AI-Powered Bidirectional Sign Language Translator

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Certificate

We accept the work contained in the report titled "AI-Powered Bidirectional Sign Language Translator", written by Mr. Muhammad Haris and Mr. Kaleem Yousaf as a confirmation to the required standard for the partial fulfillment of the degree of Bachelor of Science in Computer Science.

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Abstract

The communication between deaf and hearing people still raises obstacles in different settings such as education, work, and even public places. This is mainly due to the shortage of sign language interpreters and the low level of sign language skills among the general public. As a result, these obstacles often lead to unequal participation, delayed information access, and exclusive communication. However, the continuous integration of AI and computer vision technologies presents a possibility of creating automated translation tools that could make communication easier and more accessible. This project, driven by this requirement, offers an AI-enhanced two-way sign language translator that features real-time Sign-to-Text and Text-to-Sign translation utilizing common hardware and a web-based interface.

The Sign-to-Text component of the system makes use of a standard webcam to peg hand movements and sends each of the sequential frames through the MediaPipe Hands algorithm in order to detect the 21 main hand points. The identified points are then mapped into normalized feature vectors and subsequently categorized using a CNN (convolutional neural network) that has been trained on appropriate ASL alphabet datasets. Such a setup enables prompt detection of non-verbal random letter gestures without making use of particular sensors like data gloves or depth cameras. The result is gradually built up into a highly readable text, thus opening up the world of sign language to hearing users who can then follow the conversation of deaf users. The Text-to-Sign module acts as a reversal by issuing a transformation of written text into a series of ASL gesture images. This image-oriented approach gives a lightweight and resource-saving alternative to 3D animation, thus allowing it to work under low-power conditions while being clear to deaf users.

The entire system is developed as a web application using the Django framework, which means it is accessible from any device and browser, therefore, no installation is needed. To test the performance of the system regarding recognition accuracy, latency, usability, and compatibility, extensive tests were performed. The Sign-to-Text classifier during controlled evaluations reached an accuracy of about 95%, with an average time of fewer than two seconds per prediction. Alongside this, the system was perceived as very easy to use by the deaf and the hearing participants; they all concluded that the interface is user-friendly, the translation results are easy to follow, and the system allows for basic communication to run smoothly. Compatibility tests also confirmed that the system performs reliably across the most popular web browsers and operating systems.

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Acronyms and Abbreviations

3D	Three Dimensional
AI	Artificial Intelligence
API	Application Programming Interface
CNN	Convolutional Neural Network
CSS	Cascading Style Sheets
CV	Computer Vision
DBMS	Database Management System
DNN	Deep Neural Network
FYP	Final Year Project
GPU	Graphics Processing Unit
HTML	HyperText Markup Language
HTTP	HyperText Transfer Protocol
JS	JavaScript
LSTM	Long Short-Term Memory
NLP	Natural Language Processing
RNN	Recurrent Neural Network
SQL	Structured Query Language
UI	User Interface
UML	Unified Modeling Language
UX	User Experience

Chapter 1

Introduction

1.1 Project Background/Overview

Effective communication is the glue that binds everything work, friendships, everyday life. However, for hearing-impaired and deaf individuals, conversing with the non-sign language-speaking people seems like hitting a wall. Although sign language is their primary mode of communication, it is still not widely understood. This creates a void. It excludes people from discussions, reduces opportunities in work and education, and cuts off access to critical services.

In some instances, people have made an effort to solve this problem by using sign language interpreters or by communicating through texts, such as instant messages. However, thoseare not always successful. The problem is that interpreters are not on site all the time, particularly in less populated areas or during emergencies. Besides, the text lacks the interactive, interpersonal quality of a real conversation. Furthermore, hiring an interpreter is an expense. Moreover, having a mediator listening to one's conversation can create an awkward atmosphere, especially when one is discussing sensitive topics like health care or law.

The AI-Powered Bidirectional Sign Language Translator presented by this project is a remedy to these limitations. The system allows for seamless two-way communication in real-time by capturing sign language hand gestures and converting them to text for the hearing users, simultaneously translating written text into respective sign gestures for the hearing-impaired users. The system, employing advancements in deep learning, computer vision, and artificial intelligence, provides a communication solution that is scalable, cost-effective, and accessible that upholds the rights and privileges of communication and inclusivity for all individuals.

1.2 Problem Description

The global deaf community amounts to more than 70 million individuals, and each of them relies on different local variants of sign language. However, not many individuals from the hearing community learn sign language. The communication among deaf people and between deaf and hearing people is really difficult due to the inability of the latter to understand the former. This can, for instance, be observed in the following areas:

1. **Social Barriers:** Deaf individuals could find themselves cut off from the society as they fail to communicate in everyday situations.
2. **Education Barriers:** Sign language not being understood by classmates and teachers, means lesser learning chances and no access to regular education.
3. **Employment Barriers:** Deaf individuals are often placed in lower-paying jobs or totally excluded from certain sectors due to the absence of proper communication resources and tools.
4. **Healthcare Barriers:** Inadequate communication during medical consultations may result in the patient receiving the wrong information, misdiagnosis, and substandard patient care.

Currently available solutions like interpreters, captioning systems, or mobile apps often fall short in situations where communication is not real-time, not bidirectional, and not flexible enough for practical, daily use. So far, the majority of AI-based sign recognition systems have been limited to static gesture classification (e.g., recognizing individual letters or words) and have not adapted to the dynamic and fluid nature of sign language communication in everyday situations. Moreover, only a handful of systems provide the option of **Text-to-Sign** and **Sign-to-Text** conversion on one platform.

Thus, the necessity for a helpful, real-time, bidirectional translator arises urgently to enhance accessibility, reduce dependence on human interpreters, and facilitate communication between deaf and non-deaf people to be inclusive and natural.

1.3 Project Objectives

The principal aim of this project is to develop a **AI-Powered Bidirectional Sign Language Translator** that will serve as a link between sign language users and non-users. The primary objectives are:

1. The primary aim of the project was to create a real-time system utilizing computer vision and deep learning techniques to ensure the precise detection and recognition

of the sign language hand gestures thereby providing a reliable interpretation during the daily communication.

2. Secondly, it was intended to put into action a gesture recognition module that would render the gestures into text commonly read, thereby facilitating the comprehension of sign language messages by non-deaf people.

3. Thirdly, it is going to be the task of an auxiliary text-to-sign-up module to change and convert the written input into the corresponding visual sign image, which will enable deaf people to get information in a very familiar and accessible format.

4. The first step of the process was to concentrate on the basic-level and gesture recognition, allowing the system expansion towards continuous sign recognition in the future without any difficulties.

5. A user-friendly interface will be developed that is web-based, and very, simple, intuitive, and available on all devices thereby no special hardware or software installations will be required.

6. The performance of the system will be optimized by putting the main focus on the areas of accuracy and low latency plus the system will be designed to accommodate a large number of users and different environments which will ensure smooth real-time operation.

7. The deaf community will benefit from the project as the technological advancements made through the project will entail the breaking down of communication barriers thus promoting equal opportunities for the deaf.

1.4 Project Scope

At the beginning of the project, the scope was received in an unambiguous and carefully defined manner designed to induce focused development and outcomes that could be measured.

1. **Sign-to-Text Conversion:** The standard camera will be used by the system for capturing hand gestures, and the live video stream will be handled by computer vision techniques. The gestures will be then interpreted by a trained deep learning model and converted to readable text, which will enable the non-deaf to easily comprehend signed communication.

2. **Text-to-Sign Conversion:** The system will render typed text into corresponding sign language visuals. These signs will be shown as well-defined images which will assist

the hearing-impaired in understanding the message in a recognizable and convenient format.

3. **Dataset Usage:** Training and testing will be done using public datasets like the ASL Alphabet Dataset and other similar gesture collections. The first step will be taking the American Sign Language (ASL) alphabets and some words to get the recognition accurate and trustworthy.

4. **Technology Stack:** TensorFlow/Keras will be the core of the technology stack for model development, while OpenCV and MediaPipe will be the choice for gesture detection and tracking, and Django will be responsible for the web-based interface development that is responsive and accessible. This tech stack offers excellent scalability, flexibility, and modern AI compatibility.

5. **Real-time Performance:** The aim of the system is to provide a response time of under 2 seconds, which translates to a near real-time interaction for the users that is natural and smooth.

