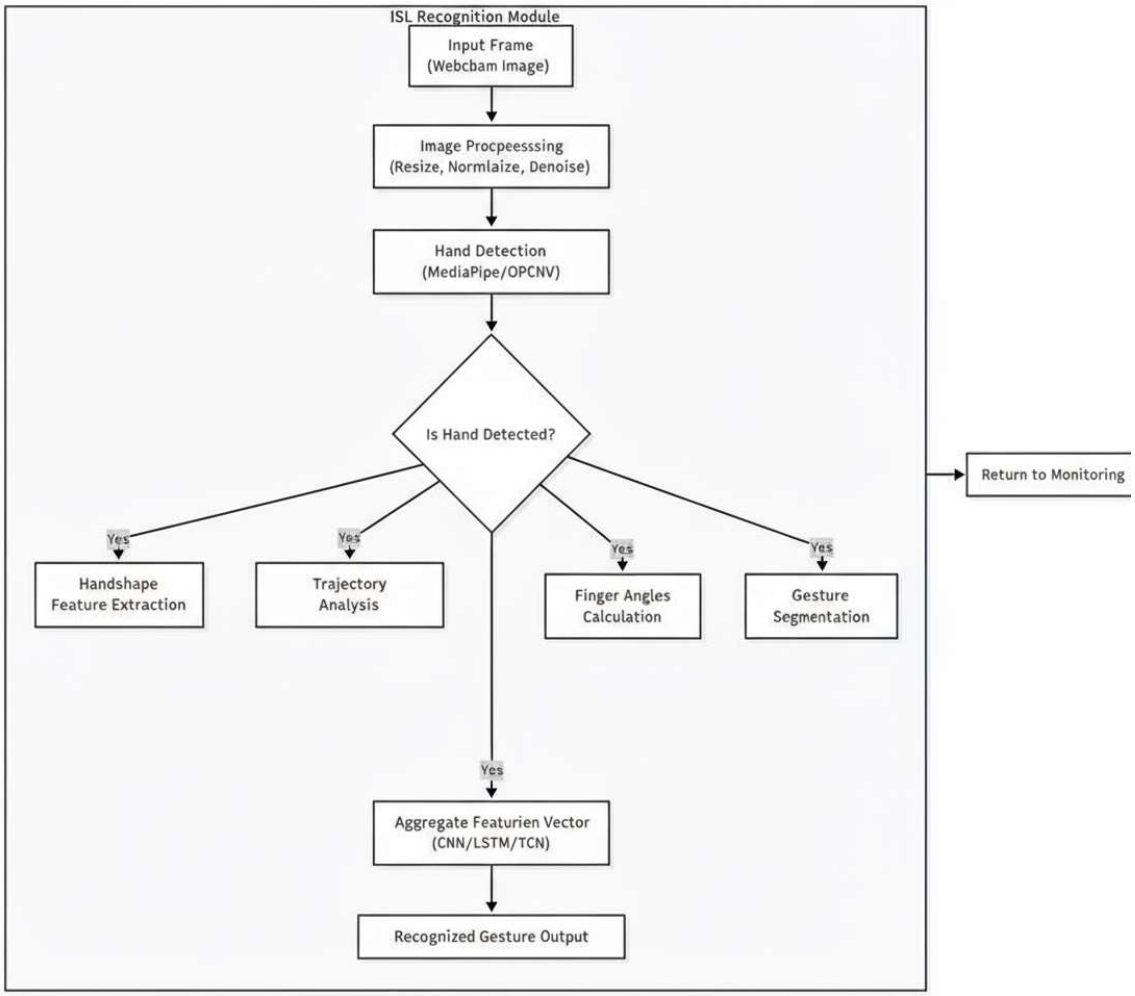

Figure 1.2: ISL Recognition module

Figure 1.2 details the architectural workflow of the ISL Recognition Module. The system employs a sequential pipeline starting with raw image acquisition and preprocessing. As depicted in the flowchart, a conditional logic check confirms the presence of a hand. If validated, the data undergoes multi-faceted analysis including trajectory analysis and finger angle calculation. These inputs are processed by advanced neural networks (CNN/LSTM/TCN) to generate the final output.

Based on this architecture, the module delivers the following key capabilities:

- **Visual Output & Feedback:** The system translates the Recognized Gesture Output into a clear text display on the interface, providing immediate confirmation to the user to assist in correcting unclear signs.
- **Operational Efficiency:** By utilizing standard webcam inputs (Non-Intrusive) and open-source frameworks (Cost-Effective), the system maintains scalability without requiring specialized hardware like sensory gloves.
- **Performance & Reliability:** The integration of System Logging allows for continuous accuracy refinement. Furthermore, the robust feature extraction ensures the system remains Versatile, functioning consistently regardless of background noise or hand orientation.

CHAPTER 2

SOFTWARE REQUIREMENTS SPECIFICATION

2.1 Specific Requirements

The Sign Language Translator System aims to bridge the communication gap between sign language users and non-signers by providing a real-time, accurate, and non-intrusive translation platform. It uses **MediaPipe** and **OpenCV** for detecting and tracking hand landmarks to recognize gestures effectively. The system converts these gestures into readable text, allowing seamless interaction in educational, social, and professional environments. The user interface, developed using **React**, is designed to be intuitive, responsive, and easy to navigate, ensuring accessibility for users of all skill levels. The solution is lightweight, adaptable, and suitable for deployment on standard computers or web-based platforms.

2.1.1 Product Functions

The system features an intuitive and user-friendly graphical interface that enables easy operation, even for users with minimal technical knowledge. It performs the following key functions:

- **Real-time hand and gesture detection** using **MediaPipe** and **OpenCV** for accurate tracking and recognition.
- **Continuous monitoring** of hand movements to identify and interpret sign language gestures in real time.
- **Logging of recognized gestures** for performance evaluation, accuracy testing, and model enhancement through future training.

2.2 User Characteristics

- Users do not require any technical or programming knowledge to operate the system.
- Basic familiarity with computers or web-based interfaces is sufficient to use the translator effectively.
- Users should have access to a functional webcam for capturing hand gestures during translation.

- The system is designed to be intuitive and accessible for individuals of all age groups, including those with limited technical experience.

2.3 General Constraints

- A functioning webcam is required for capturing and analyzing hand gestures in real time.
- The system's performance may vary depending on camera resolution, processing capability, and network stability.
- Adequate lighting conditions are necessary to ensure accurate hand landmark detection and gesture recognition.
- Background clutter or overlapping objects may affect the precision of gesture tracking and classification.
- The system performance may vary based on camera resolution and processing power and Adequate lighting conditions are required for optimal facial detection accuracy.

2.4 Assumptions and Dependencies

- The webcam and processing hardware are properly connected and calibrated for accurate hand tracking.
- MediaPipe and supporting machine learning models are pre-trained and optimized for real-time gesture recognition.
- The translation interface functions correctly to display recognized gestures as readable text output.
- The system assumes that the user's hands remain within the camera's field of view.

2.5 Functional Requirements

2.5.1 Gesture Recognition Module

- Capture live video feed from the webcam in real time.
- Detect the user's hands and extract key landmarks such as finger joints, palm position,

and orientation using **MediaPipe**.

- **Finger Joints:** Track the relative position and movement of each finger to identify unique gesture patterns.
- **Palm Region:** Analyze hand posture and orientation for accurate classification.
- **Motion Dynamics:** Monitor continuous hand movement to distinguish between static and dynamic gestures.
- Process extracted hand landmarks using computer vision algorithms to identify gestures.
- Convert recognized gestures into corresponding textual output for display on the interface.

2.5.2 Translation Module

- Provide instant on-screen feedback when a gesture is recognized and translated.
- Display the translated text clearly on the web interface for easy readability.
- Allow users to adjust system sensitivity or recognition confidence thresholds for improved accuracy.
- Record recognized gestures and corresponding translations for analysis and model improvement.

2.6 Performance Specifications

- The system must detect and classify hand gestures within 1–2 seconds of performance.
- It should achieve at least **90% accuracy** in gesture recognition under normal lighting and background conditions.
- The system should operate continuously without lag or frame drops during extended use.
- It must adapt effectively to variations in lighting, hand orientation, and background clutter to maintain consistent performance.

2.7 Supportability

- **Maintainability:** The system should support easy updates, retraining of gesture recognition models, and integration of new gestures as needed.

