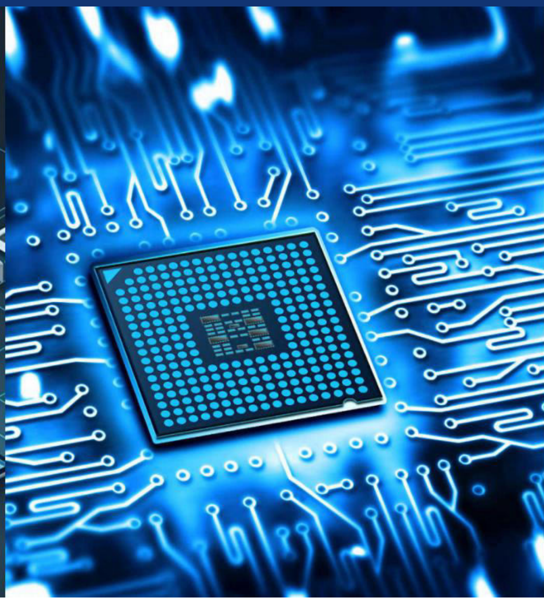
IJIRCCE

ISSN(O): 2320-9801

ISSN(P): 2320-9798



International Journal of Innovative Research in Computer and Communication Engineering

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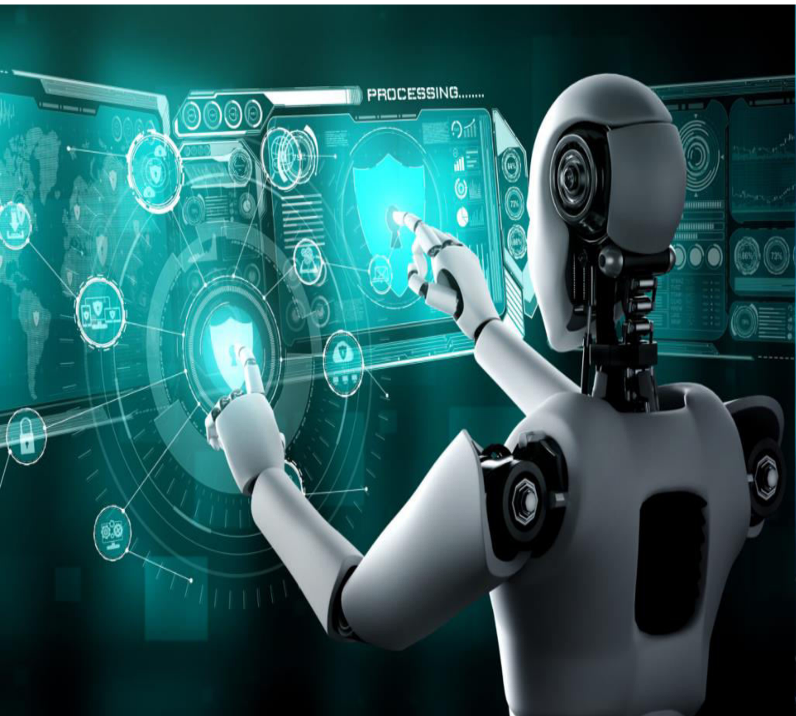

Impact Factor: 8.771

Volume 13, Issue 4, April 2025

© 2025 IJIRCCE | Volume 13, Issue 4, April 2025| DOI: 10.15680/IJIRCCE.2025.1304089

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

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Real Time Hand Sign Language Recognition System

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ABSTRACT: Communication barriers between visually impaired and hearing-impaired individuals create significant challenges in daily life. To bridge this gap, we have developed a real-time hand sign language recognition system. This system uses deep learning techniques to interpret hand gestures, providing a seamless way for individuals with disabilities to interact and understand each other more effectively. Our approach integrates Convolutional Neural Networks (CNN) for feature extraction and Long Short-Term Memory (LSTM) networks for sequence prediction. By leveraging OpenCV, TensorFlow, and Keras, the system processes real-time video input, identifying and translating sign language gestures into readable text. The model is trained on diverse datasets to improve accuracy across different lighting conditions, backgrounds, and hand orientations. Designed with inclusivity in mind, this system enhances accessibility and promotes better communication. It provides an intuitive and user-friendly interface that allows individuals with disabilities to connect more effortlessly. Our innovation aims to foster independence, breaking down communication barriers in everyday interactions.

