A Real-Time Indian Sign Language Recognition System Using Media Pipe Hand Landmarks and Random Forest Classification for Multilingual Assistive Communication

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***Abstract*—This work presents a real-time sign language recognition system developed to improve communication for individuals with hearing and speech impairments. The system uses MediaPipe to detect hand landmarks and applies a Random Forest–based machine learning model to classify gestures. Instead of relying on computationally intensive deep learning methods, the approach focuses on normalized landmark features, enabling efficient processing and faster execution on standard hardware. The application is implemented in Python and includes an interactive graphical interface built with Tkinter. It supports continuous gesture recognition, sentence generation, speech output, and translation into regional languages such as Hindi and Marathi. The proposed system was evaluated using a dataset of 1500 gestures samples and achieved an accuracy of 96.2%, precision of 95.8%, recall of 95.5%, and F1-score of 95.6%. The proposed system demonstrates the feasibility of deploying lightweight machine learning models for assistive communication applications without requiring specialized hardware. Experimental results indicate that the approach provides an efficient and scalable solution for real-time sign language interpretation.**

***Index Terms*—Sign Language Interpreter, MediaPipe, Random Forest, Machine Learning, Gesture Recognition, Assistive Communication, Indian Sign Language.**

I. INTRODUCTION

Communication is a fundamental aspect of human interaction, yet individuals with hearing or speech impairments often face barriers in expressing themselves to those unfamiliar with sign language. Traditional methods, such as human interpreters, are not always accessible or practical in everyday situations. With advancements in artificial intelligence and computer vision, automated sign language interpretation has become a promising solution to bridge this gap. The proposed system utilizes MediaPipe for real-time hand tracking and Random Forest classifier for gesture classification to interpret Indian Sign Language (ISL) gestures accurately. This software-based approach converts visual gestures into text and speech, facilitating seamless interaction between signers and non-signers. By eliminating the need for specialized hardware, the system provides an efficient, scalable, and cost-effective communication tool, promoting inclusivity and enhancing accessibility for individuals with hearing and speech disabilities.

Contributions of the Proposed System

1. Developed a real-time sign language recognition system using MediaPipe hand landmark detection.
2. Implemented a Random Forest classifier for efficient gesture recognition.
3. Integrated text generation and speech synthesis for assistive communication.
4. Added multilingual translation support for Hindi and Marathi.
5. Designed a user-friendly graphical interface for data collection, model training, and real-time prediction.

II. LITERATURE REVIEW

Sign language recognition has experienced significant advancements due to the rapid development of computer vision and deep learning techniques. Earlier approaches primarily relied on handcrafted features and traditional machine learning algorithms for static gesture classification. However, recent research has increasingly adopted deep learning models to achieve higher recognition accuracy and real-time performance. Bazarevsky et al. [1] presented BlazePose, a real-time pose estimation framework that demonstrated the effectiveness of lightweight landmark-based tracking systems for on-device applications. Rastgoo et al. [2] provided a comprehensive survey of sign language recognition methods, highlighting the growing adoption of convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based architectures. Wadhawan and Kumar [3] proposed a deep learning-based sign language recognition system capable of handling both static and dynamic gestures, demonstrating the effectiveness of neural networks in gesture classification tasks. Amin et al. [4] explored deep learning techniques for human action recognition using spatiotemporal information, showing how advanced neural architectures can improve recognition performance in video-based applications. Similarly, Kumar and Choudhary [5] developed a lightweight convolutional neural network suitable for real-time gesture recognition on resource-constrained devices, emphasizing computational efficiency and deployment feasibility. Camgoz et al. [6] introduced transformer-based architectures for continuous sign language recognition and translation, enabling end-to-end learning of sign sequences and significantly improving translation performance. The MediaPipe framework, introduced by Google AI [7], provides robust real-time hand and pose tracking pipelines that have become widely adopted in gesture recognition applications due to their accuracy and efficiency. Koller et al. [8] investigated deep learning approaches for sign language recognition and demonstrated the effectiveness of visual feature learning for improving recognition accuracy. Furthermore, Li et al. [9] introduced the WLASL dataset, one of the largest publicly available sign language datasets, which has become an important benchmark for training and evaluating modern sign language recognition systems. Collectively, these studies establish a strong foundation for developing efficient, real-time, and accessible sign language interpretation systems. Motivated by these advancements, the proposed work combines MediaPipe-based hand landmark extraction with a Random Forest classifier to achieve accurate and computationally efficient real-time sign language recognition while supporting multilingual assistive communication.