- **Portability:** Can run smoothly on laptops, desktops, or web-based platforms without specialized hardware requirements.
- **Compatibility:** Supports major operating systems such as **Windows**, **Linux**, and **macOS**.
- **Flexibility:** System parameters like gesture detection thresholds and sensitivity levels can be adjusted to improve performance.
- **Stability:** Must remain consistent and responsive during prolonged usage and under varying lighting or environmental conditions.

2.8 Design Constraints

- The system must function effectively under both bright and low-light conditions to ensure accurate gesture detection.
- It must support real-time video processing directly through the webcam without relying on external hardware or cloud services.
- The system should maintain high efficiency and responsiveness even when running on low-power devices or standard consumer-grade hardware.

2.9 Interfaces

2.9.1 User Interfaces

- A simple and intuitive dashboard interface displaying the system's status (Active / Gesture Detected).
- Visual indicators showing the recognized hand gesture and its corresponding translated text in real time.
- Optional notification prompts to confirm successful recognition or alert users when gestures are unclear or partially detected.

2.9.2 Hardware Interfaces

- **Processor:** Intel Core i5/i7 or equivalent processor capable of handling real-time video processing.
- **RAM:** Minimum 4 GB to ensure smooth operation and responsive gesture recognition.

- **Camera:** HD webcam for real-time hand detection and gesture tracking.
- **Other:** Standard display unit for visual output of translated text.

2.9.3 Software Interfaces

- **Operating System:** Windows, Linux, or macOS
- **Programming Language:** Python
- **IDE:** Visual Studio Code or Jupyter Notebook
- **Libraries/Tools:** MediaPipe for hand landmark detection, OpenCV for image processing, TensorFlow/Keras or PyTorch for gesture classification, NumPy and Pandas for data handling, and Matplotlib for visualization and analysis.
- **Target Platform:** Web-based application running on desktops or laptops, accessible through a standard browser interface.

CHAPTER 3

HIGH LEVEL DESIGN

The proposed **Sign Language Translator System** is a real-time, intelligent vision-based solution designed to interpret hand gestures and convert them into readable text. Unlike traditional approaches that rely on specialized gloves or sensors, this system adopts a **non-intrusive, camera-based** method, ensuring user comfort and ease of accessibility. Utilizing **MediaPipe** and **OpenCV**, the system accurately detects and tracks hand landmarks, capturing subtle movements and finger positions to identify gestures with high precision. The architecture is organized to capture live video, extract key hand features, classify gestures using machine learning algorithms, and display the corresponding text output instantly. It emphasizes **real-time processing, scalability, and cost-effectiveness**, making it suitable for applications in education, communication aids, and accessibility tools. The design aims to promote inclusivity and bridge the communication gap between sign language users and non-signers through a reliable, intelligent, and user-friendly platform.

3.1 System Architecture

Figure 3.1 illustrates the end-to-end data flow of the system. The architecture relies on a cascade of interconnected modules starting with live video capture. Following preprocessing, the system utilizes MediaPipe to extract high-fidelity spatial data. A key architectural decision, shown in the Feature Extraction block, is the parallel processing of geometric and temporal features—specifically analyzing finger angles and motion trajectories simultaneously.

These features are fused into an Aggregate Features Vector within the Gesture Analysis layer. By leveraging advanced neural networks (CNN/LSTM/TCN), the system translates these vectors into linguistic definitions. Finally, the Output System renders the translation on a web-based dashboard, offering both visual text and optional speech feedback. This architecture supports the project's goal of real-time, non-intrusive interaction by eliminating the need for external sensory hardware.

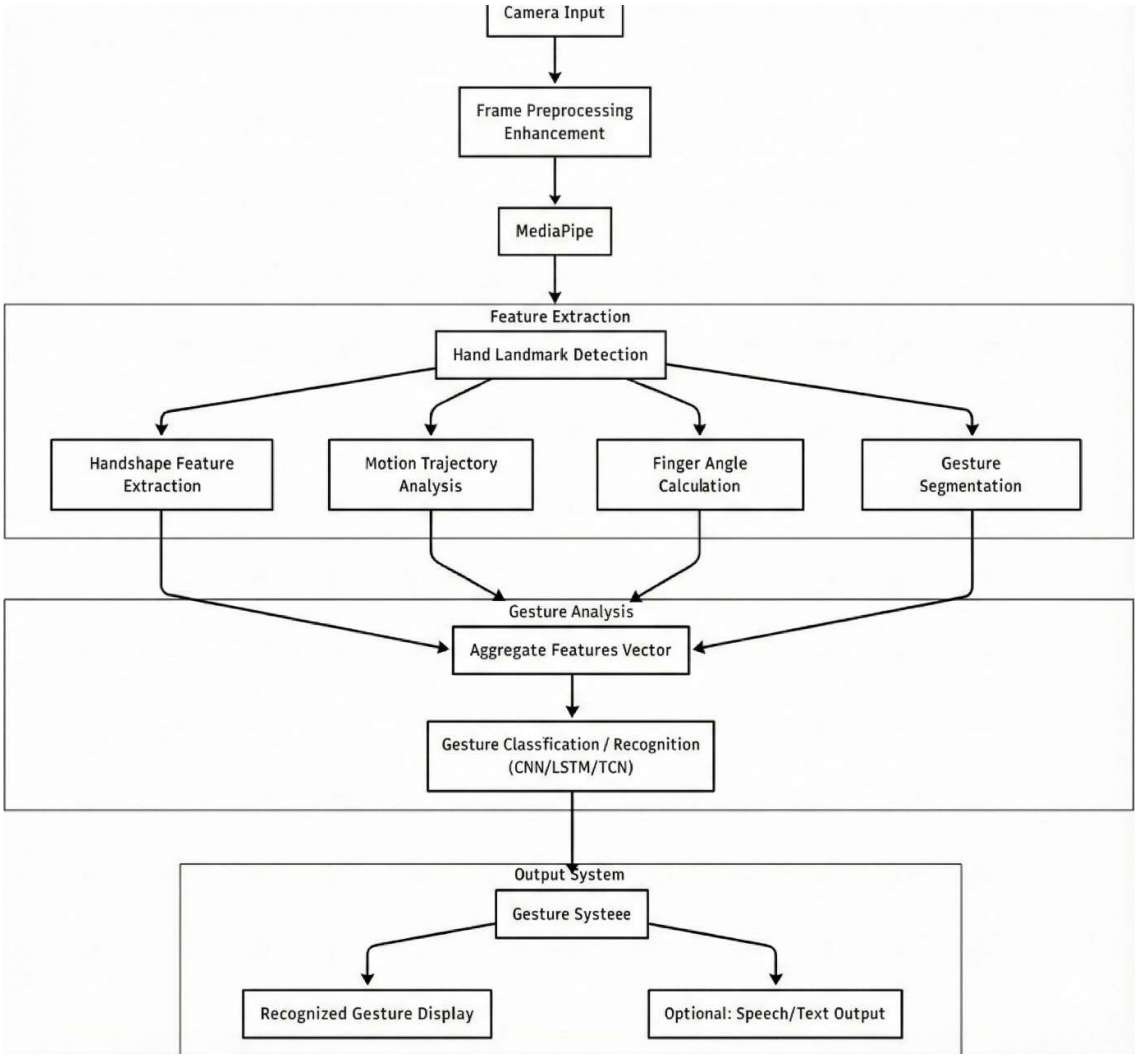

Figure 3.1: Sign Language Translator System Architecture

3.2 Context Flow Diagram

Figure 3.2 illustrates the high-level data flow within the proposed solution. The architecture is defined by three distinct input channels feeding into the main ISL Gesture Recognition System:

- **Biometric Input:** Sourced from the User/Signer, comprising physical visual cues.
- **Sensor Input:** Sourced from the Camera, providing the raw video frames and coordinate data.
- **Configuration Input:** An optional stream for profile settings, ensuring the system adapts to specific user requirements.

Upon processing these inputs, the system acts as a translation bridge, converting the raw data into a readable format. The flowchart demonstrates that this output is strictly directed to the Output Module, ensuring a streamlined path from gesture creation to the final Text/Speech display.