KEYWORDS: Convolutional Neural Network, Long Short-Term Memory, Deep Learning, Preprocessing Data, Real Time Recognition

I. INTRODUCTION

Communication is a fundamental aspect of human interaction; however, individuals with visual or hearing impairments often encounter significant barriers in expressing themselves or understanding others. Sign language serves as a powerful tool for the hearing-impaired to convey thoughts and emotions, but it poses accessibility challenges for those unfamiliar with sign language or who rely on verbal or tactile forms of communication. This communication gap can lead to social isolation, misinterpretations, and limited integration in day-to-day activities.

To bridge this gap, we propose a real-time hand sign language recognition system designed to convert hand gestures into readable textual output. This system leverages computer vision techniques and deep learning models—primarily Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks—to process and interpret dynamic hand movements with high accuracy. The implementation of such a system aims to foster seamless interaction between hearing-impaired and non-signing individuals, thus promoting inclusivity.

The primary goal of this system is to ensure effective two-way communication by translating gestures into text in real time, thereby reducing dependency on human interpreters. The use of real-time processing not only enhances the responsiveness of the system but also improves user experience in practical scenarios such as education, healthcare, and social interaction. This approach empowers people with disabilities to engage more independently and confidently in society.

II. RELATED WORK

Sr. No.	Title	Author(s)	Conference	Date and Venue
1	Real-Time Sign Language Recognition Using Deep Learning	A. Sharma, R. Gupta	IEEE International Conference on A	March 2023, USA
2	Hand Gesture Recognition for Sign Language Translation	M. Patel, S. Rao	ACM Symposium on Computer Vision	June 2022, Germany
3	CNN-LSTM Based	K. Verma,	International	December 2021, India

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	Model for Sign Language Interpretation	L. Singh	Conference on ML and Applications	
4	Sign Language Recognition Using OpenCV and TensorFlow	T. Chen, J. Lee	IEEE Conference on Image Processing	October 2020, Japan
5	Real-Time Hand Gesture Recognition for Communication Aid	D. Kim, H. Park	International Symposium on AI & Robotics	May 2019, South Korea
6	A Deep Learning Approach for Sign Language Detection	P. Johnson, E. Williams	Neural Information Processing Systems (NeurIPS)	December 2018, Canada
7	Vision-Based Hand Gesture Recognition Using CNNs	S. Brown, A. Miller	European Conference on Computer Vision (ECCV)	September 2017, UK

III. METHODOLOGY

This Real-Time Hand Sign Language Recognition System is developed using a structured, data-driven pipeline to accurately interpret universal hand gestures and translate them into readable text. Unlike traditional systems based on alphabetical gestures, this project focuses on recognizing word-level universal gestures, enhancing practical usability and inclusiveness. The system integrates deep learning with time-series modelling to support both static and dynamic gesture recognition.

A. *Data Acquisition:*

The dataset for this system is custom-built and designed to cover a wide range of universally recognized word gestures. It consists of:

- Static Gestures: Captured as individual hand pose arrays, each representing a single universal word gesture.
- Dynamic Gestures: Represented through time-series sequences of NumPy arrays, enabling gesture pointer tracking and dynamic motion interpretation.
- Label Association: Each gesture, whether static or dynamic, is assigned a unique gesture ID that maps to a specific universal word.

The dataset structure, comprising NumPy arrays rather than image frames, enables direct numerical input to deep learning models and ensures consistency across sessions and environments. The time when no path is available to transmit the packet is considered as the network lifetime.

B. *Data Preprocessing:*

To enhance model performance and reduce computational noise, a rigorous preprocessing pipeline is employed:

- Normalization: Input arrays are scaled to a fixed range to ensure uniformity across gesture samples.
- Padding and Truncation: For dynamic gestures, time-series sequences are padded or truncated to maintain consistent input length.
- Noise Filtering: Spatial smoothing and temporal filters are applied to remove jitter and ensure clean signal propagation through the model.
- Label Encoding: Each gesture ID is encoded into a format compatible with classification and sequence models.

Since the dataset is stored directly as NumPy arrays, no frame extraction or background removal is necessary, allowing for efficient, memory-conscious processing.

