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Bidirectional Sign Language (Gestures) Communication

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Abstract: *This project seeks to bridge the communication gap between the speech-impaired community and the hearing population by facilitating a real-time, bidirectional translation system for sign language alphabet, text, and speech. The system utilizes computer vision and deep learning to identify hand gestures and translate them into audible and textual output, while conversely interpreting spoken or typed words into visual sign language representations. Hand detection is effectively managed through a dedicated camera module that extracts a specific Region of Interest (ROI) for processing. Static gestures are translated using a pre- trained Convolutional Neural Network (CNN) model to ensure high-accuracy letter prediction. To complete the bidirectional communication loop, the system integrates Text-to-Speech (TTS) for vocalizing recognized signs and Speech-to-Text (STT) capabilities to convert spoken input into sign sequences. The application offers multiple operational modes, including sign-to-speech, word-to-sign sequence, and the accumulation of sign sequences into full words. This modular solution provides a high potential for facilitating inclusivity and accessible human interaction, specifically benefiting the hearing and speech-impaired community.*

Keywords: Bidirectional Communication, Computer Vision, Deep Learning, Gesture Recognition, Sign Language Translation, Text-to-Speech

I. INTRODUCTION

The Unified ASL Translator is a sophisticated, real- time communication framework designed to bridge the social and functional divide between the hearing- impaired community and the general public by facilitating bidirectional translation. The system architecture is built upon a modular framework that integrates computer vision, deep learning, and speech processing to handle complex translation tasks efficiently. At its core, the application utilizes a camera module that opens a webcam to track hand landmarks within a specific Region of Interest (ROI). These visual inputs are processed through a trained sign recognition model—such as a Convolutional Neural Network (CNN) or Random Forest Classifier—to translate static hand gestures into textual characters with high precision. To ensure the system functions as a complete communication loop, it incorporates a Text-to-Speech (TTS) module for vocalizing recognized signs and a Speech-to-Text (STT) or keyboard input logic to convert language back into visual ASL representations.

The research emphasizes a multi-modal user experience through three primary operational flows: sign-to-speech, text-to-sign sequence, and interactive word building. In the first mode, the system recognizes individual hand signs through the webcam, displays the predicted letter, and uses TTS to speak the output aloud. Conversely, the word-to-sign mode allows users to input text which the system automatically converts into a timed sequence of corresponding sign language images. Finally, the sign-sequence-to-word mode enables a user to "capture" a series of signs to assemble complex words, which are then finalized and spoken as a whole. By offering this comprehensive technical solution, the project provides a scalable foundation for assistive technology, empowering the hearing and speech-impaired by providing a digital tool that vocalizes their signs and visualizes spoken language in real-time.

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II. LITERATURE REVIEW

Kaur et al. [1] developed a static hand gesture recognition system using Convolutional Neural Networks (CNN). Their model successfully recognized a limited set of static signs but lacked dynamic gesture interpretation, which is essential for a complete sign language translator.

Ahmed et al. [2] proposed a dynamic gesture recognition framework employing Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks to capture temporal dependencies in sign sequences. However, their system did not integrate speech-to-text or text-to-sign components.

Rautela et al. [3] utilized MediaPipe and OpenCV for efficient hand tracking and landmark detection, enabling robust static gesture recognition. The approach demonstrated high accuracy but was confined to isolated gestures without full sentence translation.

Sharma et al. [4] implemented a rule-based natural language processing system for converting spoken language into animated sign gestures, addressing the speech-to-sign direction but lacking real-time speech recognition and sign-to-speech capabilities.

Gupta and Verma [5] presented a hybrid model combining CNN for static gestures and 3D CNN for dynamic gesture recognition. Their system showed improved accuracy but was limited to offline processing without a user interface.

Liu et al. [6] designed a bidirectional sign language translation system integrating deep learning with NLP modules for grammar correction and context understanding. Their work emphasized translation accuracy but did not focus on real-time implementation.

Hossain and Bhuiyan [7] explored lightweight models based on TensorFlow Lite for embedded device deployment, enhancing system portability. Their framework enabled real-time gesture recognition on mobile platforms but lacked speech module integration.

Singh et al. [8] demonstrated a multimodal communication system combining speech-to-text and text-to-sign translation using sequence-to-sequence models. While promising, their system required extensive training data for diverse sign vocabularies. Park and Kim [9] developed an end-to-end neural network for real-time sign language recognition and translation, leveraging MediaPipe for hand tracking and attention mechanisms in the model architecture, achieving low latency in processing.