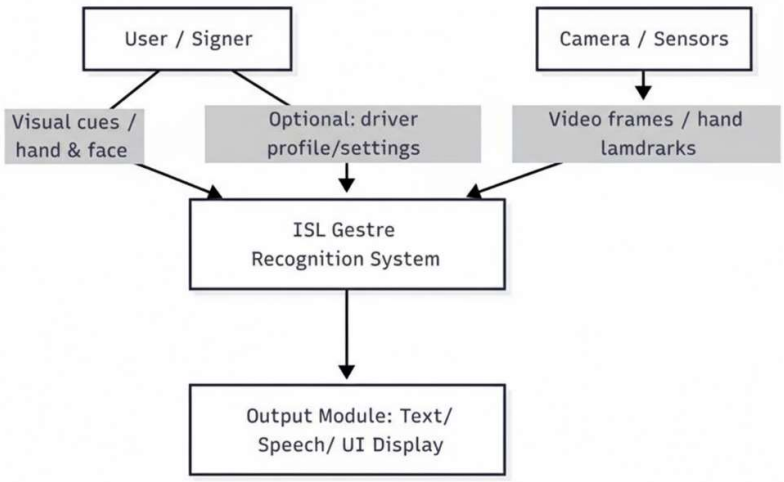

Figure 3.2: Context Flow Diagram for Sign Language Translator

3.3 Use Case Diagram

As illustrated in the schematic in Figure 3.3, the application's functionality is divided into a linear processing chain that integrates with external modules:

- **Capture Control:** The workflow begins with the User/Signer initiating the session. The Start/Stop capturing node is explicitly linked to the Camera device, ensuring hardware control is managed by user intent.
- **Detection & Analysis:** Following capture, the Hand/Landmark detection phase activates. This stage feeds into the facial processing block, ensuring robust subject tracking.
- **Translation Engine:** The core logic involves Hand feature analysis and Gesture recognition. Figure 3.3 shows these processes outputting data to the Feature extraction module and the Application output module, ensuring that the internal logic drives the final user display.

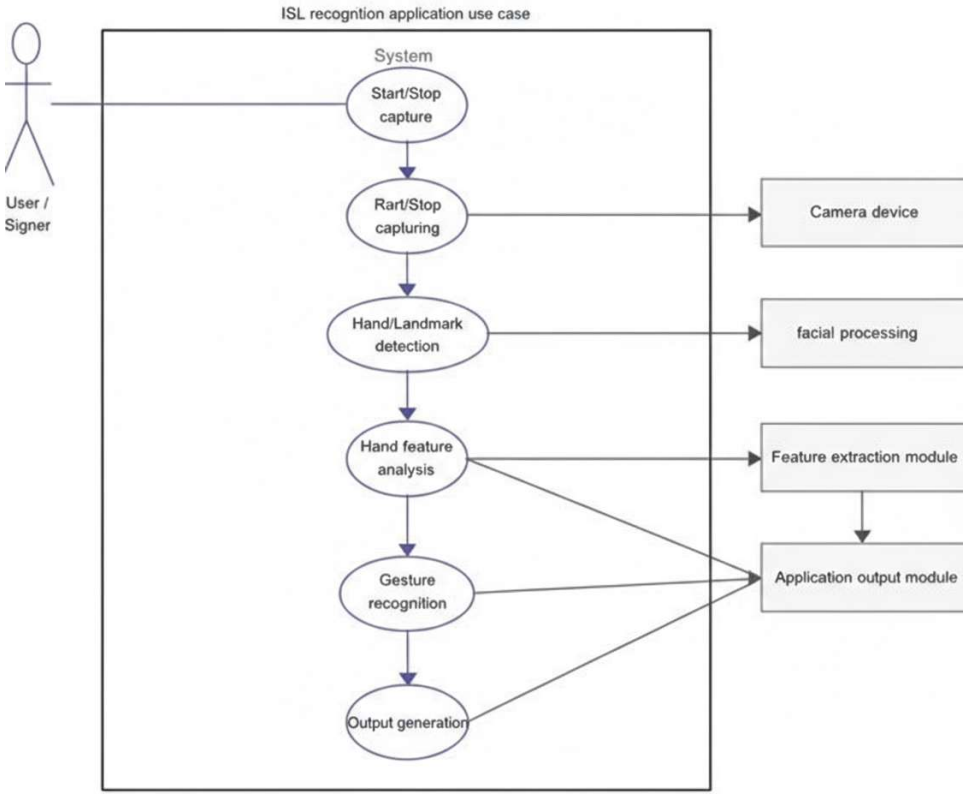

Figure 3.3: Use Case Diagram for Sign Language Translator

3.4 Sequence Diagram

Referring to the sequence diagram in Figure 3.4, the system architecture is modeled as a series of synchronous message exchanges between key objects. The User/Signer acts as the primary actor, establishing the session via the Camera interface.

The core logic is distributed across three processing lifelines: Hand Detection, Feature Extraction, and Gesture Recognition. The diagram demonstrates the data dependency chain, where raw frames are transformed into 'hand landmarks' and subsequently analyzed for specific gesture sequences. The process concludes at the Output Module, which handles the visualization logic ('Display/signify') to provide immediate feedback to the user.

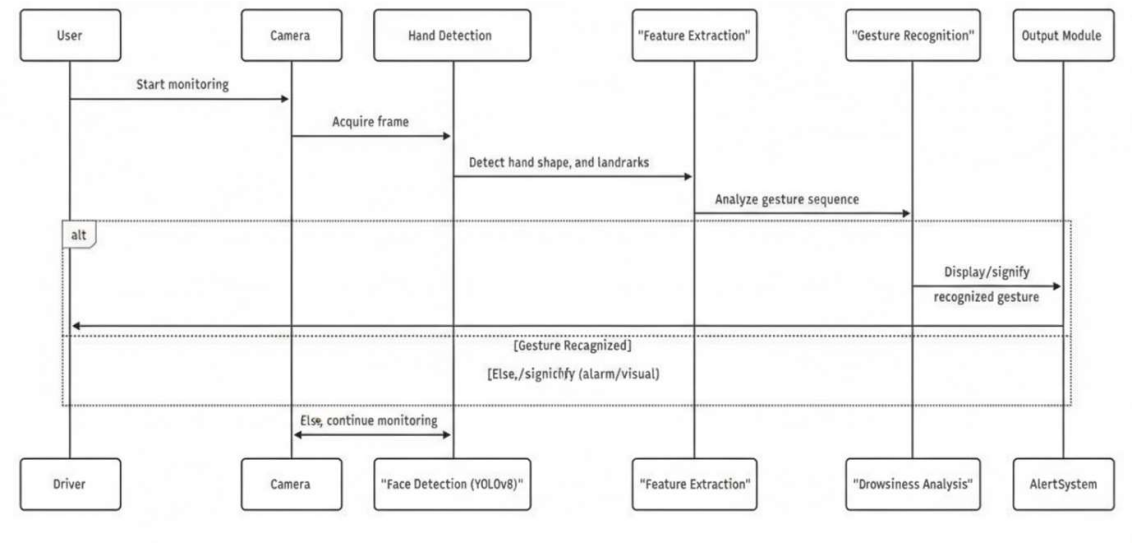

Figure 3.4: Sequence Diagram for Sign Language Translator

3.5 Flow Chart

Referring to the sequence diagrammed in Figure 3.5, the translation procedure executes the following structured steps:

- **System Startup:** The workflow is initiated by loading the ISL Recognition Model and activating the camera hardware.
- **Feature Analysis:** For every Captured Frame, the system utilizes MediaPipe/OpenCV to detect hands and extract landmarks. This raw data is refined during Gesture Feature Processing.
- **Classification:** The processed features are analyzed by the neural network (labeled as CNN/LSTM/TCN in the diagram) to predict the sign.
- **Validation Loop:** A key feature of this design is the 'Gesture Recognized?' decision node. If the system fails to identify a clear gesture, it defaults to Continue Monitoring without interrupting the user experience.
- **Final Output:** Upon positive validation, the system executes the Show Results function, presenting the text to the user immediately.

