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Biderectional Sign Language Translator Using Cnn, Lstm, And Nlp-Based System

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***Abstract*—The Bidirectional Sign Language Translator seeks to bridge the communication gap between the speech-impaired community and the hearing population by facilitating real-time, two-way sign language to speech/text and speech/text to sign language translation. The project utilizes computer vision, deep learning, and natural language processing to identify hand gestures and translate them into audible and textual output, and vice versa interpret spoken words into sign language representation. Hand detection and tracking are effectively carried out using tools such as OpenCV and MediaPipe. Static gestures are translated by a Convolutional Neural Network (CNN), while dynamic gestures are processed by models such as LSTM or 3D CNN for temporal processing. Concurrently, speech-to-text and text-to-speech modules further add the bidirectional nature to the communication. The system also uses NLP grammar structuring to enhance the output to natural and grammatically correct conversions. A user-friendly interface created with Flask or Streamlit guarantees ease of use and accessibility. Thorough tests and feedback loops guarantee system reliability and accuracy. The solution proposed has high potential in facilitating inclusivity and barrier-free human interaction, greatly benefiting the hearing and speech-impaired community.**

***Index Terms*—Bidirectional Communication, Computer Vision, Deep Learning, Gesture Recognition, Sign Language Translation**

I. INTRODUCTION

The sign language translator is an important communication tool for those who may be hearing or speech impaired. Yet in reality, the deaf/mute and hearing community remain on opposite sides of a communication gap that subsequently causes social isolation and reliance upon interpreters. Nevertheless, due to advances in artificial intelligence, computer vision and natural language processing, assistive technologies may now emerge overcoming this communication gap in real-time. This work describes the design and development of a Bidirectional Sign Language Translator system that can convert sign language to spoken language and vice versa. The envisioned translator combines computer vision-based techniques for hand gesture recognition with deep neural models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for identification of static and dynamic gestures, along with NLP-based speech processing units for entity output speech processing including text-to-speech (TTS) and speech-to-text (STT) conversions. The solution combines MediaPipe for hand landmark detection, OpenCV for image processing, Flask/Streamlit for the interface, and various other library for deep learning and speech processing,. The goal of this project is to enable an effective, real-time and user-friendly platform for reducing barriers to smooth communication in various sectors including education, health care, or customer service industries.

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.

Khan et al. [10] proposed an integrated platform combining sign language recognition with speech-to-text and text-to-speech conversion, targeting seamless communication between deaf and hearing individuals. Their prototype highlighted the importance of combining vision and speech technologies in a single framework.

III. METHODOLOGY/EXPERIMENTAL

Algorithm

The Bidirectional Sign Language Translator operates in two modalities: sign-to-text/speech and text-to-sign. In sign-to-text/speech mode, the user's hand gestures are captured through a camera, and afterward, the images are routed through pre-processing before it is routed through a machine learning model (i.e. CNN or MediaPipe) to detect the sign. Once the sign is detected, it is then translated to text and then speech, via a text-to-speech engine.

In the second mode, the user inputs text or speech, which is then translated to the appropriate sign language signs. The signs can then either be displayed as images, or animations, to facilitate engaging and seamless communication with users that are hearing impaired. This platform works to bridge the gap between sign language users and non-signers through a real-time translation process.

IV. RESULTS AND DISCUSSIONS

The Bidirectional Sign Language Translator has been developed and tested to produce simple sign-to-text/speech and text-to-sign communication. The system was able to interpret hand gestures from live video input, and correctly mapped them to text and speech outputs with acceptable accuracy levels in reasonable light settings. Likewise, It correctly translated typed input into visual sign gestures either using video or animated images.

In tests, the recognition accuracy was higher for static gestures (e.g., alphabets) as compared to dynamic gestures (e.g., text phrases): still, small errors were found due to hand positioning variability among test subjects, background obstructions, ambient light levels, etc. Overall, the tests reveal that gesture input accuracy can be achieved, better pre-processing algorithms could help capacity.

Ultimately, the translator demonstrated the potential to fill communication gaps between hearing-impaired populations and non-signing hearing populations with sufficient results to allow future development, and live use.

