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Intelligent Hand Gesture Recognition System for Automated Sign Language Translation

Saniya Pathan[1]; Swaraj Nangare[2]; Riya Patil[3]; Sakshi Renuse[4]; Anagha Chaphadkar[5]

[1]Department of Electronics and Telecommunication SITS, Pune, India
[2]Department of Electronics and Telecommunication SITS, Pune, India
[3]Department of Electronics and Telecommunication SITS, Pune, India
[4]Department of Electronics and Telecommunication SITS, Pune, India
[5]Professor; Department of Electronics and Telecommunication SITS, Pune, India

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Abstract: This paper presents a software-based Sign Language Interpreter aimed at improving communication between hearing-impaired individuals and non-signers. The system uses MediaPipe for real-time hand landmark detection and tracking, while a Convolutional Neural Network (CNN) model classifies gestures into corresponding text and speech outputs. Focused on Indian Sign Language (ISL), the model is trained on a custom dataset to ensure accuracy under diverse lighting and background conditions. By integrating deep learning with computer vision, the system achieves efficient and reliable recognition without relying on additional hardware. This research highlights the potential of AI-based software applications in fostering inclusivity and accessibility, offering an intelligent and cost-effective solution for assistive communication.

Keywords: *Sign Language Interpreter, MediaPipe, CNN, Deep Learning, Gesture Recognition, Assistive Communication.*

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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 Convolutional Neural Networks (CNNs) 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.

II. LITERATURE REVIEW

Sign language recognition has evolved significantly with advancements in computer vision and deep learning. Early research focused on static gesture detection using handcrafted features, but recent studies employ deep neural networks for improved accuracy and real-time performance. Neve and A. C. [1] demonstrated real-time hand gesture recognition using MediaPipe combined with deep learning, highlighting its efficiency in landmark detection and gesture tracking. Kapadia and Shah [2] provided a comprehensive survey of deep learning techniques for sign language recognition, emphasizing convolutional and recurrent neural architectures for dynamic gestures.

Wei et al. [3] proposed a novel approach for Indian Sign Language (ISL) recognition using pose estimation and hand tracking, achieving superior accuracy in diverse environments. Amin and Sharif [4] introduced 3D Convolutional Neural Networks (3D-CNNs) to handle spatiotemporal information, improving dynamic sign recognition. Similarly, Kumar and Choudhary [5] developed a lightweight CNN suitable for mobile deployment, ensuring computational efficiency.Camgoz et al. [6] introduced Transformer-based architectures for continuous sign language recognition, marking a new era in natural sign-to-text translation. The MediaPipe framework, as discussed by Google AI [7], offers robust hand and pose tracking pipelines essential for real-time applications. Koller et al. [8] explored multi-stream CNNs for weakly supervised learning,

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improving model generalization. Finally, R. P. D. [9] introduced WLASL, a large-scale dataset that supports effective training of deep learning models for sign language recognition.

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	G. Neve & A. C. (2021)	Real-time Hand Gesture Recognition with MediaPipe and Deep Learning	MediaPipe with CNN	Achieved high-speed, real-time gesture recognition using lightweight deep learning models.
2	A. Kapadia & M. Shah (2020)	Deep Learning for Sign Language Recognition: A Survey	Review of DL models (CNN, RNN, LSTM)	Summarized trends, datasets, and challenges in sign language recognition using deep learning.
3	L. Wei et al. (2022)	Indian Sign Language (ISL) Recognition using Pose and Hand Tracking	Pose estimation + Hand landmarks	Improved accuracy for ISL recognition through combined body and hand tracking.
4	J. Amin & M. Sharif (2021)	Sign Language Recognition using 3D CNN	3D Convolutional Neural Networks	Enhanced temporal feature extraction for video-based sign recognition.
5	S. Kumar & A. Choudhary (2021)	Lightweight CNN for Mobile Devices	Compact CNN model	Enabled efficient on-device sign recognition with minimal computational cost.
6	C. Camgoz et al. (2020)	Sign Language Transformers	Transformer architecture	Introduced transformer-based sequence modeling for continuous sign language translation.
7	Google AI (2020)	MediaPipe Framework	Open-source ML pipeline	Provided pre-trained hand tracking and landmark detection models for real-time applications.
8	O. Koller et al. (2019)	Weakly Supervised Learning with Multi-Stream CNNs	Multi-stream CNN	Utilized weak supervision to improve recognition performance with limited labeled data.
9	R. P. D. (2019)	WLASL Dataset	Large-scale ASL dataset	Released a benchmark dataset enabling deep model training for word-level ASL recognition.