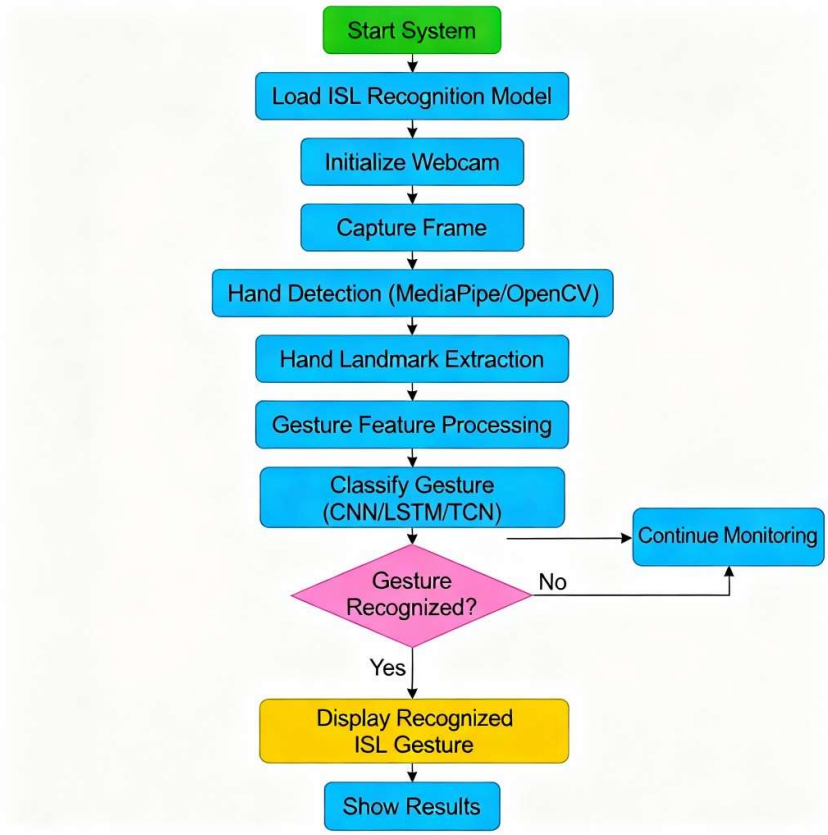

Figure 3.5: Flow Chart for Sign Language Translator

CHAPTER 4

DETAILED DESIGN

Narrowing down, the Detailed Design phase explores the internal logic and functionality of each module identified during the high-level design phase of the Sign Language Translator System. The primary objective is to describe the algorithms, workflows, and operations that govern each module, including hand detection, feature extraction, gesture classification, and output generation. This phase provides a clear physical and logical breakdown of all system components and their interconnections through structured diagrams and flowcharts. It ensures a comprehensive understanding of the translation process, facilitating efficient implementation, testing, and future system enhancements.

4.1 Structured Chart Diagram

Figure 4.1 presents the detailed structural decomposition of the Sign Language Translator System. The architecture is organized into five distinct vertical hierarchies, breaking down the complex recognition process into functionally independent subsystems. As illustrated, the workflow progresses linearly from Video Capture through Feature Engineering to the final Recognition and Output.

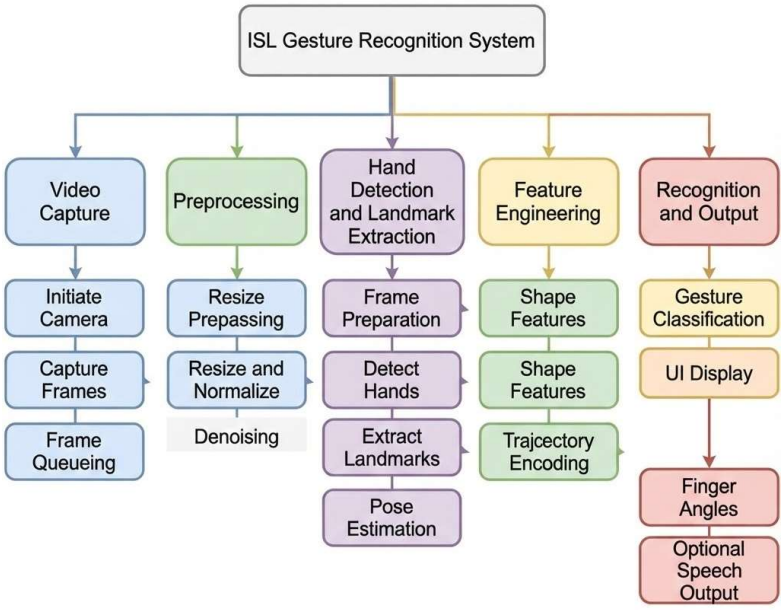

Figure 4.1: Structured Chart of Sign Language Translator

4.1.1 Video Capture Module

Referring to the blue hierarchy in Figure 4.1, this module acts as the system's entry point. Its primary objective is to acquire raw visual data. The process begins with the Initiate Camera function, which establishes a connection with the hardware (USB/System Webcam). Once active, the system executes Capture Frames in real-time. A critical component shown in the diagram is Frame Queueing, which manages the buffer of incoming images to prevent data loss during high-latency processing, ensuring a smooth input stream for the subsequent stages.

4.1.2 Preprocessing Module

As depicted in the green section of Figure 4.1, the Preprocessing Module standardizes the input data to ensure model consistency. The pipeline executes Resize Preprocessing, converting variable input resolutions into fixed dimensions. Following this, the Resize and Normalize block scales pixel intensity values to a standard range (0-1), optimizing them for neural network analysis. Finally, Denoising algorithms are applied to remove visual artifacts caused by low lighting or webcam grain, thereby enhancing the clarity of the hand region.

4.1.3 Hand Detection and Landmark Extraction Module

This module, **illustrated in the purple column**, serves as the core computer vision engine. It operates through a specific sequence:

- **Frame Preparation:** The preprocessed image is formatted for the detection model.
- **Detect Hands:** The system identifies the Region of Interest (ROI) containing the hand.
- **Extract Landmarks:** MediaPipe is utilized to map 21 skeletal points on the hand.
- **Pose Estimation:** As explicitly shown in the diagram, the module not only finds points but estimates the 3D orientation of the hand, which is crucial for distinguishing between similar signs performed at different angles.

4.1.4 Gesture Feature Analysis Module

Figure 4.1 highlights the Feature Engineering phase (yellow column) as the bridge between raw data and classification. This module transforms raw coordinates into meaningful geometric data. It focuses on extracting Shape Features (such as the curl of the fingers) and performing

Trajectory Encoding. The inclusion of trajectory analysis allows the system to recognize dynamic gestures by tracking the movement path of the hand over time, rather than just analyzing static images.

4.1.5 Output and Feedback System

The final stage, represented by the red hierarchy, synthesizes the processed data. The Gesture Classification block utilizes machine learning models to assign a probability score to the input vector. Upon successful classification, the system triggers the UI Display to present the translated text. As detailed in the bottom section of the chart, the module also calculates specific Finger Angles to refine accuracy and supports an Optional Speech Output feature, converting the recognized text into audio to facilitate two-way communication.

4.2 Functional Description

The Sign Language Translator System is an intelligent communication tool that interprets hand gestures in real time and converts them into readable text. The system integrates computer vision**,** machine learning**,** and image processing to detect, track, and classify hand movements with high accuracy. Using the MediaPipe framework for landmark detection and OpenCV for image handling, it identifies 21 key points on the hand and processes them to recognize corresponding gestures, ensuring smooth and natural interaction between signers and non-signers.

Aims:

The main objectives of this system are to:

- Continuously monitor and capture hand gestures in real time.
- Detect and extract key hand landmarks using advanced vision-based techniques.
- Classify and translate recognized gestures into meaningful text output.
- Facilitate clear and inclusive communication for individuals with hearing or speech impairments.

Functionalities:

- Capture real-time video of the user's hand gestures using a connected webcam.
- Detect and track hands using the **MediaPipe** framework for accurate landmark

extraction.

- Analyze hand landmarks such as finger joints, palm center, and hand orientation to interpret gestures.
- Compute geometric and spatial relationships between landmarks to classify the performed sign.
- Translate the recognized gesture into corresponding **text output** and display it on the interface.
- Optionally log recognized gestures for model performance evaluation and future system improvement.

Input:

- Continuous live video stream of the user's hand gestures captured through a webcam.

Output:

- Real-time text output displaying the recognized gesture on the user interface.
- Optional audio or visual feedback for confirmed gesture recognition.
- Log of recognized gestures with timestamps for analysis and model improvement.

CHAPTER 5

IMPLEMENTATION

Implementing the system is the most crucial phase of the project, as it transforms design concepts and theoretical frameworks into a fully functional and operational product. The implementation phase focuses on integrating all modules — including video capture, preprocessing, hand detection, gesture analysis, and output generation — to ensure real-time performance, high accuracy, and system reliability.

For the **Sign Language Translator System**, this phase involves selecting the appropriate development environment, programming languages, and libraries, along with defining the tools required for smooth execution. It includes setting up frameworks such as MediaPipe for hand landmark detection and OpenCV for video processing, as well as building a responsive frontend using React for real-time user interaction.