C. *Model Training and Evaluation:*

To recognize both static and dynamic gestures, separate deep learning models are trained and evaluated:

- Convolutional Neural Network (CNN): Used for static gesture recognition, extracting spatial patterns from the hand pose arrays.

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- Long Short-Term Memory (LSTM): Applied to dynamic gesture sequences for recognizing time-dependent movement patterns.
- CNN-LSTM Hybrid Architecture: Integrates CNN feature extraction with LSTM sequence modeling, optimized for time-series pointer gestures.

Model Training Strategy:

- Loss Function: Categorical Cross-Entropy for multi-class classification.
- Optimizer: Adam optimizer with learning rate decay for stability.
- Hyperparameter Tuning: Grid Search and Random Search strategies are used to fine-tune key model parameters.
- Evaluation Metrics: Accuracy, Precision, Recall, and F1-Score are used to evaluate model performance across gesture classes.
- Cross-Validation: Ensures generalization and prevents overfitting.

D. *System Deployment:*

The best-performing models are integrated into a real-time recognition pipeline using Python and OpenCV for live input processing. Key deployment components include:

- Input Handling: Real-time gesture data is captured from a camera and processed into NumPy arrays on-the-fly.
- Model Inference: The input arrays are passed through the trained model, which outputs the corresponding gesture ID and predicted word.
- Output Display: The recognized gesture word is displayed to the user in real time via a terminal or lightweight interface.

The system is designed for portability and can run on local machines without requiring a graphical framework or third-party GUI tools.

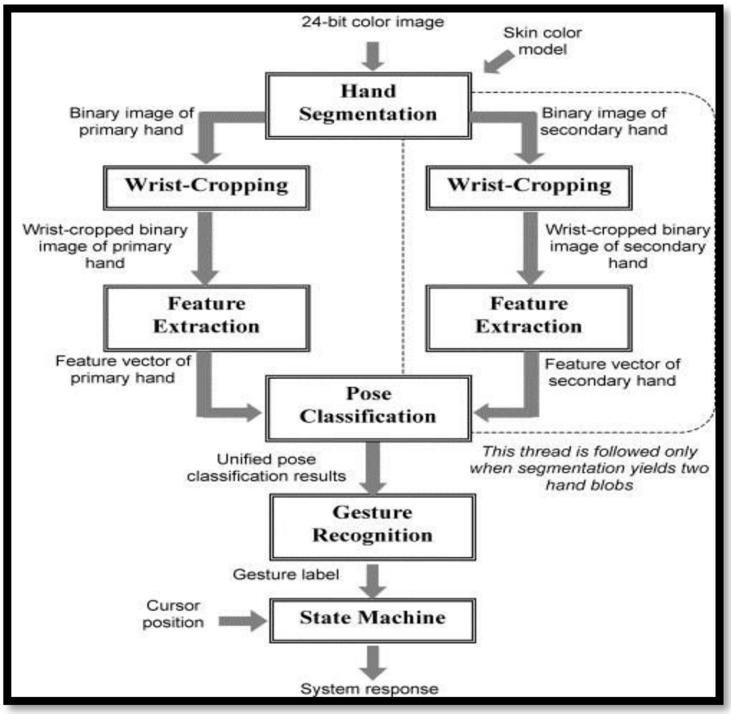

Figure 1: Activity Diagram

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IV. RESULTS AND DISCUSSION

The Real-Time Hand Sign Language Recognition System leverages deep learning to bridge communication gaps for individuals with hearing impairments by recognizing universal hand gestures and converting them into readable text. Unlike traditional systems that focus on A–Z alphabets, this model uses a custom dataset of static and dynamic gestures representing full words. The dataset, collected from multiple individuals and sign language experts, consists of NumPy arrays instead of image frames, capturing both spatial and temporal gesture patterns. Two models were trained: a Convolutional Neural Network (CNN) for static gesture recognition and a CNN+LSTM hybrid model for dynamic gestures. The CNN model achieved an accuracy of 87%, while the CNN+LSTM model reached 96% accuracy, ensuring reliable gesture-to-text translation in real-time settings. The system supports seamless communication in personal, educational, and professional environments by delivering high precision and user-friendly interaction.