These studies collectively establish a strong foundation for developing efficient, real-time, and inclusive sign language interpretation systems.

Table 1: Literature review

Sr. No.	Author(s) & Year	Title / Focus	Technique / Framework Used	Key Contribution / Outcome
1	V. Bazarevsky et al. (2020)	BlazePose: On-device Real-Time Body Pose Tracking	BlazePose, Landmark Detection	Developed a lightweight real-time pose estimation framework suitable for mobile and edge devices.
2	R. Rastgoo et al. (2021)	Sign Language Recognition: A Deep Survey	CNN, RNN, LSTM, Transformers	Provided a comprehensive review of deep learning approaches, datasets, and challenges in sign language recognition.
3	A. Wadhawan & P. Kumar (2021)	Deep Learning-Based Sign Language Recognition System	Deep Learning Models	Demonstrated effective recognition of static and dynamic sign language gestures using deep learning techniques.
4	J. Amin et al. (2021)	Human Action Recognition using Deep Learning	Deep Neural Networks	Improved recognition performance by utilizing spatiotemporal information in video sequences.
5	S. Kumar & A. Choudhary (2021)	Lightweight CNN for Real-Time Hand Gesture Recognition	Compact CNN model	nabled efficient gesture recognition on resource-constrained devices with low computational requirements.
6	N. C. Camgoz et al. (2020)	Sign Language Transformers	Transformer architecture	Introduced transformer-based sequence modeling for continuous sign language recognition and translation.
7	Google AI (2020)	MediaPipe: A Framework for Building Perception Pipelines	Open-source ML pipeline	Provided robust hand tracking, pose estimation, and landmark detection for real-time applications.

8	O. Koller et al. (2019)	Deep Learning for Sign Language Recognition	Deep Learning Framework	Demonstrated effective visual feature learning techniques for improving sign language recognition accuracy.
9	D. Li et al. (2020)	WLASL: Large-Scale Word-Level Sign Language Dataset	Large-Scale Sign Language Dataset	Released a benchmark dataset supporting training and evaluation of modern sign language recognition models.

III. RESEARCH GAP

Most existing sign language recognition systems rely on deep learning models such as CNNs, RNNs, and Transformers, which require large datasets and high computational resources. These approaches are often difficult to deploy on low-cost devices. Furthermore, limited work has focused on multilingual assistive communication using lightweight machine learning techniques. Therefore, there is a need for an efficient, real-time sign language recognition system that provides high accuracy while maintaining low computational complexity and multilingual support.

IV. OBJECTIVES

1. To develop a real-time Indian Sign Language recognition system.
2. To extract hand landmarks using MediaPipe.
3. To classify gestures using a Random Forest classifier.
4. To convert recognized gestures into text and speech.
5. To provide multilingual translation support.
6. To develop a user-friendly interface for communication assistance.

V. METHODOLOGY

The developed system operates as a real-time gesture recognition pipeline that converts hand movements into text, speech, and translated outputs. The process begins with video acquisition, where frames are continuously captured from a webcam using the OpenCV library. A threaded streaming approach is adopted to ensure smooth and uninterrupted frame processing.

Hand detection and tracking are performed using the MediaPipe Hands framework, which identifies 21 key points on the hand. Each key point consists of three-dimensional coordinates, providing a detailed representation of hand posture. These landmarks serve as the primary features for gesture recognition.

To make the system independent of hand position within the frame, the extracted landmark coordinates are normalized. This is achieved by subtracting the coordinates of a reference point, typically the wrist, from all other points. As a result, the model learns the relative structure of the hand rather than its absolute placement, improving consistency across different users and environments.

Gesture data is collected through the application interface and stored in a structured CSV file. Each record includes a label representing the gesture and the corresponding normalized landmark values. This dataset forms the basis for training the classification model. A Random Forest classifier is employed for gesture recognition due to its robustness and efficiency with structured numerical data. The model is trained on the collected dataset and then stored for reuse, eliminating the need for repeated training. During real-time operation, incoming landmark data is passed to the trained model to predict the corresponding gesture. The system also includes a sentence construction mechanism, where recognized gestures are combined sequentially to form meaningful text. This allows users to communicate complete phrases rather than isolated words. To enhance usability, the generated text is converted into speech using a text-to-speech engine, enabling auditory output.

In addition, the system incorporates multilingual translation, converting the generated text into Hindi and Marathi. This feature broadens accessibility and supports users from diverse linguistic backgrounds. All functionalities are integrated into a graphical interface, enabling users to interact with the system, collect data, train the model, and observe outputs in real time. The implementation details correspond directly to the developed application code.