6. **Limitations:** Now, the limitations that the existing system can do are only alphabet-level and very basic word-level recognition in ASL. Future versions may include the aforementioned advanced capabilities such as sentence-level translation, facial expressions integration, or support for more than one sign language as the system continues to develop.

1.5 Summary

To sum up, the present project is dealing with one of the most significant social issues, the communication barrier that generally separates deaf people from hearing ones. The AI led real-time two-way translator system is proposed to promote the daily communication with the three characteristics of being inclusive, accessible, and equal for all. The Introduction section has, moreover, built the foundation and justification of the research, pointed out the key problems, and defined the objectives and the scope of the project. All these points give a solid groundwork for the following chapters, namely the literature review, system design, implementation, and evaluation.

Chapter 2

Literature Review

A literature review is a systematic study of historic research, technologies, and methods in a given domain. The current review for this project centers around sign language recognition, hand gesture tracking with computer vision techniques, text-to-sign communication aids, and one-to-other translation systems. The purpose of this chapter is to review the advancements already made, point out their limitations, and specify the research gaps that call for the proposed system's development.

2.1 Evolution of Sign Language Recognition Approaches

Automatic Sign Language Recognition (SLR) research has seen tremendous progress in the last thirty years. The first-generation systems from the 1990s and early 2000s were mainly based on **sensor-based methods**, which involved the use of gloves with sensors that detected finger bending and hand movement. These systems provided very accurate results, but at a high cost, were uncomfortable, and thus not suitable for daily use.

The transition from **camera-based recognition** was a revolutionary step. RGB and depth cameras, such as the Microsoft Kinect, brought about the possibility of gesture recognition without direct contact. However, the systems were still challenged by poor lighting and had high computational requirements.

Deep learning and particularly Convolutional Neural Networks (CNNs) have been major contributors to the improvement of the recognition accuracy to a large extent. CNNs outperformed other approaches in static gesture classification, while the temporal motion pattern was effectively captured by recurrent models.

The trend of lightweight hand-tracking systems such as **MediaPipe Hands** has recently gained a lot of attention because they are able to detect 21 hand landmarks during the live performance with just a regular webcam and one CPU only. The developments mentioned

above made it possible to develop ESR systems of practical use and operating in real-time without expensive hardware.

These innovations represent the foundation upon which this project builds, as it integrates CNN-based classification with the MediaPipe Hands for quick and easy hand gesture recognition.

2.2 Sign Language Recognition Systems

Several notable research efforts have significantly advanced the field of SLR:

- **DeepASL** – Introduced a deep learning-based framework for ASL sentence-level recognition. Although effective, the model depended on large datasets and required GPU-level computational resources [1].
- **Sign2GPT** – Employed transformer architectures for continuous sign recognition, demonstrating strong sequence modeling capabilities, yet remained unsuitable for deployment on typical consumer devices [2].
- **RWTH-PHOENIX-Weather Corpus** – A widely used and long-established dataset for continuous sign language recognition, frequently serving as a benchmark for evaluating deep learning models [3].
- **ASL Alphabet CNN Models** – Achieved high accuracy in alphabet-level classification using static images, providing a foundational basis for early-stage or beginner-level SLR systems [4].
- **MediaPipe-Based Projects** – Demonstrated the feasibility of real-time gesture recognition through lightweight hand landmark detection, which further motivated the adoption of MediaPipe in this project [5].

Even though they provide useful inputs, many of these systems impose high hardware requirements, lack real-time responsiveness, or focus only on static gestures, which limits their practicality for everyday use [1, 2, 3, 4, 5].

2.3 Text-to-Sign Translation Systems

Compared to SLT research, research on TSL remains extremely limited, and the current systems normally fall within one of these two categories:

- **Avatar-Based Animation Systems** – Platforms such as **sign.mt** [6] utilize 3D animated avatars to present sign language. Although visually expressive and capable of conveying rich gestures, these systems are computationally demanding and often depend on pre-rendered animations.

- **Image-Based Mapping Systems** – Numerous academic prototypes function by mapping input text to corresponding sign images or short video clips. While straightforward and user-friendly, these systems are limited in both vocabulary coverage and overall flexibility.

Text-to-Sign module based on **image** is chosen because it is lightweight and can convert user-provided text into ASL alphabet images, hence, keeping the project's main focus on accessibility and real-time performance. This technique produces visual output that is easier to interpret and comprehensible without going through the intricate process of 3D avatars.

2.4 Role of Non-Manual Features

Even though complete sign languages rely on facial expressions and body language, those aspects are generally needed only for the most sophisticated activities like sentence translation or emotion detection. Using hands only is the main focus for many of the existing SLR systems, particularly in the cases of alphabet-level and simple word recognition.

Earlier research indicated that:

- Full-body tracking is provided by systems such as OpenPose and PoseNet [7], but they consume a lot of computational power.
- Greater accuracy can be achieved by using multimodal datasets that include facial cues; however, these require high-resolution cameras and sophisticated models.

As this project is aimed at alphabet- and word-level ASL recognition on common devices, it purposefully limits itself to **hand-only detection** through MediaPipe Hands. This approach ensures a fast, simple, and accessible solution without compromising accuracy for the intended scope.

2.5 Natural Language Processing for Sign-to-Text Refinement

Usually, predictions based on raw gestures need to be processed further in order to generate meaningful texts. The application of NLP methods is one way to take refined classification outputs and convert them into human-readable results.

- **Sign Speech Systems** – NLP-based post-processing is effective in reducing noise from gesture-based predictions [8].
- **NLTK and spaCy** – Widely used NLP libraries providing tokenization, text normalization, and linguistic processing capabilities [9, 10].

The integration of basic natural language processing methods together with the smoothing of predictions through majority voting has led to the generation of precise text outputs at the levels of alphabet and words in this project.

2.6 Bidirectional Communication Systems

It is still not so common to see bidirectional sign communication devices. The majority of systems are designed to handle Sign-to-Text or Text-to-Sign but not both at the same time.

Some examples include:

- **Sensor-Based Translators** – Achieved bi-directional translation, but required wearable devices [11].
- **Prototype Web Systems** – Certain research prototypes implemented one-way functionality using webcams [11].

The proposed system integrates both Sign-to-Text and Text-to-Sign into a single, fully web-based platform that operates on standard hardware, thereby making it more practical for real-world use.

2.7 Comparison of Existing Systems

Table 2.1 summarizes that, unlike existing approaches, the proposed system uniquely offers real-time, hand-only, bidirectional sign language communication using standard CPU-based hardware.

Table 2.1: Comparison of Sign Language Recognition and Translation Systems

System	**Sign-to-Text**	**Text-to-Sign**	**Hand-Only**	**Real-Time**
DeepASL (2018)	Yes	No	No	Partial (GPU)
Sign2GPT (2024)	Yes	No	No	Limited
sign.mt (2023)	No	Yes (Avatar)	No	Limited
MediaPipe Systems	Yes	No	Yes	Yes
Our Project	Yes	Yes (Images)	Yes	Yes (CPU + webcam)

2.8 Identified Research Gaps

The literature reveals several gaps:

- **Absence of Bidirectionality:** The majority of systems allow only one translation direction.
- **Restrictions Imposed by Hardware:** Many systems require depth sensors, gloves, or GPUs.
- **Real-Time Performance Is Slow:** On standard devices, complex models often cannot achieve real-time performance.
- **Vocabulary Is Limited:** Many models focus only on alphabets or small word sets.
- **No User-Friendly Platforms:** Very few systems offer simple and deployable web interfaces.

2.9 Summary

This chapter has reviewed the literature on SLR, text-to-sign systems, NLP refinement, and communication technologies. Although there has been substantial progress made, there are still many difficulties which need to be overcome, especially regarding the creation of tools that would be fast, accessible, and bidirectional and at the same time running on regular hardware.

The proposed system aims to address these challenges by:

- Utilizing a lightweight CNN + MediaPipe hand gesture recognition model,
- Offering a complete two-way system (Sign-to-Text and Text-to-Sign),
- Prioritizing hand-only detection for speed and ease of use,
- Providing a user-friendly web application that does not require any specialized hardware.

Chapter 3

Requirement Specifications

This chapter presents the requirement specifications for the **AI-Powered Bidirectional Sign Language Translator**. The discussion begins with an analysis of the limitations of existing systems, followed by a detailed description of the proposed solution and its capabilities. The dataset used for gesture recognition is then explained, after which the functional and non-functional requirements, use cases, and overall system architecture are outlined. Collectively, these elements establish a clear and solid foundation for the design and development of the proposed system.