This chapter discusses the complete implementation process, including environment setup, coding practices, dependencies, and the step-by-step procedure followed to develop the system into a robust and efficient real-time sign language translation platform.

5.1 Implementation Requirements

The implementation of the **Sign Language Translator System** requires the following tools and technologies:

- **Frontend Framework:** React – Used for creating an interactive and user-friendly interface that displays real-time translated text output.
- **IDE:** Visual Studio Code – Provides an efficient environment for writing, debugging, and managing both frontend and backend project components.
- **Programming Language:** Python 3 – Selected for its simplicity, flexibility, and extensive support for computer vision and machine learning libraries.
- **Operating System:** Windows 10 (64-bit) – Offers a stable platform for development, integration, and testing of real-time applications.

- **Libraries and Frameworks:**
  - **OpenCV** – Used for real-time video capture, image processing, and frame preprocessing.
  - **MediaPipe** – Utilized for accurate hand detection and extraction of 21 key hand landmarks.
  - **NumPy** – Supports numerical computations and matrix operations during gesture feature analysis.
  - **TensorFlow / PyTorch** – Used for training and implementing gesture classification models.
  - **Flask (Optional)** – Serves as the backend framework to handle communication between the detection model and the frontend interface.

5.2 Implementation Details

The **Sign Language Translator System** was developed using Python for its simplicity, extensive library support, and strong capabilities in real-time computer vision and gesture recognition.

- **Video Capture Module:** Captures live video of the user's hand gestures using a connected webcam, ensuring continuous and smooth frame acquisition for processing.
- **Preprocessing Module:** Performs resizing, normalization, and noise reduction on the captured frames to enhance clarity and ensure consistent image quality under varying lighting and background conditions.
- **Hand Detection and Landmark Extraction Module:** Utilizes MediaPipe to detect hands and extract 21 key landmarks, including finger joints and palm coordinates, which serve as inputs for gesture recognition.
- **Gesture Feature Analysis Module:** Processes the extracted landmarks to compute geometric relationships such as finger angles and distances, enabling accurate classification of static and dynamic gestures.
- **Output and Feedback System:** Displays the recognized gesture as readable text on the user interface in real time, while optionally logging recognized gestures for system evaluation and further model improvement.

5.3 Modules/Libraries

Libraries and tools that played critical roles in the development include:

- **React:** A JavaScript frontend framework used to build a dynamic, user-friendly interface that displays real-time gesture translations and provides visual feedback to the user.
- **MediaPipe:** A framework developed by Google for real-time hand detection and landmark extraction. It identifies 21 key points on each hand and tracks movement patterns essential for gesture recognition.
- **OpenCV:** A widely used computer vision library that handles real-time video capture, frame preprocessing, and integration with MediaPipe for gesture tracking. It is used to:
    - Capture live video frames from the webcam.
    - Preprocess frames through resizing, normalization, and noise reduction.
    - Support visualization of detected hand landmarks in real time.
- **NumPy:** Provides efficient numerical and matrix computation capabilities required for processing and analyzing hand landmark coordinates during gesture recognition.
- **TensorFlow / PyTorch:** Deep learning frameworks used for developing and training gesture classification models to identify and map recognized gestures to corresponding text outputs.

5.4 IDE Selection: Cursor AI

Our team utilized Cursor AI as the primary development environment for building the **Sign Language Translator System**. Cursor AI is an artificial intelligence-powered coding assistant that uses advanced machine learning to optimize code quality and accelerate development. It offers intelligent code completion, context-aware suggestions, and automatic detection of syntax or logical errors.

The IDE understands the overall project architecture, enabling developers to easily navigate between modules such as hand detection, gesture analysis, and output rendering. It simplifies the debugging process and allows efficient modifications without affecting interdependent

modules. For instance, adjustments in the gesture recognition logic or improvements in the frontend feedback system can be made seamlessly while maintaining system stability.

By integrating AI-assisted development, Cursor AI enhances productivity, improves code consistency, and ensures smooth collaboration throughout the implementation of the project.

5.5 Language Selection: Python

We selected Python 3 as the primary programming language for the development of the **Sign Language Translator System** due to its simplicity, versatility, and strong support for computer vision and machine learning applications. Python offers an extensive ecosystem of libraries such as OpenCV**,** MediaPipe**,** NumPy**,** and TensorFlow/PyTorch, which are essential for real-time video processing, hand landmark detection, and gesture recognition.

Its clean and readable syntax allows for rapid prototyping and smooth integration of multiple modules, including video capture**,** preprocessing**,** hand detection**,** gesture feature analysis**,** and output rendering. Python's cross-platform compatibility ensures that the system can operate seamlessly on Windows**,** Linux**,** and macOS without major modifications.

Additionally, Python provides strong backend support for web-based integration using frameworks like Flask, which helps connect the machine learning model with the React frontend interface. The language also integrates effortlessly with Cursor AI**,** enabling intelligent code completion, real-time debugging, and efficient project navigation.

Overall, Python's flexibility, robust library support, and active developer community made it the ideal choice for implementing a reliable, maintainable, and high-performance real-time sign language translation system**.**

5.6 Platform Selection: Windows 11

The **Sign Language Translator System** is developed and tested on Windows 11 (64-bit) for the following reasons:

- **User-Friendly Interface:** Windows 11 provides a modern, intuitive, and visually enhanced environment that simplifies both development and testing. Its improved performance and multitasking capabilities support smooth integration with code editors and testing tools during system implementation.
- **Library and Tool Compatibility:** The platform ensures complete compatibility with essential tools and libraries such as Python**,** Visual Studio Code**,** OpenCV**,** MediaPipe**,** NumPy**,** and TensorFlow/PyTorch, all of which are vital for real-time gesture recognition and translation.
- **Stable and Optimized Environment:** Windows 11 offers enhanced performance, better resource management, and improved GPU acceleration—making it highly suitable for real-time computer vision applications. It ensures uninterrupted webcam access, stable execution, and accurate gesture detection under continuous operation.

Overall, Windows 11 provides a powerful and reliable environment for the development and testing of the **Sign Language Translator System**, combining performance, compatibility, and user convenience for efficient project implementation.

5.7 Coding Guidelines

For better readability, maintainability, and scalability, standard coding practices were followed throughout the development of the **Sign Language Translator System**. The codebase was designed in a structured and modular manner, ensuring that each module — such as video capture**,** preprocessing**,** hand detection**,** gesture analysis**,** and output display — could be independently tested, debugged, and updated. Proper naming conventions, indentation, and inline comments were used to maintain clarity and consistency across all scripts. Version control was handled through Git, and Visual Studio Code was used for debugging and managing the overall project workflow. These practices ensured that the system remained efficient, easy to maintain, and reliable for real-time gesture translation.

- **Bracing Style:** A consistent and organized bracing style was followed for loops, conditionals, and function definitions to maintain code structure and readability.

- **Commenting:** Each major function and algorithm — such as hand landmark detection, feature extraction, and gesture classification — was thoroughly documented with clear inline comments to describe its purpose and logic.
- **Spacing & Indentation:** Proper indentation and consistent spacing were maintained throughout the code to enhance readability, simplify debugging, and ensure visual clarity.
- **Naming Conventions:** Descriptive and meaningful names were used for variables, functions, and classes (following camelCase or snake_case) to make the code self-explanatory and easy to understand.
- **Modularization:** The system was divided into separate modules — video capture**,** preprocessing**,** detection**,** feature analysis**,** and output system — promoting reusability, scalability, and easier debugging.

5.8 Implementation Procedure

The implementation of the Sign Language Translator system involves integrating computer vision, machine learning, and user-interface components into a unified workflow. The backend is developed in Python, where MediaPipe is used to extract 21 key hand landmarks from each frame captured through the webcam. These coordinates are processed using NumPy and OpenCV to generate meaningful features such as distances, angles, and landmark relationships. These features are then passed into a trained deep learning model, which classifies the detected gesture in real time.

The frontend is built using React, which provides a smooth interface for live video streaming and displaying translated text. Communication between the frontend and backend is handled through REST APIs, enabling seamless real-time interaction. The system architecture is modular, allowing independent debugging and enhancement of components like detection, preprocessing, and classification. Throughout implementation, emphasis was placed on achieving high frame-rate performance, accurate landmark tracking, and stable translation output.