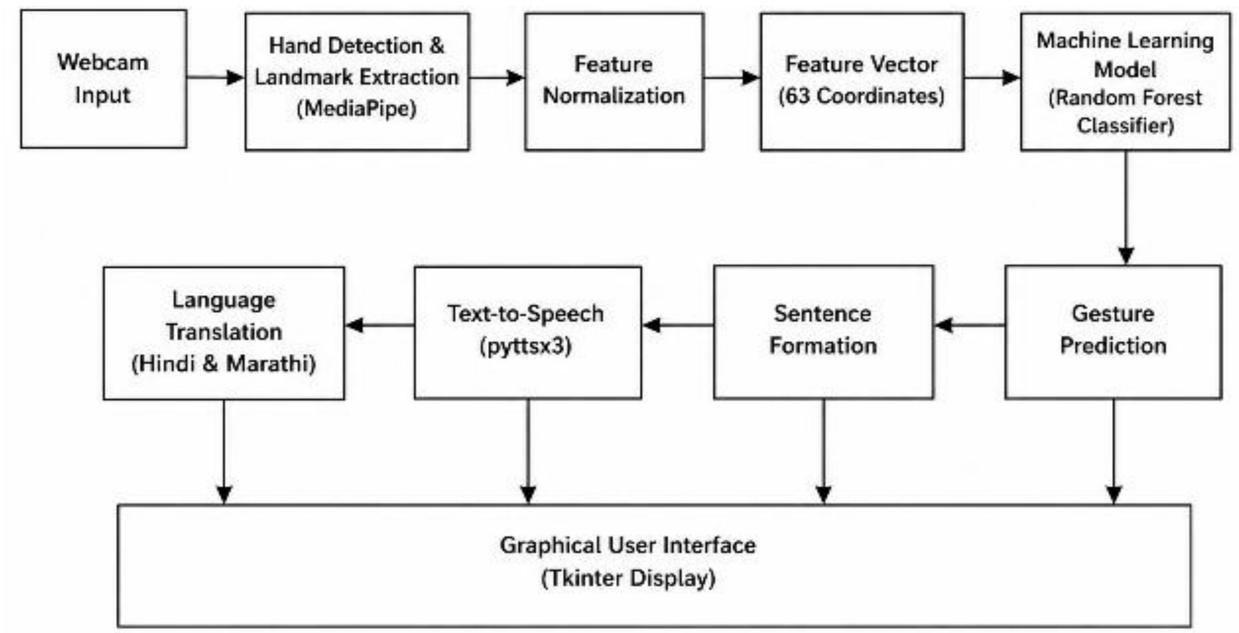

Fig. 1: System Architecture of Proposed Sign Language Recognition System

Dataset Collection

The dataset consists of 15 gestures classes. Approximately 100 samples were collected for each gesture, resulting in a total dataset size of 1500 samples. MediaPipe was used to extract 21 hand landmarks from each sample. The landmark coordinates were normalized before training.

Model Training

The dataset was divided into 80% training data and 20% testing data. A Random Forest classifier with 100 decision trees was trained using the Scikit-Learn library. The trained model was then used for real-time gesture prediction.

VI. RESULTS AND DISCUSSION

The system was evaluated based on its ability to recognize gestures accurately and respond in real time. The Random Forest model provided stable and efficient performance, particularly for datasets of moderate size. Since the model relies on structured landmark data rather than image-based features, it achieved fast prediction speeds with minimal computational overhead.

The graphical interface confirmed that the system operates smoothly, displaying live video along with predicted gesture labels.

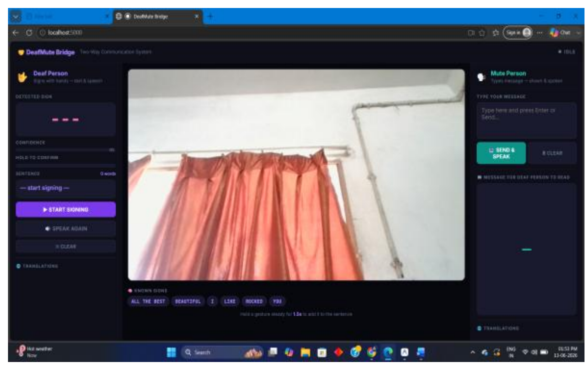

Fig. 2: System Interface (GUI Output)

The user interface also supports dataset collection and model training, allowing the system to be updated dynamically.