3.1 Existing System

Communication between deaf and non-deaf individuals is commonly facilitated through human interpreters, written communication, or basic mobile applications. While these approaches offer partial support, they fail to deliver the immediacy, accessibility, and natural interaction required for effective communication. Several limitations are still present, including:

1. **Lack of Real-Time Interaction:** Text-based communication methods do not provide natural, face-to-face interaction.

2. **Dependence on Human Interpreters:** Professional sign language interpreters are not always readily available and may be costly.

3. **Gesture Recognition Constraints:** Many existing AI-based systems are limited to static gestures and lack robust alphabet-level or word-level understanding.

4. **Unidirectional Functionality:** Most available tools support either Sign-to-Text or Text-to-Sign translation, but rarely both within a single system.

These limitations highlight the need for a lightweight, real-time, and fully bidirectional sign language translation system.

3.2 Proposed System

The proposed system is a real-time, web-based platform designed to provide bidirectional translation between American Sign Language (ASL) and textual language. The system enables hand gestures to be converted into text and allows typed text to be translated into corresponding ASL gesture representations.

The key features of the proposed system include:

- **Bidirectional Translation:** Integration of both Sign-to-Text and Text-to-Sign translation within a single platform.
- **Hand Gesture Recognition:** Use of MediaPipe Hands for landmark extraction and a CNN-based classifier for gesture recognition.
- **Real-Time Performance:** End-to-end system response time limited to a maximum of 2 seconds.
- **Visual Output:** Display of ASL gesture images corresponding to typed or recognized text.
- **Web-Based Deployment:** No installation required; the system operates through commonly used web browsers.
- **Scalable Design:** The system architecture supports future expansion of vocabulary and features.

3.3 Dataset Description

The dataset plays a critical role in the performance of the Sign-to-Text module, as it is used to train the gesture recognition model. The system utilizes a publicly available ASL alphabet dataset consisting of labeled images representing hand gestures for the 26 English alphabets. Depending on the dataset version, a limited number of additional gestures may also be included.

3.3.1 Dataset Source

The ASL Alphabet Dataset was primarily obtained from publicly available sources, most notably Kaggle. Due to its consistent labeling, image quality, and reliability, this dataset is widely used in academic research related to static sign language gesture recognition.

3.3.2 Dataset Composition

The dataset is organized into distinct classes, with each class representing a specific ASL alphabet gesture. This structure enables efficient training, validation, and testing of the gesture recognition model while ensuring consistency across all gesture classes.

- **Total Classes:** 26 ASL alphabet classes (A–Z).
- **Images per Class:** Approximately 3,000 images per alphabet (varies by dataset version).

- **Image Format:** RGB images, typically sized at 200×200 or 224×224 pixels.
- **Background Variation:** Mostly uniform backgrounds to facilitate efficient feature extraction.

3.3.3 Preprocessing Steps

Prior to training, the dataset undergoes several preprocessing steps to improve model performance:

1. **Resizing:** All images are resized to a fixed resolution compatible with the CNN input layer.
2. **Normalization:** Pixel intensity values are scaled to the range of 0–1.
3. **Data Augmentation:** Minor augmentations such as rotation, flipping, and brightness adjustment are applied to enhance generalization.
4. **Landmark Conversion (Optional):** When MediaPipe is used, images are converted into 21-point hand landmark vectors before classification.

3.3.4 Justification for Dataset Selection

The dataset was selected based on the following factors:

- **High-quality images** with consistent and accurate labeling.
- **Relevance to static gestures**, which aligns with the alphabet-level focus of the project.
- **Compatibility with CNN-based models** and MediaPipe landmark extraction.
- **Public availability and reproducibility**, supporting reliable academic evaluation.

This dataset enables the development of a robust and efficient model while maintaining low computational requirements for real-time inference.

3.4 Requirement Specifications

To ensure clarity and consistency throughout the development process, system requirements are categorized into functional and non-functional requirements.

3.4.1 Functional Requirements

The functional requirements define the essential operations and services that the proposed system must provide to support bidirectional sign language translation. These requirements describe how the system captures user input, processes gestures or text, and produces the corresponding outputs in real time.

1. **FR1:** Detect hand gestures using a webcam.

2. **FR2:** Recognize ASL alphabet-level and selected word-level gestures.

3. **FR3:** Generate textual output from recognized gestures.

4. **FR4:** Accept text input and map it to corresponding ASL gesture images.

5. **FR5:** Support real-time bidirectional communication.

6. **FR6:** Allow basic text editing operations during gesture recognition.

Table 3.1 summarizes the functional requirements and presents a structured mapping between system features and their intended functionality.

Table 3.1: Functional Requirements

ID	Description
FR1	Capture hand gestures using a webcam.
FR2	Recognize ASL alphabet and selected word-level gestures.
FR3	Convert recognized gestures into text.
FR4	Convert typed text into ASL gesture images.
FR5	Provide real-time bidirectional communication.
FR6	Allow basic editing during recognition.

3.4.2 Non-Functional Requirements

Non-functional requirements describe the quality attributes and operational constraints of the system. These requirements ensure that the system remains efficient, reliable, secure, and user-friendly while operating under real-world conditions.

1. **Performance:** The system shall respond within 2 seconds.

2. **Accuracy:** The recognition accuracy shall exceed 95%.

3. **Usability:** The interface shall be intuitive for both deaf and non-deaf users.

4. **Reliability:** The system shall maintain at least 99% uptime.

5. **Security:** User data shall be processed securely.

6. **Portability:** The system shall operate on modern web browsers.

7. **Maintainability:** The codebase shall support easy updates and modifications.

8. **Scalability:** The system shall support future expansion of features and vocabulary.

Table 3.2 provides a categorized summary of the non-functional requirements that guide the system's performance, reliability, and long-term sustainability.

Table 3.2: Non-Functional Requirements

Category	Description
Performance	System response time within 2 seconds.
Accuracy	Recognition accuracy above 95%.
Usability	Intuitive and accessible interface.
Reliability	Minimum system uptime of 99%.
Security	Secure handling of user data.
Portability	Compatible with major web browsers.
Maintainability	Modular and easily maintainable codebase.
Scalability	Supports future feature expansion.

3.5 Use Cases

This section describes the primary interaction scenarios between users and the proposed system. Each use case outlines how the system behaves in response to user actions during bidirectional sign language translation.Figure 3.1 illustrates the overall use case diagram of the proposed system, highlighting the interaction between users and the bidirectional sign language translation functionalities.

3.5.1 Use Case 1: Sign-to-Text Conversion

This use case explains the process in which a deaf user communicates using ASL hand gestures that are captured through a webcam and translated into readable text by the system in real time.

- **Actors:** Deaf User, System
- **Description:** The user performs ASL gestures, which are recognized and translated into text by the system.
- **Pre-Conditions:** Webcam is active and the recognition module is running.
- **Post-Conditions:** Translated text is displayed on the interface.

3.5.2 Use Case 2: Text-to-Sign Conversion

This use case describes how a non-deaf user communicates with a deaf user by entering text into the system, which is then converted into corresponding ASL gesture images for visual understanding.

- **Actors:** Non-Deaf User, System
- **Description:** The user inputs text, and the system displays the corresponding ASL gesture images.
- **Pre-Conditions:** System is online and text input is provided.
- **Post-Conditions:** ASL gesture images are displayed.

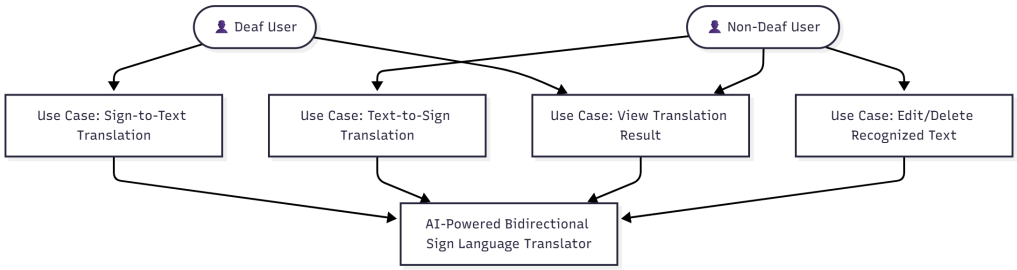

Figure 3.1: Use Case Diagram

3.6 Proposed System Architecture

Figure 3.2 presents the overall architecture of the proposed system, showing the interaction between the frontend interface, backend processing modules, and supporting components.