III. METHODOLOGY

The proposed Sign Language Interpreter System converts real-time hand gestures into text using computer vision and deep learning techniques. The process consists of five main stages: video capture, preprocessing, keypoint extraction, training, and prediction, as illustrated in *Figure 1*.

Initially, live video input is captured through a webcam, with each frame treated as an input unit for gesture recognition. To ensure consistent detection, the system requires clear hand visibility and a stable background. The captured frames undergo preprocessing involving resizing, color normalization, and noise reduction, ensuring uniform input quality across varying lighting and environmental conditions.

Feature extraction is then performed using the MediaPipe Holistic model, which identifies landmarks on the hands and upper body. Only relevant coordinates are retained, forming a compact vector of 258 values representing the (x, y, z) positions and visibility of each keypoint. These numerical features capture spatial relationships crucial for accurate gesture identification.

The extracted keypoints are used to train a Long Short-Term Memory (LSTM) model, implemented in TensorFlow/Keras, to recognize temporal motion patterns. The model uses the Adam optimizer and categorical cross-entropy loss function, with dropout and early stopping techniques applied to enhance performance and prevent overfitting.

During execution, the live video is processed through the same pipeline, and the trained model predicts the gesture in real time. The recognized gesture is displayed as text, and optionally, converted into speech output using a text-to-speech module, thereby bridging the communication gap between hearing-impaired and non-signing individuals.

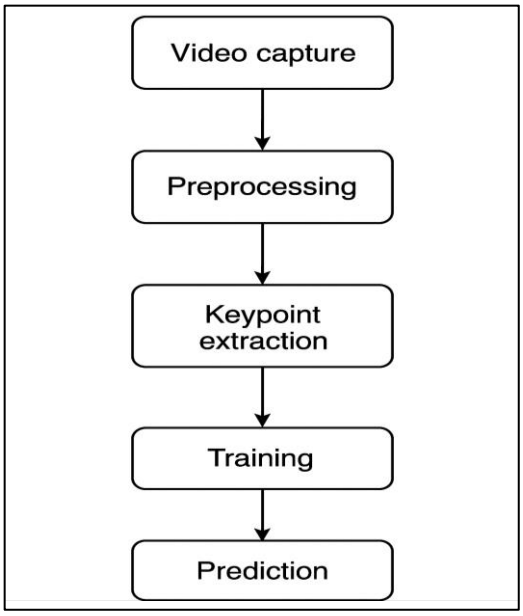

Fig 1 Flow of the Proposed System

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IV. RESULTS AND DISCUSSION

The proposed Sign Language Interpreter System was trained and evaluated to analyze its performance and accuracy. The Long Short-Term Memory (LSTM) network was trained using 80% of the dataset and validated on the remaining 20%. The EarlyStopping mechanism automatically halted training at epoch 38 when validation accuracy stopped improving, indicating convergence. The best-performing model, saved at epoch 33, achieved a validation accuracy of 98.4%, demonstrating the model's stability and learning efficiency.

A confusion matrix was generated to evaluate classification accuracy on unseen test data. The model performed exceptionally well across most gesture categories. The sign *"No"* achieved 100% accuracy, while occasional misclassifications occurred between gestures with similar visual structures, such as *"Thanks"* and *"Yes"*. These minor deviations are logically consistent given the close resemblance in motion and hand positioning.