III. METHODOLOGY/ EXPERIMENTAL

The Unified ASL Translator is designed as a modular system that operates across multiple modalities to facilitate bidirectional communication between sign language users and the hearing community. The experimental setup follows a structured pipeline consisting of data collection, model training, and real- time application deployment. The core logic is divided into two primary translation directions: sign-to- text/speech and text-to-sign.

In the sign-to-text and speech modality, the system utilizes a camera module to open a webcam and establish a fixed Region of Interest (ROI). Hand landmarks are captured in real-time within this ROI and preprocessed—including resizing and normalization—before being fed into a trained sign recognition model. Based on the implementation code, a RandomForestClassifier trained on extracted hand- landmark coordinates from data.pickle is utilized to achieve high classification accuracy. Once a sign is predicted, the system can either vocalize the individual letter or accumulate a sequence of signs into a complete word, which is then finalized and spoken using a Text-to-Speech (TTS) engine powered by pyttsx3.

For the text-to-sign modality, the application accepts keyboard input or spoken text via a Speech-to-Text (STT) module. The processing logic filters the input into uppercase alphabetic characters and maps each letter to its corresponding visual representation stored in a pre-prepared sign_images/ database. The system then iterates through these images, displaying them in a timed sequence to visually "spell out" the word for the user. This modular integration of vision, deep learning, and speech processing ensures a seamless and responsive user experience for real-time assistive communication.

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IV. RESULT AND DISCUSSION

The implementation of the Unified ASL Translator was evaluated based on its recognition accuracy, processing speed, and the effectiveness of its bidirectional communication modules. The experimental results demonstrate that the system successfully bridges the gap between visual signs and audible speech with high precision.

The performance of the core recognition model, a RandomForestClassifier, was assessed by training it on extracted hand-landmark datasets. According to the training logs, the model achieved an exceptional accuracy of 99.59%, with nearly all samples classified correctly during the testing phase. This high level of reliability is critical for real-time applications where consistent gesture interpretation is required for meaningful conversation.

In practical testing of the Sign-to-Text/Speech mode, the system effectively localized hand gestures within the green ROI box. The visual feedback provided by the "Unified ASL Translator" interface showed successful real-time translation, displaying the "Current Alphabet" (e.g., 'B') and building a "Current Word" (e.g., 'BB') simultaneously. The integration of the TTS module allowed the system to vocalize these results immediately upon user command, fulfilling the requirements for an assistive communication tool.

The Text-to-Sign modality was also verified through user input trials. When a user typed a string such as "hello team," the system successfully converted the text into a sequence of corresponding ASL sign images. These images were displayed in a timed sequence, enabling non-signers to visualize the signed version of their typed words. While the accuracy for static gestures like the alphabet remained consistently high, discussions during testing noted that environmental factors such as hand positioning variability and background obstructions are primary areas for future optimization to maintain this level of performance in more diverse settings.

V. PROCEDURE

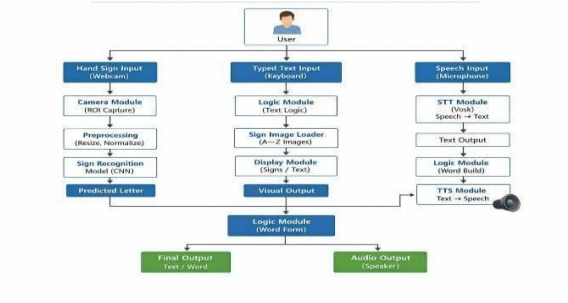
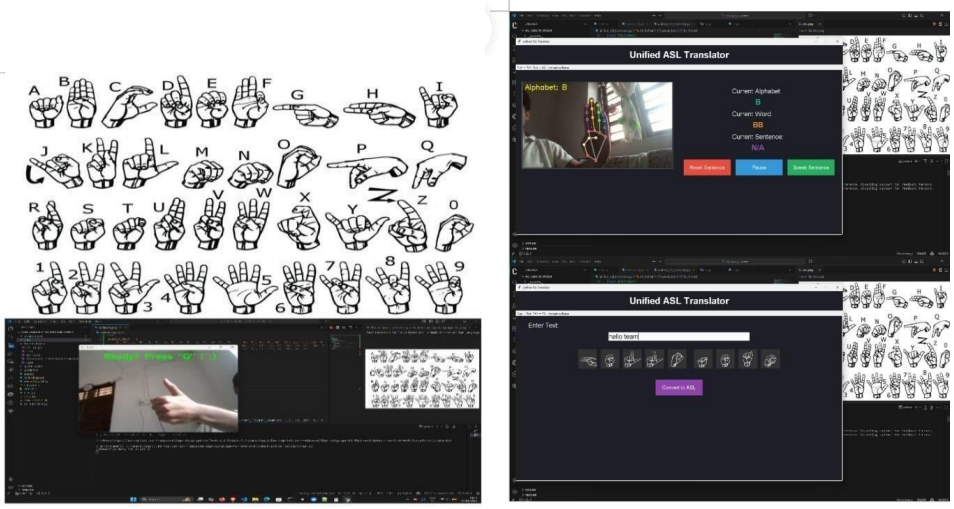