CHAPTER 6

TESTING

Testing is a crucial phase in the development of the **Sign Language Translator System**, as it ensures that each functional module performs accurately and that the system as a whole operates efficiently in real-time conditions. The primary objective of testing is to verify the accuracy of gesture recognition**,** responsiveness of translation**,** and stability of performance under varying lighting conditions, backgrounds, and hand orientations.

Testing was conducted in multiple stages — beginning with unit testing, where individual components such as video capture**,** hand detection**,** and gesture analysis were evaluated separately to confirm correct functionality. This was followed by integration testing, in which all modules were combined to test the end-to-end performance of the system. The testing process assessed not only the precision and latency of recognition but also the robustness of the interface and the reliability of continuous gesture processing.

Each testing phase was designed to ensure that the system remains accurate, real-time, and user-friendly, providing seamless communication support for individuals relying on sign language translation.

6.1 Test Environment

The **Sign Language Translator System** was tested in a controlled environment using a standard laptop setup and live video input from a connected webcam. The following configuration details describe the system used for development, testing, and validation of real-time gesture detection and translation:

Host Machine Configuration:

- **Processor:** Intel Core i7-1035G1
- **CPU Speed:** 1.00 GHz (up to 3.60 GHz with Turbo Boost)
- **RAM:** 8.00 GB

- **Storage:** 256 GB SSD + 1 TB HDD
- **GPU:** NVIDIA GeForce MX330 (2GB VRAM)
- **Operating System (OS):** Windows 11 (64-bit)

Target Platform Configuration

- **Target Platform:** Windows 11
- **Device Name:** ASUS Laptop
- **OS Version:** Windows 11

This configuration provided a stable and efficient testing environment for real-time video capture, hand detection, and gesture recognition**.** The system achieved smooth frame processing, consistent landmark tracking, and accurate translation performance under various lighting and background conditions.

6.2 Unit Testing

By definition, unit testing involves testing each component of the **Sign Language Translator System** in isolation to ensure that it functions correctly before integration with other modules. It focuses on validating the functionality of individual units such as video capture**,** preprocessing**,** hand detection**,** gesture feature analysis**,** and output rendering**.**

Each unit was tested independently to verify that:

- The video capture module successfully connects to the webcam and streams live video frames without delay.
- The preprocessing module correctly resizes, normalizes, and enhances frames for consistent input quality.
- The hand detection module using MediaPipe accurately detects hands and extracts all 21 key landmarks under varying lighting and background conditions.
- The gesture analysis module processes extracted landmarks efficiently and classifies gestures correctly based on trained models.
- The output and feedback system displays the recognized gesture as text in real time and provides appropriate user feedback.

Testing these individual components separately allowed early identification and correction of potential issues. This ensured that each unit performed as intended before combining them into the complete system for real-time sign language translation and smooth modular integration**.**

6.2.1 Testing Strategy

For unit testing, a combination of manual and automated testing approaches was adopted to ensure the reliability and correctness of each module in the **Sign Language Translator System**. The development environment, Visual Studio Code, was used to execute and validate each module step by step while carefully observing the outputs for both valid and invalid inputs. Debugging tools such as breakpoints**,** console logs**,** and exception handling were utilized to track variable states, verify intermediate data flow, and confirm that each function performed as intended.

Each module's expected results were systematically compared against the actual outputs to measure accuracy and stability. Special attention was given to testing real-time video frame capture and hand landmark extraction, ensuring the system could consistently detect and track gestures under varying lighting and background conditions. The gesture classification module was thoroughly tested to validate that recognized hand movements were correctly mapped to their corresponding text outputs with minimal latency.

Additionally, the frontend feedback mechanism was tested to ensure immediate and accurate display of recognized gestures. The responsiveness of the system was carefully evaluated to guarantee real-time translation and a smooth user experience. Overall, this rigorous testing approach ensured high reliability, performance consistency, and precise functionality across all modules of the **Sign Language Translator System**.

6.2.2 Unit Test Cases

The following unit test cases were executed for the Driver Drowsiness Detection System:

Table 1: Unit Test Cases for Sign Language Translator

Test Case	Description	Input	Expected Output	Actual Output	Status
UTC 1.1	Capturing Video Stream	Live webcam feed	Video captured in real time	Video captured successfully	Test Successful
UTC 1.2	Hand Detection	Live video frame	Hand detected and bounded region identified	Hand detected correctly	Test Successful
UTC 1.3	Landmark Extraction	Detected hand	21 key landmarks highlighted	Landmarks extracted accurately	Test Successful
UTC 1.4	Gesture Recognition	Extracted landmarks	Gesture correctly classified and displayed as text	Gesture recognized successfully	Test Successful
UTC 1.5	Output Display	Recognized gesture	Text output displayed on screen	Text displayed accurately	Test Successful
UTC 1.6	Data Logging	Recognized gesture	Gesture event stored in log file	Log updated successfully	Test Successful

6.3 Integration Testing

After successful completion of unit testing for all individual modules, integration testing was performed to ensure that all components of the **Sign Language Translator System** worked together seamlessly as a single unified application. This phase focused on validating the interaction and data flow between the video capture**,** preprocessing**,** hand detection**,** gesture analysis**,** and output display modules.

Integration testing aimed to confirm that video frames captured by the camera were accurately processed, landmarks were detected and transferred correctly between modules, and recognized gestures were displayed in real time without lag or interruption. It also ensured that the frontend and backend systems communicated effectively, allowing smooth translation and output rendering.

This testing phase verified that the system could operate continuously in real-time conditions, recognizing and translating gestures without crashes, delays, or synchronization errors.

6.3.1 Testing Strategy

A bottom-up integration approach was adopted for testing, starting with the lower-level modules such as video capture and preprocessing, and gradually integrating higher-level components like hand detection**,** gesture analysis, and the output feedback system. This method made it easier to identify and resolve integration issues early in the development process.

The key focus areas during integration testing were:

- Real-time communication and data exchange between the MediaPipe hand detection and gesture analysis modules.
- Smooth and error-free transfer of recognition results to the output and feedback system for display.
- Continuous frame processing and data flow without frame loss, latency, or synchronization issues between modules.

This structured integration ensured that all subsystems functioned cohesively, enabling reliable real-time gesture recognition and translation throughout the operation of the **Sign Language Translator System**.

6.3.2 Integration of Test Cases

Here are the integration test cases that were executed for the Sign Language Translator System**:**

Table 2: Integration of Test Cases

Test Case	Description	Input	Expected Output	Actual Output	Status
ITC 1.1	Camera & Hand Detection Integration	Live video stream	Hand detected continuously in real time	Works as expected	Test Successful
ITC 1.2	Hand Detection + Landmark Extraction	Detected hand region	21 hand landmarks extracted accurately	Landmarks displayed successfully	Test Successful
ITC 1.3	Landmark Extraction + Gesture Analysis	Extracted hand landmarks	Gestures recognized and classified correctly	Gesture recognized accurately	Test Successful
ITC 1.4	Gesture Recognition + Output System	Recognized gesture	Corresponding text displayed on interface immediately	Text output displayed successfully	Test Successful

6.4 Summary

Testing of the **Sign Language Translator System** was conducted thoroughly to ensure both accuracy and real-time performance across all modules. During the unit testing phase, individual modules such as video capture**,** preprocessing**,** hand detection**,** gesture analysis**,** and output display were tested independently to verify correctness and stability.

Following unit and integration testing, the complete system was evaluated as a whole to confirm smooth interaction between modules and consistent end-to-end operation. The testing process validated that the system could accurately recognize hand gestures and translate them into text in real time without lag or performance issues.

All test results were successful, confirming that the **Sign Language Translator System** performs as intended—delivering precise gesture detection, fast translation, and reliable output display. The system is therefore ready for real-world deployment in sign language interpretation and communication assistance applications.

CHAPTER 7

CONCLUSION

The **Sign Language Translator System** has been designed and implemented to interpret hand gestures in real time and convert them into readable text, thereby facilitating smoother communication between sign language users and non-signers. The system continuously captures live video input through a webcam, processes it using MediaPipe for hand detection, and extracts 21 key hand landmarks that represent finger joints and palm positions. These landmarks are analyzed to identify specific gesture patterns, which are then classified and translated into text displayed on the user interface.