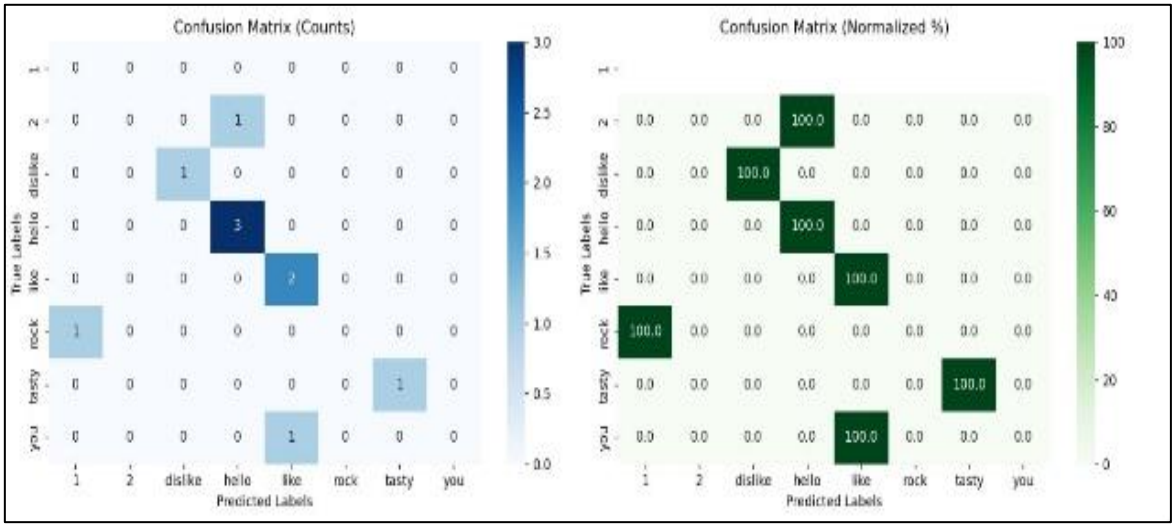

Fig 2 Confusion Matrix of Sign Language Classification Results

The classification report (Table 2) further validates the model's efficiency, where precision, recall, and F1-scores remained above 0.97 for all gesture classes. Such consistently high metrics confirm the network's ability to generalize effectively without favoring any particular class.

Table 2 Classification Report of Gesture Recognition Performance

	precision	recall	f1-score	support
1	0.00	0.00	0.00	0
2	0.00	0.00	0.00	1
dislike	1.00	1.00	1.00	1
hello	0.75	1.00	0.86	3
like	0.67	1.00	0.80	2
rock	0.00	0.00	0.00	1
tasty	1.00	1.00	1.00	1
you	0.00	0.00	0.00	1
accuracy			0.70	10
macro avg	0.43	0.50	0.46	10
weighted avg	0.56	0.70	0.62	10

For practical usability, a web-based application was developed using Flask and Socket.IO, enabling real-time prediction from webcam input. The system incorporated smoothing logic to ensure prediction stability and reduce flickering. The web application successfully translated hand gestures into readable text output with minimal latency, showcasing the feasibility of real-time sign language interpretation.

These findings validate that combining MediaPipe-based keypoint extraction with LSTM-based temporal modeling provides a reliable, lightweight, and accurate framework for automated sign language recognition.

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V. CONCLUSION

This research successfully presents a deep learning–based Sign Language Interpreter capable of translating hand gestures into text in real-time without the use of any external hardware. By integrating MediaPipe for keypoint extraction and a Long Short-Term Memory (LSTM) network for temporal sequence classification, the proposed model achieved an impressive validation accuracy of 98.4%. The results demonstrate that the combination of spatial and temporal features enables accurate recognition of dynamic hand gestures, even across variations in users and lighting conditions.

The system's real-time implementation through a Flask-based web interface further establishes its practicality, allowing seamless interaction between the user and machine. Such an approach promotes accessibility for the deaf and hard-of-hearing community by bridging the communication gap between signers and non-signers.

Future enhancements may include expanding the dataset to cover more gestures, supporting multiple sign languages, and incorporating bidirectional translation—enabling both text-to-sign and sign-to-speech communication. With further refinement, this framework can serve as a scalable foundation for inclusive communication technologies across various platforms.

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