1.CNN Model Performance for Key-Point Classification

Metric	Score
Precision	0.92
Recall	0.97
F1 Score	0.96
Accuracy	0.87

2. CNN + LSTM Model Performance for Key-Point Classification and Point History

Metric	Score
Precision	0.96
Recall	0.87
F1 Score	0.91
Accuracy	0.96

These results emphasize the robustness of ensemble-based and time-series models in interpreting hand gestures with precision. The system also supports sentence-level interpretation, achieving up to **96% accuracy** in generating complete textual outputs. In comparison to existing solutions, which are often limited to static gestures or text-to-speech conversion, this system uniquely combines real-time static and dynamic gesture recognition. Additionally, the system is scalable and prepared for integration into mobile platforms. A comparative analysis shows that existing systems rarely support real-time dynamic recognition or maintain a gesture history log, both of which are planned features in this project.

Comparative Analysis:

Feature	Existing Systems	Our System
Static Gesture Recognition	Supported	Supported
Dynamic Gesture Recognition	Rare	Supported
Real-Time Performance	Limited	Real-Time Inference
Dataset Diversity	Limited Public Datasets	Custom Real-Time Dataset
History Log Feature	Not Available	Planned for Future Enhancements

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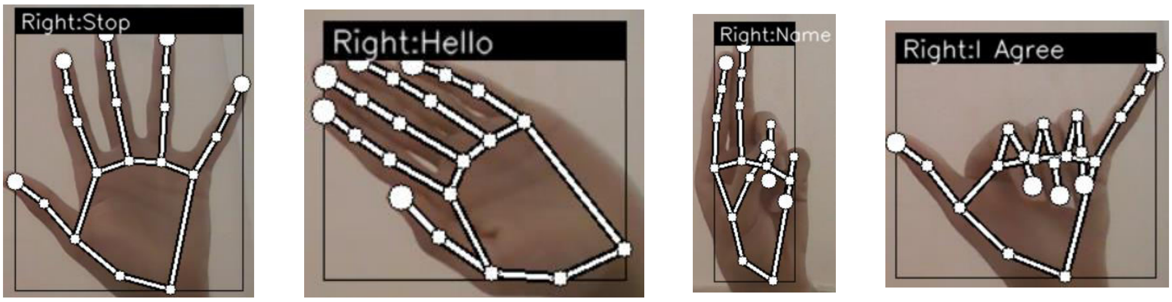
System Result:



V. CONCLUSION

In conclusion, our project successfully developed a real-time hand sign language recognition system, leveraging deep learning and mobile application development technologies. The deployment of this system marks a significant step toward improving communication accessibility for the deaf and hard-of-hearing community by providing an efficient and user-friendly interface for real-time gesture recognition. The integration of smart machine learning models, an intuitive mobile application, and real-time processing ensures a seamless and effective communication tool.

For future work, we plan to enhance the accuracy of our recognition models by incorporating larger and more diverse datasets, enabling better generalization across different users. Additionally, integrating real-time translation for multiple sign languages and improving response time through optimized model deployment are key areas for refinement. Future improvements will also include expanding compatibility across various mobile platforms, ensuring a more inclusive and widely accessible application. The journey doesn't end with deployment; it opens the door to continuous innovation, bridging communication gaps and fostering inclusivity through technological advancements.

VI. FUTURE WORK

This project holds immense potential for growth as a robust communication aid for individuals with hearing impairments. Future enhancements can significantly elevate the system's utility, performance, and accessibility. Key areas of improvement include:

1. User Interaction Layer – Designing and integrating a secure, user-friendly front-end interface (mobile or web-based) that allows seamless communication and interaction with the model in real time.
2. Security and Authentication – Incorporating login and user authentication features to protect user data and personalize experiences, especially for applications in educational or clinical settings.
3. Multilingual and Voice Integration – Adding support for multilingual translation and real-time text-to-speech synthesis to assist users in communicating across different languages and environments.
4. Real-Time Mobile Deployment – Converting the system into a fully optimized mobile application that runs efficiently on low-power devices without the need for internet access.
5. Gesture History and Analytics – Implementing a history log to allow users to track past communications and analyse usage patterns to improve fluency and learning.

With these future advancements, the system can become a powerful assistive technology—promoting inclusivity, empowering users with hearing disabilities, and enabling smooth interaction in daily life, education, and workplaces.

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