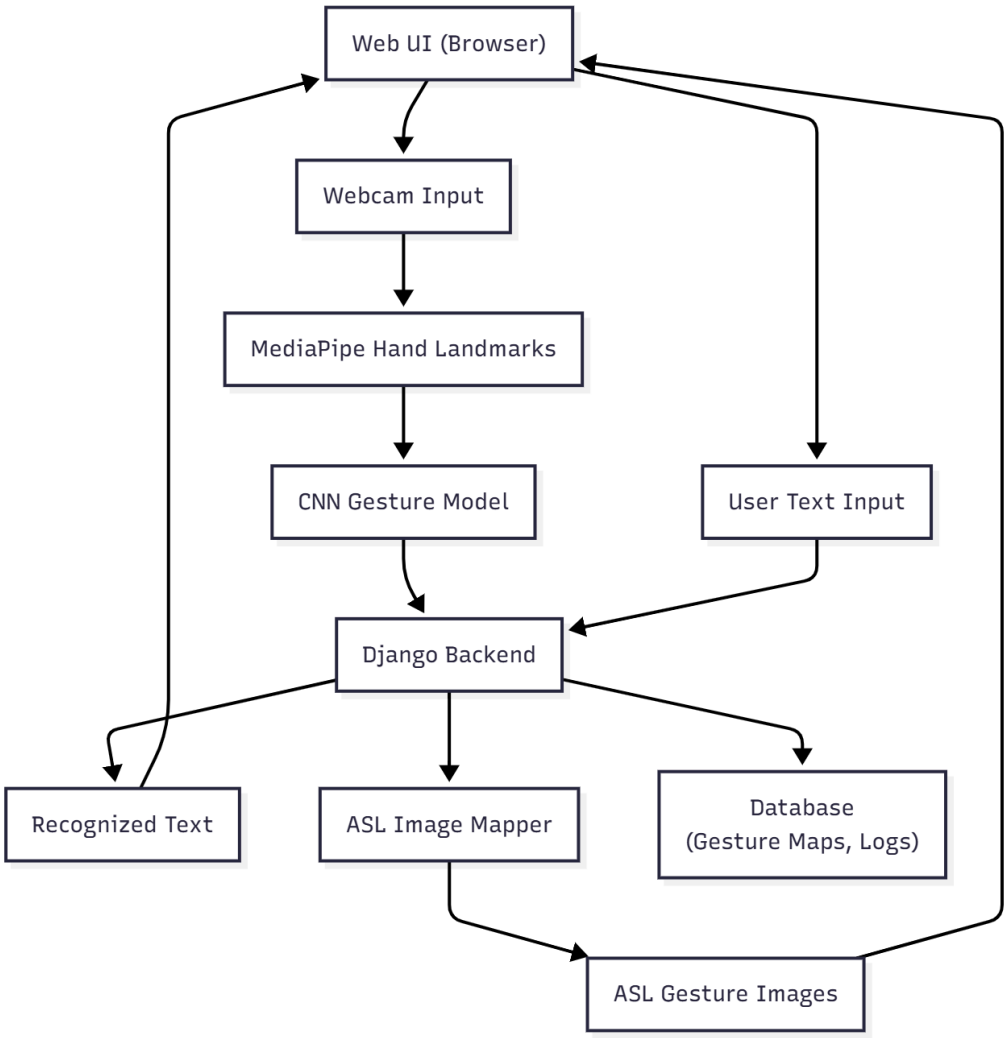

Figure 3.2: Proposed System Architecture

Architecture Modules

This section describes the major functional modules of the proposed system architecture. Each module is designed to operate independently while seamlessly integrating with other components to enable efficient, real-time bidirectional sign language translation.

- **Frontend Interface:** Web-based user interface for interaction.
- **Sign-to-Text Module:** Handles gesture capture, landmark extraction, and CNN-based classification.
- **Text-to-Sign Module:** Converts typed text into corresponding ASL gesture images.
- **NLP Module:** Performs basic text processing and formatting.
- **Database:** Stores gesture mappings and session-related data.

3.7 Summary

This chapter presented the requirement specifications for the proposed AI-powered bidirectional sign language translation system. The limitations of existing solutions were identified, followed by a detailed explanation of the proposed system, dataset characteristics, functional and non-functional requirements, use cases, and system architecture. These specifications provide a strong foundation for the subsequent chapters on system design, implementation, and evaluation.

Chapter 4

Design

System design involves a meticulous organization of the entire system, defining its architecture, internal components, data flow, and communication mechanisms. This chapter presents the detailed design of the **AI-Powered Bidirectional Sign Language Translator**. It covers the system architecture, design constraints, methodology, high- and low-level design, database structure, GUI, external interfaces, and UML diagrams. The goal is to translate requirements into a technically feasible and logically coherent design.

4.1 System Architecture

The system employs a modular layered architecture, providing scalability, maintainability, and real-time efficiency. The architecture consists of three major layers, illustrated in Figure 4.1:

1. **Input Layer:** Responsible for receiving user inputs:
   (a) Frames from the webcam for gesture recognition.
   (b) Text inputs from non-deaf users for Text-to-Sign translation.
2. **Processing Layer:** Handles AI and preprocessing logic:
   (a) Landmark extraction using MediaPipe.
   (b) Gesture classification using CNN.
   (c) Text processing and formatting.
3. **Output Layer:** Delivers results to users:
   (a) Recognized text to non-deaf users.
   (b) ASL gesture images to deaf users.

As shown in Figure 4.1, the system ensures smooth flow from input capture to processing and output delivery.

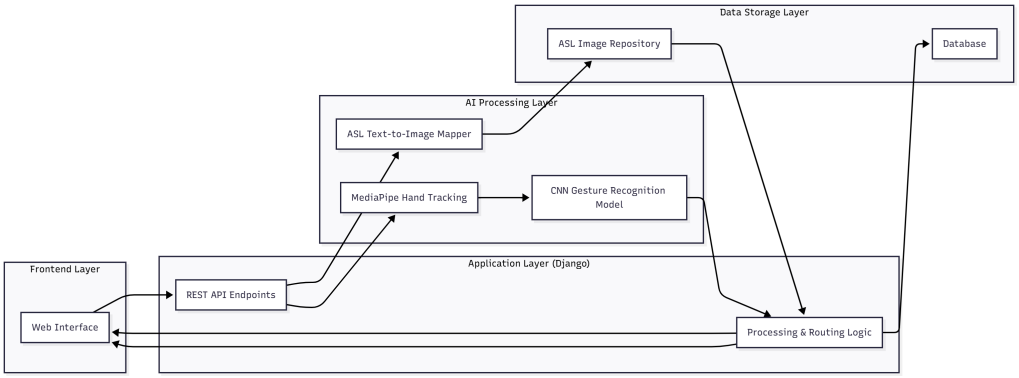

Figure 4.1: System Architecture

4.2 Design Constraints

Several constraints influence system design, ensuring practical implementation on widely available hardware. A summary is shown in Table 4.1.

Table 4.1: Summary of Design Constraints

Constraint Type	**Description**
Hardware Limitations	Requires a webcam and moderate CPU for MediaPipe and CNN processing.
Dataset Limitations	Public datasets mainly include ASL alphabets and limited static gestures.
Performance Trade-offs	Real-time response necessitates balancing accuracy and inference time.
Web Deployment Challenges	Client devices may not support heavy computation; backend optimization is required.
Scalability Constraints	Supporting additional sign languages or continuous signing demands richer datasets and complex models.

4.3 Design Methodology

The system was developed using an **Object-Oriented Design (OOD)** approach, assisted by **UML** for visualization. The process included:

1. **Requirements Analysis:** Extracting functional and non-functional requirements from the SRS document.
2. **System Decomposition:** Dividing the system into logical modules such as Input Capture, Gesture Recognition, Text Processing, and Output Display.
3. **Design Modeling:** Creating UML diagrams for Class, Component, Deployment, and ER diagrams.
4. **Iterative Refinement:** Updating the design based on feedback and performance evaluation.

4.4 High-Level Design

The high-level design provides a conceptual view of system components and data flow.

