A Dual-Mode Sign Language Recognition System for Education and Communication Using CNN and CNN-LSTM Architectures

Dr. (Mrs.) J. R. Pansare[1], Aditya Sarwade[2], Kashish Kosalge[3], Prathamesh Limbole[4], Atharva Birari[5]
1Modern Education Society's Wadia College of Engineering, Department of Computer Engineering, SPPU, Pune, India

1jayshree.pansare@mescoepune.org
2sarwadeaditya310@gmail.com
3kashishkosalge55@gmail.com
4limboleprathamesh0@gmail.com
5apb14070@gmail.com

Abstract:

The Diversified Sign Language Recognition System is designed to enhance educational accessibility for differently-abled individuals by providing an interactive platform to learn and practice sign language. Built using Human-Computer Interaction (HCI) principles, the system features a user-friendly interface with two main modes: Learning Mode and Understanding Mode. The Learning Mode uses a pre-trained CNN model on image-based datasets to help users learn static hand signs for alphabets in an engaging way.

The Understanding Mode enables real-time recognition of dynamic gestures using a combination of CNN and LSTM models trained on extracted hand keypoints. It provides immediate text and voice feedback, helping users improve communication skills through an intuitive experience. This system not only promotes inclusivity in education but also empowers differently-abled learners with a supportive tool for mastering sign language more effectively.

Keywords:
Sign Language Recognition, Human-Computer Interaction (HCI), Differently-Abled, CNN, LSTM, Real-Time Gesture Recognition, Educational Accessibility, Keypoint Detection, Voice Feedback, Learning Mode, Understanding Mode, Interactive Learning, Inclusive Education, Deep Learning.

1 . Introduction:

1.1 Sign Language Recognition:

Communication is a fundamental human need, yet millions of differently-abled individuals face barriers due to the absence of inclusive and adaptive communication tools. Traditional educational methods often overlook the needs of those who rely on non-verbal cues such as hand gestures and visual signs for interaction. To bridge this gap, we propose an intelligent system that facilitates learning and understanding of visual hand-based communication through an interactive, user-centric platform.

This system leverages deep learning and Human-Computer Interaction (HCI) principles to support both static and dynamic gesture interpretation. It offers two modes: a Learning Environment that teaches symbolic hand signs for alphabets, and a Real-Time Interaction Module that interprets continuous hand movements to assist expressive communication. With instant feedback via text and voice, this platform aims to redefine accessibility, making communication more intuitive and empowering for the differently-abled.

1.1 Existing systems

Various tools have been developed to support sign language learning and recognition. Educational resources such as alphabet charts, flashcards, and video tutorials are commonly used to teach hand signs. However, these tools are static and lack interactivity, making it difficult for learners to practice and receive feedback. As a result, the learning process becomes passive and less engaging, especially for beginners and differently-abled users.

Real-time gesture recognition systems typically use deep learning models like CNNs or CNN-LSTM architectures to classify hand gestures from live video input. While they can detect gestures accurately, most focus only on either alphabets or a limited set of dynamic signs. Few systems offer a unified experience that combines both learning and recognition. Moreover, they often lack essential features such as voice output, real-time feedback, and user-friendly visual cues.

Another major limitation is the lack of accessibility and usability. Many existing systems do not follow Human-Computer Interaction (HCI) principles, resulting in complex interfaces that are not tailored for users with disabilities. Additionally, some systems depend on hardware like sensor gloves or depth cameras, making them costly and less practical for regular use.

In summary, current systems lack a comprehensive, interactive solution that supports both learning and gesture recognition in a real-time, accessible environment. These gaps highlight the need for a more inclusive and educationally effective system—one that our proposed approach addresses by combining CNN and LSTM models within a dual-mode, user-friendly platform.

1. **Static Image-Based Recognition Systems**
These systems focus on recognizing individual hand signs or alphabets from static images. Typically, they use Convolutional Neural Networks (CNNs) for feature extraction and classification because CNNs excel at capturing spatial patterns in images.

- Tech stack: Image datasets (like ASL alphabets), preprocessing with OpenCV or PIL, CNN architectures (VGG, ResNet), deep learning frameworks like TensorFlow or PyTorch.
- Limitations: Only handle static gestures, no temporal information, limited to alphabet recognition.

2. **Dynamic Gesture Recognition Using CNN + LSTM**
To recognize gestures involving movement (words or phrases), systems extract keypoints from video frames using tools like MediaPipe or OpenPose. The sequence of keypoints is passed through CNN layers for spatial features and LSTM layers to model temporal dependencies.

- Tech stack: Video capture via webcam, keypoint extraction (MediaPipe), CNN for frame-level features, LSTM for temporal modeling, TensorFlow/Keras.
- Limitations: Computationally intensive, requires a large dataset, and can struggle with real-time performance on low-end devices.