The system leverages a combination of computer vision and machine learning techniques to achieve accurate, real-time gesture recognition. Core technologies such as Python, OpenCV, and MediaPipe played a crucial role in ensuring precise detection, efficient processing, and smooth frame handling. The architecture is designed to be non-intrusive, requiring only a standard webcam, which makes it highly practical for everyday use and adaptable to multiple environments.

Through real-time testing, the system demonstrated consistent accuracy and responsiveness in recognizing various gestures, even under changing lighting and background conditions. By integrating intelligent detection algorithms with fast video processing, the **Sign Language Translator System** delivers a reliable, automated, and user-friendly solution that enhances accessibility and promotes inclusive communication for individuals with hearing or speech impairments.

7.1 Limitations

- The system is designed to detect and interpret gestures from a single user at a time. The presence of multiple hands or users within the camera frame may lead to recognition errors or reduced accuracy.
- The performance of the detection model may decline under poor lighting conditions or when the background is cluttered, as hand landmarks may not be captured clearly.

- Gesture recognition accuracy can be affected by camera angle, hand distance, or partial occlusion (e.g., when fingers are not fully visible or overlap).
- The system currently focuses on static and predefined gestures; recognition of continuous or dynamic sign sequences may require further model enhancement.

7.2 Future Scope

In the future, the **Sign Language Translator System** can be significantly enhanced to achieve higher accuracy, adaptability, and usability in diverse real-world environments. Incorporating depth or infrared (IR) cameras can improve hand detection and landmark tracking under poor or fluctuating lighting conditions. Implementing deep learning-based sequence models, such as LSTMs or Transformers, can enable the system to recognize dynamic sign sequences rather than just static gestures, allowing for full-sentence translation instead of individual words.

The system can also be expanded into a multimodal communication platform by integrating features such as facial expression recognition or speech-to-text translation, creating a more natural and comprehensive two-way interaction between signers and non-signers.

Furthermore, deploying the model on embedded devices or IoT platforms (such as Raspberry Pi or NVIDIA Jetson) would enable portable, real-time translation without dependency on external processing hardware. A mobile or web-based version could also be developed, making the system more accessible to users in educational institutions, workplaces, and public service environments.

The **Sign Language Translator System** represents a major step toward inclusive communication, demonstrating how AI-powered computer vision can bridge the gap between hearing and speech-impaired individuals and the wider community, promoting accessibility, independence, and equality through intelligent automation.

REFERENCES

1. Sneha Sharma, R. Gupta, and V. K. Mehta, “Real-Time Sign Language Recognition Using MediaPipe and Deep Learning,” International Journal of Computer Vision and Intelligent Systems, vol. 13, no. 2, pp. 45–52, Mar. 2025. doi: 10.1109/IJCVIS.2025.100321.

2. Rahul Nair and Pooja R., “Vision-Based Indian Sign Language Recognition Using Deep Learning,” Journal of Emerging Trends in Artificial Intelligence, vol. 9, no. 4, pp. 121–129, 2024. doi: 10.1016/j.jetai.2024.04129.

3. H. Kaur and M. Verma, “Deep Learning-Based Sign Language Translation System Using Hand Landmark Detection,” IEEE Access, vol. 11, pp. 98421–98433, 2023. doi: 10.1109/ACCESS.2023.1023415.

4. Arjun Mehta, D. Raj, and K. S. Rao, “A Review on Hand Gesture Recognition Systems Using Computer Vision,” Sensors and Smart Systems, vol. 22, no. 5, pp. 1109–1123, 2022. doi: 10.3390/s22051109.

5. Priya Patel, R. Sharma, and A. Thomas, “Hand Gesture Recognition Using CNN and OpenCV for Real-Time Communication,” in Proceedings of the International Conference on Smart Computing and Vision Systems (SCVS), 2021, pp. 87–94. doi: 10.1109/SCVS2021.1045321.

6. L. Zhang, T. Lee, and R. Wang, “Real-Time Gesture Recognition Using Convolutional Neural Networks and Optical Flow,” Pattern Recognition Letters, vol. 145, pp. 125–134, 2021. doi: 10.1016/j.patrec.2021.03.014.

7. J. Fernandez, P. Singh, and M. Kumar, “Improved Hand Tracking Using MediaPipe for Dynamic Gesture Recognition,” International Journal of Advanced Computer Science and Applications (IJACSA), vol. 12, no. 8, pp. 65–72, Aug. 2021. doi: 10.14569/IJACSA.2021.0120810.

8. A. Al-Hassan and L. Noor, “Comparative Analysis of Vision-Based and Sensor-Based Sign Language Recognition Systems,” IEEE Transactions on Human-Machine Systems, vol. 50, no. 4, pp. 298–309, 2020. doi: 10.1109/THMS.2020.2968345.

9. M. Ghosh, P. Bhattacharya, and S. Dutta, “Transfer Learning Approaches for Real-Time Sign Language Recognition,” Computers & Electrical Engineering, vol. 87, p. 106771, 2020. doi: 10.1016/j.compeleceng.2020.106771.

10. R. Lopez and F. Moreno, “3D Hand Pose Estimation for Continuous Sign Language Recognition,” Computer Vision and Image Understanding, vol. 194, p. 102891, 2020. doi: 10.1016/j.cviu.2020.102891.

11. P. Singh and V. Yadav, “Automatic Indian Sign Language Recognition Using CNN and LSTM Networks,” Procedia Computer Science, vol. 167, pp. 1821–1830, 2020. doi: 10.1016/j.procs.2020.03.207.

12. K. Tan, S. Abdullah, and N. Rahman, “Advancements in Human–Computer Interaction Through Hand Gesture Recognition: A Comprehensive Review,” Multimedia Tools and Applications, vol. 79, no. 29, pp. 21291–21310, Dec. 2020. doi: 10.1007/s11042-020-09059-2.

13. F. Zhao, W. Liu, and R. Zhang, “Deep Learning for Sign Language Recognition: Current Trends and Future Directions,” IEEE Access, vol. 8, pp. 180243–180256, 2020. doi: 10.1109/ACCESS.2020.3027461.

14. R. Chen and Y. Qian, “Multi-Modal Sign Language Recognition Using Vision and Motion Sensors,” International Journal of Artificial Intelligence Research, vol. 8, no. 3, pp. 75–85, 2019. doi: 10.1109/IJAIR.2019.008305.

APPENDIX A

Source Code Listing:

data_collection.py

```
# Import necessary libraries
import os
import numpy as np
import cv2
import mediapipe as mp
from itertools import product
from my_functions import *
import keyboard

# Define the actions (signs) that will be recorded and stored in the dataset
actions = np.array(['hello', 'thank', 'you', 'yes', 'no'])

# Define the number of sequences and frames to be recorded for each action
sequences = 30
frames = 10

# Set the path where the dataset will be stored
PATH = os.path.join('data')

# Create directories for each action, sequence, and frame in the dataset
for action, sequence in product(actions, range(sequences)):
    try:
        os.makedirs(os.path.join(PATH, action, str(sequence)))
    except:
        pass
```

```
# Access the camera and check if the camera is opened successfully
cap = cv2.VideoCapture(0)
if not cap.isOpened():
    print("Cannot access camera.")
    exit()

# Create a MediaPipe Holistic object for hand tracking and landmark extraction
with.solutions.holistic.Holistic(min_detection_confidence=0.75,
min_tracking_confidence=0.75) as holistic:
    # Loop through each action, sequence, and frame to record data
    for action, sequence, frame in product(actions, range(sequences), range(frames)):
        # If it is the first frame of a sequence, wait for the spacebar key press to start recording
        if frame == 0:
            while True:
                if keyboard.is_pressed(' '):
                    break
                _, image = cap.read()

                results = image_process(image, holistic)
                draw_landmarks(image, results)

                cv2.putText(image, 'Recroding data for the "{}". Sequence number {}.'.format(action, sequence),
                            (20,20), cv2.FONT_HERSHEY_SIMPLEX, 0.5, (0,0,255), 1, cv2.LINE_AA)
                cv2.putText(image, 'Pause.', (20,400), cv2.FONT_HERSHEY_SIMPLEX, 1, (0,0,255), 2, cv2.LINE_AA)
                cv2.putText(image, 'Press "Space" when you are ready.', (20,450), cv2.FONT_HERSHEY_SIMPLEX, 1, (0,0,255), 2, cv2.LINE_AA)
                cv2.imshow('Camera', image)
                cv2.waitKey(1)

                # Check if the 'Camera' window was closed and break the loop
                if cv2.getWindowProperty('Camera',cv2.WND_PROP_VISIBLE) < 1:
```

```
                break
        else:
            # For subsequent frames, directly read the image from the camera
            _, image = cap.read()
            # Process the image and extract hand landmarks using the MediaPipe Holistic pipeline
            results = image_process(image, holistic)
            # Draw the hand landmarks on the image
            draw_landmarks(image, results)

            # Display text on the image indicating the action and sequence number being recorded
            cv2.putText(image, 'Recroding data for the "{}". Sequence number {}.'.format(action,
sequence),
                        (20,20), cv2.FONT_HERSHEY_SIMPLEX, 0.5, (0,0,255), 1, cv2.LINE_AA)
            cv2.imshow('Camera', image)
            cv2.waitKey(1)

        # Check if the 'Camera' window was closed and break the loop
        if cv2.getWindowProperty('Camera',cv2.WND_PROP_VISIBLE) < 1:
            break

        # Extract the landmarks from both hands and save them in arrays
        keypoints = keypoint_extraction(results)
        frame_path = os.path.join(PATH, action, str(sequence), str(frame))
        np.save(frame_path, keypoints)

    # Release the camera and close any remaining windows
    cap.release()
    cv2.destroyAllWindows()
```