V. PROCEDURE

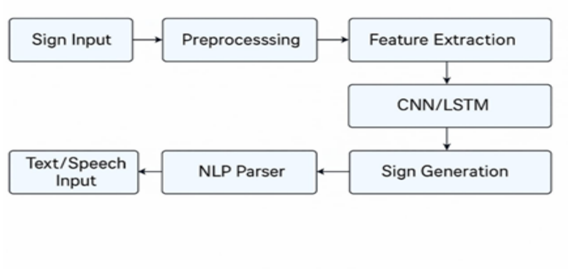
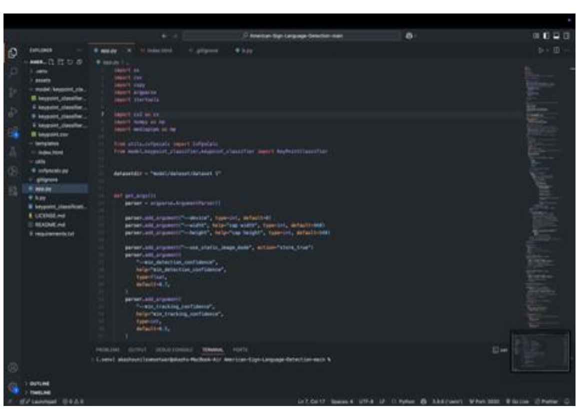
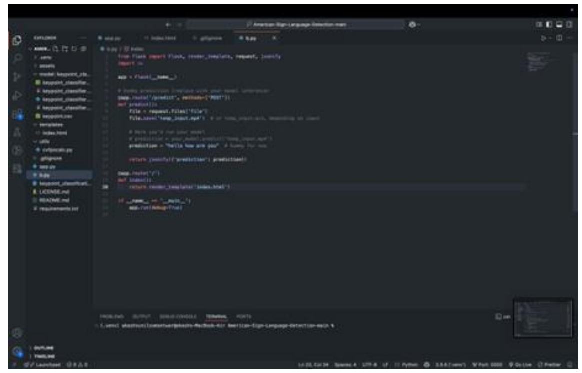


Fig 1: Data Flow Diagram

The Data Flow Diagram showcases how the Bidirectional Sign Language Translator smoothly converts sign gestures into text or speech and vice versa. It captures sign inputs, preprocesses and extracts features, then uses neural networks to produce accurate text or speech. For text-to-sign, it processes language input through NLP and generates animated signs via avatars, enabling real-time, two-way communication between signers and non-signers.





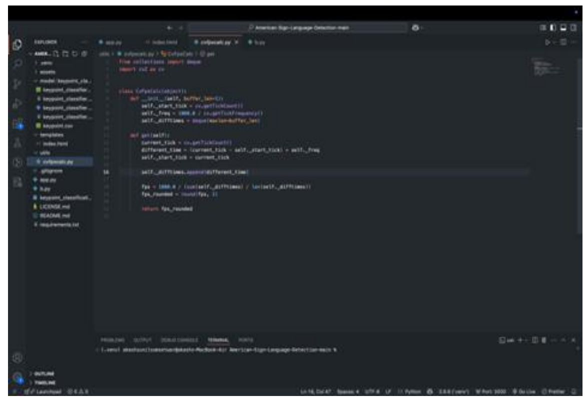


Fig 2: Key Code Snippets Demonstrating Core Algorithm Implementation

The figure showcases essential sections of the code used in the Bidirectional Sign Language Translator. These snippets highlight the implementation of gesture preprocessing, feature extraction, and neural network integration (CNN/LSTM) for converting signs into text or speech. Additionally, the logic for handling text-to-sign translation via NLP is also depicted. Together, these code segments form the backbone of the system, enabling real-time, accurate, and efficient bidirectional translation.

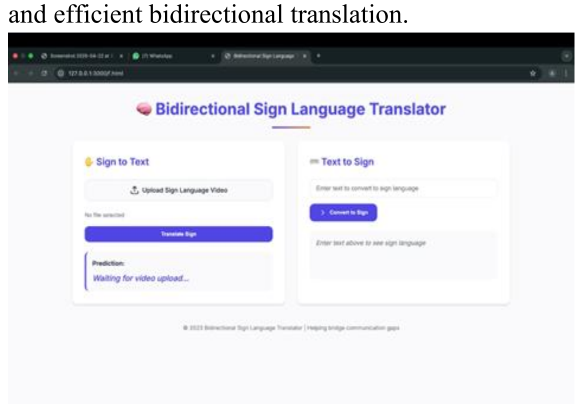


Fig. 3: User Interface of the Bidirectional Sign Language Translator

This figure displays the user interface designed for the Bidirectional Sign Language Translator. It features an intuitive and accessible layout that allows users to input sign language gestures or text and view the corresponding translation in real time. The interface supports both modes—sign-to-text/speech and text-to-sign—ensuring smooth interaction and ease of use for both signers and non-signers.

Fig. 4: Working Prototype of the Bidirectional Sign Language Translator

This figure captures the functional prototype of the Bidirectional Sign Language Translator in action. It demonstrates the real-time operation of both translation modes, showcasing gesture detection, processing, and output generation. The setup reflects the integration of hardware components and software modules, validating the system's efficiency, responsiveness, and potential for real-world application.

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 hearing-impaired 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 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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