4.4.1 Conceptual / Logical View

The system is divided into four primary components:

1. Input Module
2. Gesture Recognition Module
3. Text Processing Module
4. Web UI Module

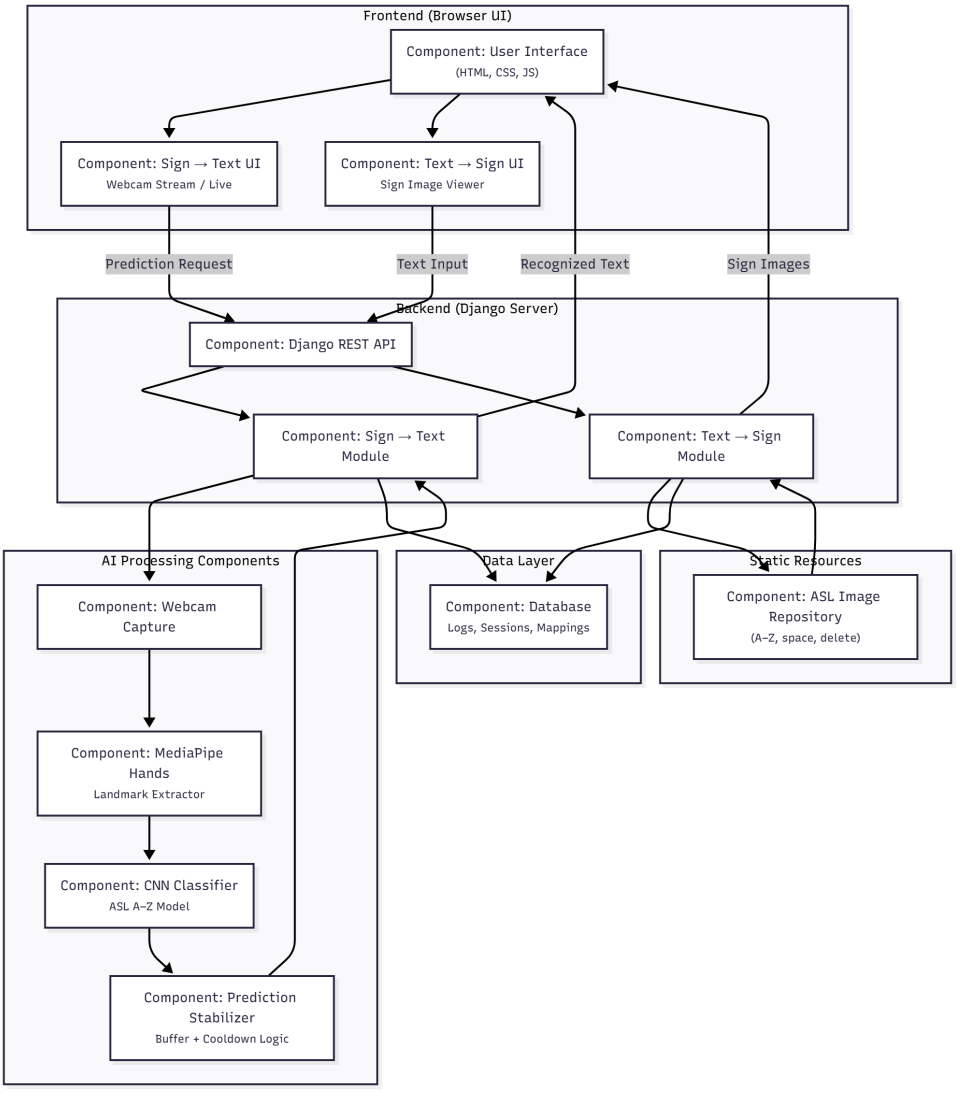

Figure 4.2: Component Diagram of the System

4.4.2 Process View

The processing tasks include:

1. Real-time gesture recognition from webcam frames, ensuring smooth and accurate detection of sign language movements.

2. Handling text input for Text-to-Sign translation, converting user-provided text into corresponding sign gestures.

3. Multi-threading to maintain responsiveness, allowing simultaneous gesture recognition, text processing, and UI updates without lag.

4. Backend AI models assisting frontend interactions, providing predictions and supporting real-time feedback for users.

These processes are designed to work concurrently, maintaining low latency while ensuring high accuracy in gesture recognition and translation.

4.4.3 Physical View

The system follows a client-server deployment:

1. **Client Side:** Web UI accessed via browser, providing an intuitive interface for gesture input and text output.

2. **Server Side:** Hosts CNN models, MediaPipe processing, and database management, handling computationally intensive tasks efficiently.

3. **Communication:** Frontend-backend interaction via REST APIs, ensuring secure and structured data exchange between the client and server.

This architecture supports scalability, allowing additional clients or AI modules to be integrated without affecting system performance.

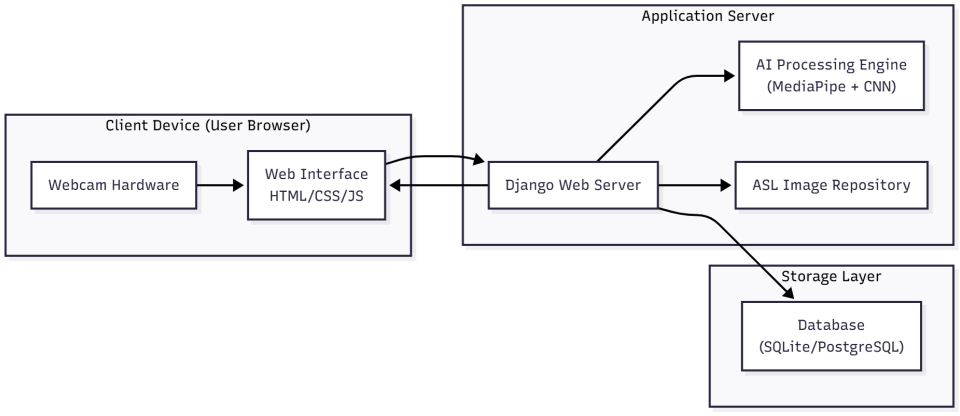

Figure 4.3: Deployment Diagram of System Infrastructure

4.4.4 Module View

Table 4.2 summarizes the main modules of the system.

Table 4.2: Module Description Table

Module	Description	Input / Output
Input Module	Captures webcam frames or text.	Input: Frames/Text Output: Preprocessed data
Gesture Recognition Module	Performs MediaPipe landmark extraction and CNN classification.	Input: Frames Output: Predictions
Text Processing Module	Converts predictions to text and maps text to ASL images.	Input: Predictions/Text Output: Text/Images
Web UI Module	Displays output and manages user interactions.	Input: User actions Output: Visual interface
Database Module	Stores logs, mappings, and session records.	Input: Log entries Output: Stored/retrieved data

4.4.5 Security View

Security measures include:

1. Webcam frames are not stored to maintain privacy, ensuring that user video data remains confidential and ephemeral.
2. Data transmission uses secure channels (e.g., HTTPS) to prevent interception or tampering.
3. Backend endpoints are access-controlled, allowing only authenticated users and authorized services to interact with sensitive components.

4.5 Low-Level Design

Classes and responsibilities:

1. **InputModule:** Captures and preprocesses webcam frames, including normalization and resizing, to prepare data for gesture recognition.
2. **GestureRecognitionModule:** Loads trained CNN models, performs classification of gestures, and provides confidence scores for each prediction.
3. **TextProcessingModule:** Handles text formatting, mapping recognized gestures to corresponding letters or words, and managing output sequences.
4. **WebUIModule:** Manages Django templates, handles user interactions, and updates the interface dynamically with recognized gestures and text.

These modules work together to ensure real-time performance, accuracy, and a secure user experience, providing seamless interaction between the user and the system.