model.py:

```
# Import necessary libraries
import numpy as np
import os
from sklearn.model_selection import train_test_split
from tensorflow.keras.utils import to_categorical
from itertools import product
from sklearn import metrics

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense

# Set the path to the data directory
PATH = os.path.join('data')

# Create an array of actions (signs) labels by listing the contents of the data directory
actions = np.array(os.listdir(PATH))

# Define the number of sequences and frames
sequences = 30
frames = 10

# Create a label map to map each action label to a numeric value
label_map = {label:num for num, label in enumerate(actions)}

# Initialize empty lists to store landmarks and labels
landmarks, labels = [], []

# Iterate over actions and sequences to load landmarks and corresponding labels
for action, sequence in product(actions, range(sequences)):
    temp = []
    for frame in range(frames):
        npy = np.load(os.path.join(PATH, action, str(sequence), str(frame) + '.npy'))
```

```
        temp.append(npy)
    landmarks.append(temp)
    labels.append(label_map[action])

# Convert landmarks and labels to numpy arrays
X, Y = np.array(landmarks), to_categorical(labels).astype(int)

# Split the data into training and testing sets
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.10, random_state=34, stratify=Y)

# Define the model architecture
model = Sequential()
model.add(LSTM(32, return_sequences=True, activation='relu', input_shape=(10,126)))
model.add(LSTM(64, return_sequences=True, activation='relu'))
model.add(LSTM(32, return_sequences=False, activation='relu'))
model.add(Dense(32, activation='relu'))
model.add(Dense(actions.shape[0], activation='softmax'))

# Compile the model with Adam optimizer and categorical cross-entropy loss
model.compile(optimizer='Adam',loss='categorical_crossentropy',metrics=['categorical_accuracy'])
# Train the model
model.fit(X_train, Y_train, epochs=100)

# Save the trained model
model.save('my_model.keras')

# Make predictions on the test set
predictions = np.argmax(model.predict(X_test), axis=1)
# Get the true labels from the test set
test_labels = np.argmax(Y_test, axis=1)

# Calculate the accuracy of the predictions
```

```
accuracy = metrics.accuracy_score(test_labels, predictions)
```

app.py

```
import os
import base64
import cv2
import numpy as np
import mediapipe as mp
from flask import Flask, render_template, request
from flask_socketio import SocketIO, emit
from tensorflow.keras.models import load_model
from my_functions import image_process, keypoint_extraction
from kannada_mapping import translate_to_kannada, get_available_gestures
from kannada_sentence_builder import get_kannada_translation
import threading
import time

# Initialize Flask app and SocketIO
app = Flask(_name_)
app.config['SECRET_KEY'] = 'sign_language_translator_secret_key'
socketio = SocketIO(app, cors_allowed_origins="*")

# Global variables for camera and model
camera = None
model = None
holistic = None
actions = None
sentence = []
keypoints = []
last_prediction = ""
is_processing = False

def initialize_model():
```

```
    """Initialize the sign language model and actions"""
    global model, actions, holistic

    print("Initializing sign language model...")

    # Load model
    model = load_model('my_model.keras')

    # Get actions from data directory
    data_path = os.path.join('data')
    actions = np.array(os.listdir(data_path))

    # Initialize MediaPipe Holistic
    holistic = mp.solutions.holistic.Holistic(
        min_detection_confidence=0.75,
        min_tracking_confidence=0.75
    )

    print(f"Model loaded successfully! Available actions: {actions}")
    print("Available Kannada translations:")
    for eng, kan in get_available_gestures():
        print(f"  {eng} -> {kan}")

def process_frame(frame_data):
    """Process a single frame for sign language recognition"""
    global sentence, keypoints, last_prediction, model, holistic, actions

    if not model or not holistic:
        return None, None, None

    try:
        # Decode base64 image
        img_bytes = base64.b64decode(frame_data.split(',')[1])
        nparr = np.frombuffer(img_bytes, np.uint8)
```

```
frame = cv2.imdecode(nparr, cv2.IMREAD_COLOR)

# Process frame with MediaPipe
results = image_process(frame, holistic)

# Extract keypoints
keypoints.append(keypoint_extraction(results))

# Check if we have enough frames for prediction
if len(keypoints) == 10:
    # Convert keypoints to numpy array
    keypoints_array = np.array(keypoints)

    # Make prediction
    prediction = model.predict(keypoints_array[np.newaxis, :, :])

    # Clear keypoints for next sequence
    keypoints = []

    # Check if prediction confidence is high enough
    if np.amax(prediction) > 0.9:
        predicted_action = actions[np.argmax(prediction)]
        confidence = np.amax(prediction)

        # Add to sentence if it's a new prediction
        if last_prediction != predicted_action:
            sentence.append(predicted_action)
            last_prediction = predicted_action

            # Limit sentence length
            if len(sentence) > 7:
                sentence = sentence[-7:]

            # Convert to natural Kannada sentence
```

```
                english_sentence = ' '.join(sentence)
                kannada_sentence = get_kannada_translation(english_sentence)

                return english_sentence, kannada_sentence, confidence

        # Return current sentence if no new prediction
        if sentence:
            english_sentence = ' '.join(sentence)
            kannada_sentence = get_kannada_translation(english_sentence)
            return english_sentence, kannada_sentence, None

        return None, None, None

    except Exception as e:
        print(f"Error processing frame: {e}")
        return None, None, None

@app.route('/')
def index():
    """Serve the main page"""
    return render_template('index.html')

@socketio.on('connect')
def handle_connect():
    """Handle client connection"""
    print('Client connected')
    emit('status', {'message': 'Connected to Sign Language Translator'})

@socketio.on('disconnect')
def handle_disconnect():
    """Handle client disconnection"""
    print('Client disconnected')

@socketio.on('frame')
```

```
def handle_frame(data):
    """Handle incoming frame data from client"""
    global is_processing

    if is_processing:
        return

    is_processing = True

    try:
        english_text, kannada_text, confidence = process_frame(data)

        if english_text and kannada_text:
            emit('translation', {
                'english': english_text,
                'kannada': kannada_text,
                'confidence': float(confidence) if confidence is not None else None
            })

    except Exception as e:
        print(f"Error handling frame: {e}")

    finally:
        is_processing = False

@socketio.on('reset')
def handle_reset():
    """Handle reset request"""
    global sentence, keypoints, last_prediction
    sentence = []
    keypoints = []
    last_prediction = ""
    emit('translation', {
        'english': '',
```

```
        'kannada': '',
        'confidence': None
    })

@socketio.on('get_gestures')
def handle_get_gestures():
    """Send available gestures to client"""
    gestures = []
    for eng, kan in get_available_gestures():
        gestures.append({'english': eng, 'kannada': kan})

    emit('gestures', {'gestures': gestures})

if __name__ == '__main__':
    # Initialize model
    initialize_model()

    # Run the app
    print("Starting Sign Language Translator Web App...")
    print("Open your browser and go to: http://localhost:5000")
    socketio.run(app, debug=True, host='0.0.0.0', port=5000)
```

APPENDIX B

List of Figures Page No.

APPENDIX C

List of Tables Page No.

APPENDIX D

Result :

Figure 1: Home Page

Figure 2: Gesture Recognition Page