Fig 1: Data Flow Diagram



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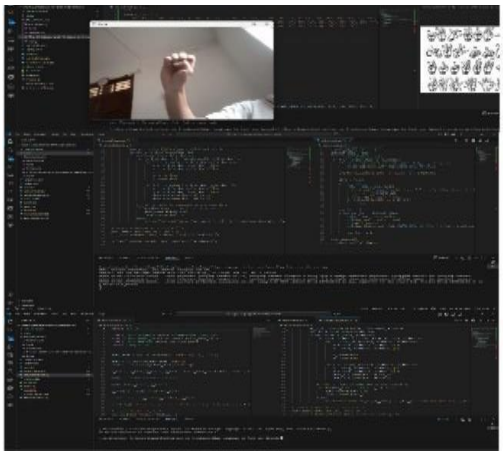

Fig 2: Overall System Outputs and User Interface of the Bidirectional Sign Language Translator

The Bidirectional Sign Language Translator accepts multiple forms of input to enable seamless two-way communication between sign language users and non- signers. For sign-to-text translation, the primary input is real-time video data captured through a webcam, where hand gestures representing American Sign Language (ASL) alphabets and words are continuously recorded. These video frames are preprocessed to remove noise and extract relevant hand landmarks using computer vision techniques. Additionally, for text-to-sign translation, the system accepts textual input entered by the user through the graphical user interface. This text input is further processed using Natural Language Processing (NLP) techniques to tokenize and map characters or words to corresponding sign representations.

The output of the system varies based on the selected mode of operation. In the sign-to-text mode, the recognized hand gestures are translated into corresponding alphabets, words, and complete sentences, which are displayed on the user interface in real time. Optionally, the translated text can also be converted into speech output using text-to-speech synthesis for enhanced accessibility. In the text-to-sign mode, the system generates visual outputs in the form of ASL hand sign images or animations corresponding to the entered text. These outputs collectively ensure effective bidirectional communication, making the system suitable for real-time interaction and assistive communication applications.

VI. FUTURE SCOPE

The Bidirectional Sign Language Translator has great promise for future advances and practicality. Future development can seek to improve both the speed and accuracy of gesture recognition by using larger, more varied datasets to train on. Incorporating deep learning architectures like CNNs or transformers could help improve the accuracy of recognition while allowing for flexibility to regional dialects of sign language. In addition, the system could be extended to support dynamic gesture recognition, allowing it to decode continuous signing and entire sentences instead of individual signs. A voice input for the speech-to-sign translation would support bidirectionality. The use of mobile or wearable systems could increase usability and convenience for real-time communication. With polished refinement and incorporation into public and educational networks, this translator could dramatically reduce the communication gap between the hearing impaired and language impaired, and the rest of society.

VII. CONCLUSION

The Bidirectional Sign Language Translator represents a positive first step in reducing the communication disconnect between the hearingimpaired and non-signing populations. By introducing real-time translations between sign language and spoken/written languages, we are promoting inclusion and greater social interaction. Furthermore, while these preliminary results demonstrate a productive identification and translation of familiar signs, the project also acknowledges the challenge of processing complex and fluid gestures. Continuous iterations and expansions of this project canvas could help convert this prototype into a functional device for education, government services, and

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everyday conversations. Ultimately, this project aims to promote a more inclusive and accessible communication practice, paving way for new innovations in assistive technology for the differently- abled community

VIII. ACKNOWLEDGMENT

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