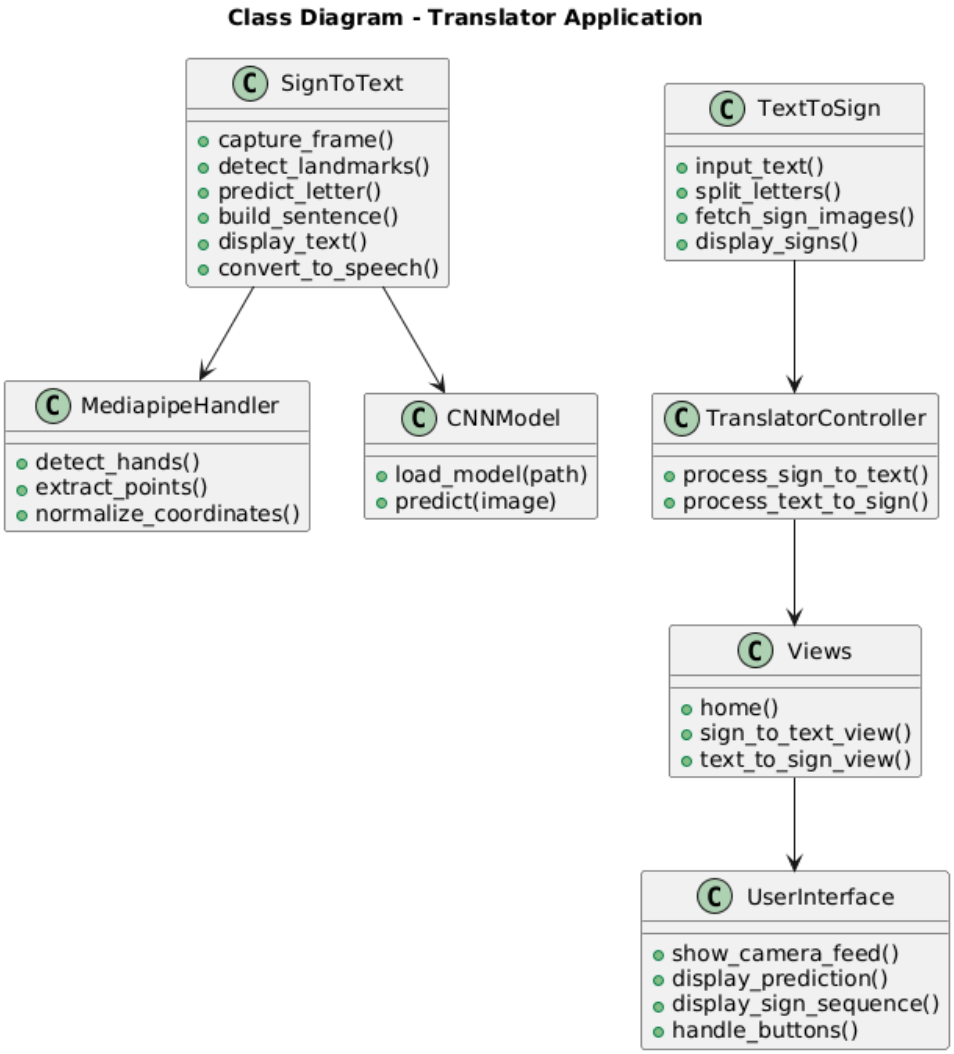

Figure 4.4: Low-Level Class Diagram

4.6 Database Design

The system uses a relational database for logs, translation history, and metadata.

4.6.1 Entity Relationship Diagram (ERD)

Primary entities:

1. User
2. TranslationHistory
3. ErrorLogs

4.6.2 Data Dictionary

1. UserID: Integer (Primary Key)

2. SessionData: Temporary session information.
3. InputData: Gesture frames or text input.
4. OutputData: Translated text or images.

4.7 GUI Design

The interface is user-friendly and consists of:

1. **Main Dashboard:** Select Sign-to-Text or Text-to-Sign.
2. **Sign Input Screen:** Live video stream with gesture tracking.
3. **Text Input Screen:** Text box with corresponding ASL images.
4. **Result Display Screen:** Shows final translation.

4.8 External Interfaces

External components:

1. **Hardware Interface:** Webcam.
2. **Software Interfaces:** MediaPipe, TensorFlow, OpenCV.
3. **Web Interfaces:** Django backend with HTML/CSS/JS frontend.
4. **Deployment Interfaces:** Cloud hosting (AWS/GCP).

4.8.1 Sequence Diagram

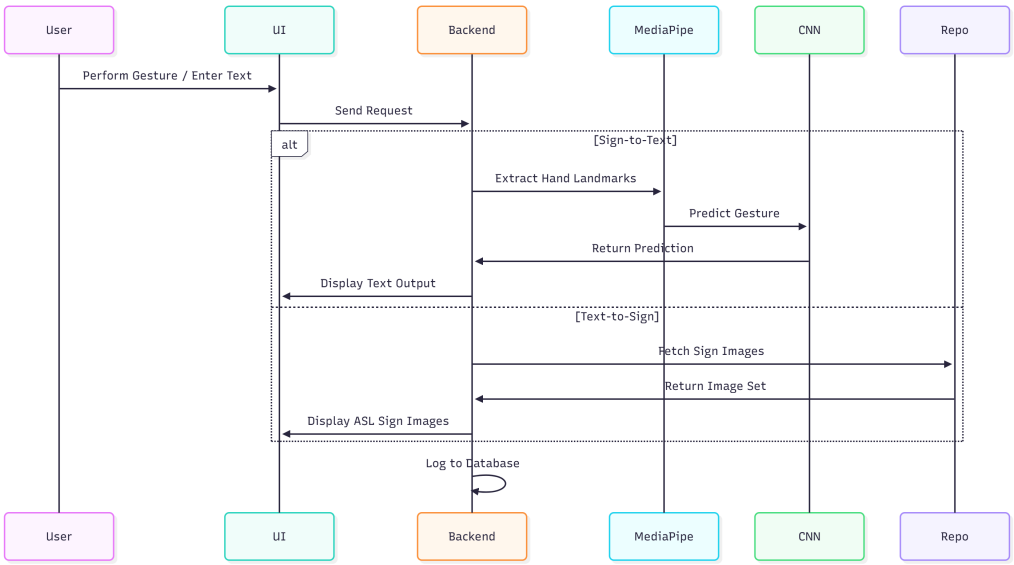

Figure 4.5: Sequence Diagram Showing System Workflow

Chapter 5

System Implementation

The term implementation is used to denote the whole process of taking the technical design of the system and turning it into a working software product by carrying out, bringing together, and testing all parts of the system. For the **AI-Powered Bidirectional Sign Language Translator**, this phase was about breaking down the architectural specifications into the different parts that worked, making sure that there was no gap in communication of the modules, and checking the performance of the whole system in real-time conditions.

5.1 System Architecture

The system deployment was accomplished by means of a modular layered architecture, which gave not only a clear-cut division of responsibilities but also an effective performance of the various tasks.

5.1.1 Internal Components

The architecture of the system is composed of the following key elements:

1. **Input Module:** Captures real-time webcam images for Sign-to-Text conversion and takes in text from non-deaf users.

2. **Processing Module:** Extracts hand landmarks through MediaPipe Hands and categorizes ASL signs with the help of a trained CNN model. In addition, it takes care of text formatting and mapping for Text-to-Sign output.

3. **Output Module:** Depending on the chosen mode, the translated text or images of ASL gestures are shown.

4. **Web Interface Module:** Built with Django, HTML, CSS, and JavaScript to provide a seamless and user-friendly interaction.

5. **Database Module:** Uses SQLite/PostgreSQL to save translation history, user activity, and error logs.

5.1.2 Component Communication

The communication between modules is established through well-defined and strict interfaces:

1. The Web Interface Module is responsible for the collection of input data (either webcam frames or typed text).
2. The Input Module sends the frames to the Processing Module.
3. The Processing Module sends back either text predictions or gesture-image mappings.
4. The Output Module displays the results to the user.
5. The Database Module keeps a record of user interactions, errors, and translation history.

5.2 Tools and Technologies Used

The implementation is characterized by the combination of deep learning frameworks, web development tools, and database technologies.

1. **Programming Languages:** Python for the backend logic, and JavaScript for frontend interactivity.
2. **Frameworks:** Django (web framework), TensorFlow/Keras (model training), MediaPipe, and OpenCV (gesture detection).
3. **Database:** SQLite (development), PostgreSQL (production deployment).
4. **Development Tools:** Google Colab (model training), Visual Studio Code (code editing).

5.2.1 Tools and Technologies Summary Table

Table 5.1 summarizes the tools and technologies utilized during the development and deployment of the proposed system.

Table 5.1: Tools and Technologies Used in System Implementation

Category	**Technologies Used**
Programming Languages	Python, JavaScript
Machine Learning Tools	TensorFlow, Keras, MediaPipe, OpenCV
Web Frameworks	Django, HTML5, CSS3, JavaScript
Databases	SQLite, PostgreSQL
Development Environment	Google Colab, Visual Studio Code
Deployment Tools	Cloud hosting (AWS / GCP), GitHub

5.3 Processing Logic and Algorithms

Core system logic implementation is centered around effective task execution and model inference optimization.