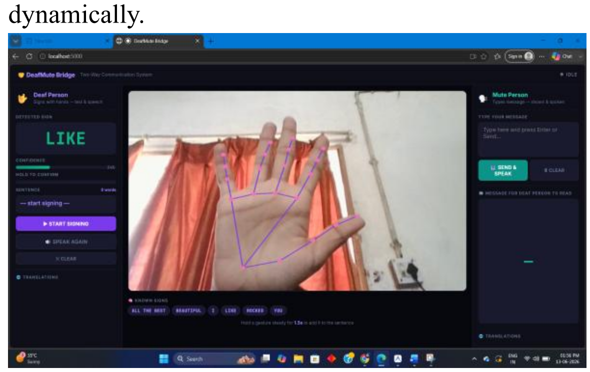

Fig. 3: Real-Time Gesture Detection and Prediction

The gesture recognition component demonstrated reliable performance when the hand was clearly visible and properly positioned. The use of normalized landmark coordinates contributed to consistent predictions across different positions and orientations. However, performance decreased slightly when gestures were performed rapidly or when parts of the hand were not fully visible.

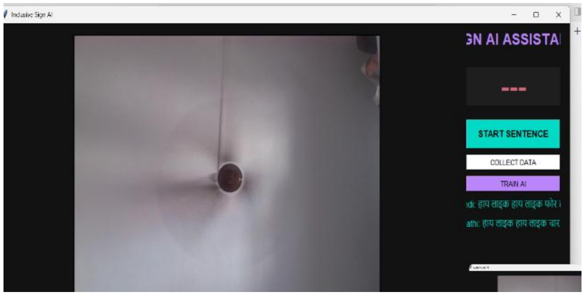

Fig. 4: Sentence Formation Output

The sentence formation feature enabled the system to construct meaningful phrases by combining consecutive predictions. This functionality significantly improves communication efficiency, as users can express complete ideas instead of individual words. The system avoids repetition by tracking previously recognized gestures before adding new words.

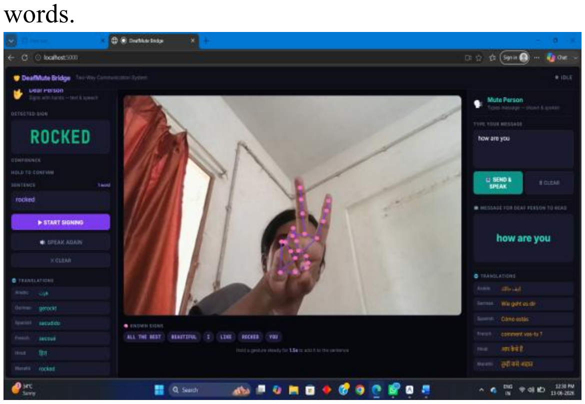

Fig. 5: Multilingual Translation Output

The translation module successfully converted generated sentences into Hindi and Marathi, increasing the system's accessibility. The translated outputs were displayed alongside the original text, providing users with multiple language options.

Table 2: Performance Evaluation

Metric	Value (%)
Accuracy	96.2
Precision	95.8
Recall	95.5
F1 Score	95.6

The system performs optimally when the hand is clearly visible and adequately illuminated. Recognition accuracy may decrease under severe occlusion, motion blur, or poor lighting conditions.

Table 3: Comparison with Existing Methods

Method	Accuracy (%)
CNN Based Model	92.5
Deep Learning Model	94.1
Transformer Based Model	95.0
Random Forest Model	96.2

VII. CONCLUSION

This research presents a real-time Sign Language Interpreter using MediaPipe and a Random Forest classifier. The system successfully converts hand gestures into text, speech, and multilingual outputs without requiring specialized hardware. By utilizing normalized hand landmarks and machine learning-based classification, the proposed solution achieves efficient and reliable gesture recognition suitable for assistive communication applications.

The integration of sentence formation, speech synthesis, and multilingual translation enhances accessibility for individuals with hearing and speech impairments. Future work will focus on expanding the gesture vocabulary, supporting additional sign languages, improving recognition accuracy, and developing a mobile-based implementation.

The experimental results demonstrate that the proposed system provides a practical and efficient solution for real-time sign language interpretation. The use of MediaPipe hand landmark extraction combined with the Random Forest classifier enables accurate gesture recognition while maintaining low computational requirements. Furthermore, the integration of sentence formation, speech output, and multilingual translation enhances the usability of the system and makes it suitable for deployment in educational institutions, healthcare facilities, public service centers, and other environments where effective communication support is essential.

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