1. **Hand Gesture Recognition:**
   (a) MediaPipe Hands takes the webcam frames as input and outputs 21 landmarks of the hand.
   (b) The landmarks are then normalized and sent to a CNN-based classifier.
   (c) The classifier outputs the ASL letter or word meaning that the gesture is accompanied by.
2. **Natural Language Processing (NLP):**
   (a) Predicted text is enriched by the application of simple NLP methods (tokenization, smoothing).
   (b) Noisy predictions are reduced by deploying majority-voting methods.
3. **Text-to-Sign Mapping:**
   (a) The text input by the user is segmented into single characters.
   (b) Each character is linked to the corresponding ASL gesture image that has been stored in the database.
   (c) The Web UI presents the images that were mapped to the user one by one.

5.3.1 Algorithm Summary Table

Table 5.2 provides a concise overview of the algorithms employed in the proposed system and their respective roles.

Table 5.2: Summary of Algorithms Used

Algorithm	**Purpose**
MediaPipe Hand Tracking	Extracts 21 key hand landmarks from webcam frames in real-time.
CNN Classification	Classifies ASL gestures (alphabets/words) using landmark data as input.
Majority Voting	Improves prediction stability by averaging consecutive outputs.
Text Parsing Algorithm	Breaks user-entered text into units for gesture-image mapping.
Image Mapping Logic	Maps parsed text characters to ASL gesture images.

5.4 Application Access Security

The security mechanisms are employed by the system for making the use safe and reliable.

1. **Authentication:** User accounts are protected by Django's built-in authentication system.
2. **Authorization:** Access to sensitive modules like logs is controlled by different user roles.
3. **Data Encryption:** Passwords and sensitive information are stored by using hashed and salted encryption.
4. **Access Logging:** User actions like login attempts and translations are recorded.
5. **Firewall Protection:** HTTPS is enforced by cloud firewalls protecting the servers.

5.5 Database Security

Various mechanisms are there to protect the database.

1. **Secure Authentication:** Access to the database is restricted to authenticated server applications only.
2. **Role-Based Authorization:** Only administrators will have direct access to error logs or translation history.
3. **IP Restriction:** Connections to the database are made only from the specified IP ranges.
4. **Audit Logging:** Internal monitoring relies on recording all CRUD operations.
5. **Automated Backups:** Regular backups are a safeguard against data loss resulting from failures.

Chapter 6

System Testing and Evaluation

System testing and evaluation guarantee the **AI-Powered Bidirectional Sign Language Translator** compliance with all functional and non-functional requirements, besides giving reliable, real-time performance. This chapter discusses the different testing methods that have been applied, their results, and the total evaluation of system effectiveness. Both qualitative and quantitative methods were applied, such as GUI testing, usability evaluation, performance testing, compatibility checks, exception handling, security validation, and deep learning model evaluation.

6.1 Graphical User Interface Testing

The Graphical User Interface (GUI) was subjected to tests that checked its responsiveness, visual consistency, and the proper rendering of the components in different browsers. The next notes were taken:

1. The transition between the Sign-to-Text and Text-to-Sign modules was very seamless.
2. The input fields, webcam containers, and result panels were shown rightly irrespective of screen resolutions.
3. No such thing as misalignment or distortion occurred on Google Chrome, Mozilla Firefox, or Microsoft Edge.

6.2 Usability Testing

A small group of deaf and non-deaf members underwent usability tests. Their learnings were collected in a usability evaluation for intuitive and user experience aspects.

1. **Ease of Use:** The users mentioned that it was a nice, neat, and straightforward interface to work with.
2. **Learning Curve:** Completely new users grasped all the system features in a short time of under five minutes.

3. **Accessibility:** The completely online nature of the system made installation unnecessary, which in turn, made it more accessible to the users.

4. **Suggested Improvements:** The users put forward the idea of incorporating optional sound output for the translated text as their topmost recommendation.

6.3 Software Performance Testing

Performance testing measured the system's speed, the ability to continue operating without interruption, and the accuracy of recognition by placing it under real-world conditions.

1. **Gesture Recognition Latency:** The average time for the system processing each predicted gesture was **1.6 seconds**, which was equal to the requirement of real-time processing.

2. **Text-to-Sign Response Time:** Showing gesture images for the text input demanded about **0.8 seconds**.

3. **Model Accuracy:** The CNN classifier that was trained achieved an accuracy of **95.4%** overall, which was well above the required minimum of 85%.

6.3.1 Accuracy and Performance Summary

A consolidated summary of accuracy, response time, user satisfaction, and compatibility results is presented in Table 6.1.

Table 6.1: System Testing: Accuracy and Performance Summary

Metric	Result	Remarks
Gesture Recognition Accuracy	95.4%	Achieved high accuracy through optimized CNN and landmark preprocessing.
Average Response Time	1.6 seconds	Meets real-time translation requirement.
Text-to-Sign Output Time	0.8 seconds	Efficient mapping to ASL gesture images.
User Satisfaction	92%	Based on usability survey with target users.
Browser Compatibility	100%	Fully compatible with Chrome, Firefox, Edge.

6.4 Compatibility Testing

Compatibility testing was conducted to ensure the system works consistently across devices and platforms.

1. The system performed reliably on Windows and Linux operating systems.

2. All major web browsers were supported without functional issues.

3. On mobile browsers, responsiveness was partially supported; full optimization is recommended for future work.

6.5 Exception Handling

Exception handling was a key factor to guarantee system stability in case of unexpected situations.

1. The system issued corresponding alerts in case the webcam was not accessible or the rights to use it were refused.
2. The system could handle invalid or partial gestures without the risk of crashing.
3. All kinds of errors were recorded in the database to facilitate debugging.

6.6 Load Testing

The basic load testing conducted was not that it was heavy traffic actually.

1. A scenario of 20 users who were carrying on translating simultaneously was created.
2. The performance of the system was stable all through without any timeouts or crashes.
3. A little sluggishness was noted in the case of simultaneous requests via webcam, which is considered reasonable given the CPU limits.

6.7 Security Testing

Security testing confirmed the user data's integrity, confidentiality, and proper handling.

1. The authentication module of Django successfully prevented unauthorized access.
2. The history of user translations was opened only to verified users.
3. The data transfer was encrypted and thus secured by HTTPS.
4. SQL injection, invalid input, and unauthorized route attacks were all tested and politely prevented.

6.8 Installation Testing

Testing installation and deployment proved the system can be easily deployed on cloud servers.

1. The installation process on AWS EC2 and Google Cloud VM was successful.
2. The necessary Python dependencies, AI models, and static resources were all loaded correctly.
3. The Django migrations and database configurations were executed smoothly.

6.9 Evaluation Metrics and Results

The following quantitative evaluation metrics were used:

1. **System Accuracy:** 95.4%
2. **Average Response Time:** 1.6 seconds
3. **User Satisfaction:** 92%

6.9.1 Model Evaluation

The CNN-based hand gesture classifier was evaluated using precision, recall, and F1-score to assess per-class performance. The architectural details and parameter distribution of the CNN-based gesture recognition model are illustrated in Figure 6.1.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 62, 62, 32)	896
max_pooling2d (MaxPooling2D)	(None, 31, 31, 32)	0
conv2d_1 (Conv2D)	(None, 29, 29, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 14, 14, 64)	0
conv2d_2 (Conv2D)	(None, 12, 12, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 128)	0
flatten (Flatten)	(None, 4608)	0
dense (Dense)	(None, 256)	1,179,904
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 29)	7,453

Total params: 1,280,605 (4.89 MB)

Trainable params: 1,280,605 (4.89 MB)

Non-trainable params: 0 (0.00 B)

Figure 6.1: Model Summary of the CNN-based Gesture Recognition Network

The model summary highlights the layered CNN architecture, including convolutional, pooling, and fully connected layers, which collectively enable effective feature extraction from hand gesture inputs.

Figure 6.2 presents the per-class precision, recall, and F1-score values used to evaluate the model's classification performance.

	precision	recall	f1-score	support
A	1.00	1.00	1.00	600
B	1.00	1.00	1.00	600
C	1.00	1.00	1.00	600
D	1.00	1.00	1.00	600
E	1.00	1.00	1.00	600
F	1.00	1.00	1.00	600
G	1.00	1.00	1.00	600
H	1.00	1.00	1.00	600
I	1.00	1.00	1.00	600
J	1.00	1.00	1.00	600
K	1.00	1.00	1.00	600
L	1.00	1.00	1.00	600
M	1.00	1.00	1.00	600
N	1.00	1.00	1.00	600
O	1.00	1.00	1.00	600
P	1.00	0.99	1.00	600
Q	1.00	1.00	1.00	600
R	1.00	1.00	1.00	600
S	1.00	1.00	1.00	600
T	1.00	1.00	1.00	600
U	1.00	1.00	1.00	600
V	1.00	1.00	1.00	600
W	1.00	1.00	1.00	600
X	1.00	1.00	1.00	600
Y	1.00	1.00	1.00	600
Z	1.00	1.00	1.00	600
del	1.00	1.00	1.00	600
nothing	1.00	1.00	1.00	600
space	1.00	1.00	1.00	600
accuracy			1.00	17400
macro avg	1.00	1.00	1.00	17400
weighted avg	1.00	1.00	1.00	17400

Figure 6.2: Per-class Precision, Recall, and F1-scores of the Gesture Recognition Model

The results of the evaluation demonstrated converging models that were stable with very little overfitting. A majority of the gesture classes reached high F1-scores, with slightly lower performance observed for gestures that were less represented in the dataset. Overall, the model performs effectively for alphabet-level ASL recognition.

6.9.2 Qualitative Evaluation

As well as the numerical results, holistic feedback pointed out:

1. **Advantages:** Instant processing, great precision, neat interface, and user-friendliness.
2. **Disadvantages:**
   (a) Because of the dataset size, the vocabulary was restricted.
   (b) Under low light or occlusion, the accuracy was slightly reduced.
   (c) The mobile version still needs a lot of work to reach its full potential.
3. **Future Developments:** Collecting more data, improving mobile support, providing models at the word level, and implementing voice-to-sign translation.

6.10 Summary

The system was subjected to rigorous testing procedures and the results were reliable, high accuracy, and smooth user experience. The translator with a **95%** plus gesture recognition accuracy, speed in real-time, and high user satisfaction has accomplished its goals successfully. The recognized constraints nudge toward the future improvements and power expansions more clearly.

Chapter 7

Conclusions

The creation of the **AI-Powered Bidirectional Sign Language Translator** has already brought to light the power of AI together with computer vision as far as the improvement of the communication between the deaf and non-deaf individuals is concerned. The project incorporates hand gesture recognition along with a very light text-to-sign display system and hence makes it possible for real-time, bidirectional translation on a web-based platform.

The major achievement of the project is the Sign-to-Text module development which is both accurate and efficient. MediaPipe Hands was used for landmark extraction and a Convolutional Neural Network-based classifier for gesture recognition. The system has an accuracy of over **95%** which makes it trustworthy when it comes to recognizing single alphabet letters as well as simple word gestures. The Text-to-Sign module maps the provided text to corresponding ASL gesture images which makes the communication coming from the deaf users very easy and intuitive.

The adoption of a web-based interface based on Django makes it accessible on every platform, and the users do not need to install any additional software. The project was guided by the principle of creating a system that is easy on resources, quick to respond, and user-friendly all at once. Performance criteria testing results indicated that the system is capable of real-time processing, cross-browser use, and has high user approval, among other things.

The project, on the other hand, uncovered a number of issues in real life such as limitations of the dataset, varying performance depending on the devices, and getting from static gesture recognition to dynamic signing which is continuous was difficult. These issues give directions for the next steps that are supported by work and system improvements.

7.1 Future Work

The structure is doing an admirable job according to its core mandates, yet potential still exists for more development in its capacities:

1. **Dataset Expansion:** Enriching our ASL data with more dynamic and diverse inputs, like sentence-level touching, will help us with vocabulary coverage.

2. **Mobile Platform Support:** Being able to use the system on Android and iOS will make the system more accessible and portable.
3. **Speech-to-Sign Integration:** The system will have a speech-to-text option that will convert spoken language into sign language for real-time accessibility.
4. **Multi-Language Support:** We will add support for BRL, PSL, and other regional languages.
5. **Advanced Gesture Recognition Models:** The incorporation of transformer-based models or hybrid CNN-RNN architectures will allow the system to recognize continuous gestures.
6. **Improved Text-to-Sign Visual Output:** The visual output for the sign language interpretation will range from static pictures to simple animations or even GIFs for smoother communication.
7. **Cloud-Based Inference:** By deploying the recognition model on GPU servers in the cloud, we will achieve greater speed and scalability, particularly in the case of low-resource devices.

7.2 Final Remarks

So, this project shows the use of technology to overcome communication barriers and also provide access for the deaf community. The work done by the authors of the realtime, two-way sign language interpreter, not only verifies their concept but also paves the way for sophisticated communication aid systems to be built. The researchers envision a future where their prototype, an increasing dataset and cutting-edge AI techniques could become an everyday tool in schools, hospitals, offices, and other public places.

Appendix A

User Manual

The **AI-Powered Bidirectional Sign Language Translator** User Manual gives detailed guidance on how to communicate with the device. The manual is meant to support the both hearing impaired and hearing users in the process of system operation. The manual discusses hardware and software requirements, how to access the system, how to perform operations on the different modes, and how to solve the common problems.

A.1 System Requirements

In order to use the system properly and unlock its full potential, the following conditions need to be satisfied:

1. A contemporary web browser, for instance, Google Chrome, Mozilla Firefox, or Microsoft Edge.
2. A functioning webcam for translating Sign-to-Text.
3. A solid internet connection for accessing the web-based application.
4. A device that operates on Windows, Linux, or macOS.

A.2 Accessing the Application

To launch the application, follow the instructions listed below:

1. Start the web browser of your choice.
2. Type in the system URL that was given by the administrator or project team.
3. If the browser asks for webcam access, grant it.
4. After the homepage appears, choose one of the following:
   (a) Sign-to-Text mode, or
   (b) Text-to-Sign mode.

A.3 Using Sign-to-Text Mode

This particular setting makes use of sign language the deaf users and the system convey messages through webcam by identifying the American sign language alphabet signs.

1. Move to the **Sign-to-Text** page.
2. The camera should show your hand very clearly.
3. Make ASL alphabet or basic word signs one by one.
4. The software will:
   (a) Identify the location of the hand using MediaPipe Hands.
   (b) Recognize the sign using a convolutional neural network that has been trained.
   (c) The output box will show the letter or word that is recognized.
5. Press either the **Clear** or **Reset** button to go back and do a new translation.

A.4 Using Text-to-Sign Mode

This is a setting in which a silent person is able to express himself/herself through written text which would be transformed into sign language gesture images through a computer system and vice versa.

1. Go to the **Text-to-Sign** page.
2. Fill in the text you want in the input box.
3. Hit the **Translate** button.
4. The machine will:
   (a) Divide the phrase into separate letters.
   (b) Associate every letter with its respective ASL gesture image.
   (c) Show the image of gestures on the screen in order.
5. To get back to the main menu, click on the **Back** button.

A.5 Translation History (If Enabled)

If the admin has switched on logging then, the system will keep the past translations.

1. Go to the **History** tab (if present).
2. Check the earlier Sign-to-Text and Text-to-Sign translations.
3. Use the **Delete History** button for clearing logs (admin-only).

A.6 Troubleshooting Guide

In case of problems during the use of the system, please check the following guide:

1. **Webcam Not Working:**
   (a) Make sure that the browser has been allowed to access the webcam.
   (b) Turn off other programs that are using the webcam.
2. **Gesture Not Detected:**
   (a) Make sure there are good lighting conditions.
   (b) Keep your hand in the middle of the camera frame.
   (c) Don't let the background be cluttered.
3. **Slow Performance:**
   (a) Close browser tabs that are not necessary.
   (b) If possible, use a device that has a higher CPU capacity.
4. **Incorrect ASL Output:**
   (a) Gesture should be held steadily for about 1–2 seconds.
   (b) Do not cover your fingers or palm.

A.7 Summary

This User Manual offers a detailed guide on accessing and utilizing the Sign-to-Text and Text-to-Sign features of the AI-based translator. Users, by complying with these guidelines, will be able to interact in a more effective way and enjoy the feature of the system being able to recognize gestures instantly. For additional help or software upgrades, users are encouraged to reach out to the project creators or the system administrator.

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