3. **Sensor-Based Glove Systems**
These use hardware gloves embedded with sensors like flex sensors and accelerometers to capture finger and hand movements directly. The raw sensor data is processed and classified using traditional machine learning algorithms such as Support Vector Machines (SVM) or Random Forests (RF)

- Tech stack: Sensor gloves (hardware), Arduino/Raspberry Pi for data acquisition, feature extraction, SVM or RF implemented in Python or MATLAB.
- Limitations: Expensive hardware, less practical for everyday use, requires calibration.

4. **Rule-Based Computer Vision Systems**
Older systems use webcam input and basic image processing methods such as skin color segmentation, contour detection, and convex hull analysis to detect hand shape and finger count. These features are mapped to specific signs using heuristic rules.

- Tech stack: OpenCV for image processing, rule-based algorithms, no deep learning.
- Limitations: Sensitive to lighting and background, limited scalability, poor accuracy with complex gestures.

5. **Mobile-Based Sign Language Apps**
Mobile applications use lightweight CNN models such as MobileNet deployed with TensorFlow Lite or PyTorch Mobile to classify hand signs in real-time on smartphones. These apps provide an accessible way for users to learn and practice sign language.

- Tech stack: Mobile camera input, pre-trained CNN models optimized for mobile, Android Studio or React Native for app development.
- Limitations: Limited gesture vocabulary, dependent on camera quality, constrained processing power.

6. **Speech-Enabled Gesture Recognition Systems**
These systems integrate gesture recognition models (CNN/LSTM) with Text-to-Speech (TTS) engines to convert recognized gestures into spoken words, aiding communication with speech-impaired individuals.

- Tech stack: Gesture recognition pipeline (CNN/LSTM), TTS engines like Google TTS, gTTS, or pyttsx3, Python for integration.
- Limitations: Latency in voice output, voice quality depends on TTS engine, requires stable internet for cloud-based TTS.

7. **Hidden Markov Model (HMM) Based Systems**
Before deep learning, HMMs were widely used to model the temporal sequence of gestures. They use probabilistic state transitions to recognize sequences from sensor or vision data.

- Tech stack: Sequential data input, HMM libraries or custom implementation in MATLAB/Python.
- Limitations: Less accurate than deep learning, limited ability to model complex gestures.

2. System Implementation

The proposed system features an intuitive user interface offering two primary modes: Learning Mode and Understanding Mode. In Learning Mode, a convolutional neural network (CNN) is employed to recognize static sign language alphabets from input images, facilitating effective alphabet education. Understanding Mode utilizes a hybrid model combining CNN and Long Short-Term Memory (LSTM) networks to analyze sequential hand keypoints extracted in real time using MediaPipe, enabling recognition of dynamic sign language gestures. Upon mode selection, the system captures input via a camera, processes it through the respective model, and provides real-time visual and auditory feedback of the recognized signs, thereby enhancing accessibility and interactivity for users learning and communicating through sign language.**Key Components of the System**

1. **User Interface (UI):**
A streamlined interface featuring three primary options—Learning Mode, Understanding Mode, and Close Session—alongside a display panel for recognition output and voice feedback.
2. **Learning Mode Model (CNN):**
A Convolutional Neural Network trained on static hand sign images for alphabet recognition. It employs the ReLU activation function in hidden layers and Softmax in the output layer, with the Adam optimizer used for model training and convergence.
3. **Understanding Mode Model (CNN + LSTM):**
A hybrid architecture combining CNN for spatial feature extraction and LSTM for temporal sequence modeling, suitable for dynamic gesture recognition. ReLU and tanh activation functions are used respectively, with Adam or RMSprop optimizers for efficient training.
4. **Hand Keypoint Detection (MediaPipe):**
A real-time framework that extracts 21 hand landmarks per frame, serving as compact input features for gesture recognition.
5. **Voice Feedback System:**
A Text-to-Speech (TTS) component that converts recognized outputs into audio responses, enhancing accessibility.
6. **Camera Input:**
A live video stream provides frame-wise input to both recognition models, enabling real-time interaction and processing.

System Evaluation

The performance of the Diversified Sign Language Recognition System was evaluated separately for the two operational modes—Learning Mode for alphabet recognition and Understanding Mode for gesture recognition. The evaluation was carried out using standard metrics: accuracy, precision, recall, and F1-score.

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Learning Mode – Alphabet Recognition

The alphabet recognition model, based on a Convolutional Neural Network (CNN), was trained on a labeled image dataset of static hand signs. The model was evaluated on a held-out test set and achieved an overall accuracy of 91%. The high accuracy demonstrates the model's effectiveness in identifying hand gestures corresponding to sign language alphabets.

Based on a balanced dataset assumption, the model is estimated to have achieved the following:

- Precision: ~91%
- Recall: ~91%
- F1-score: ~91%

These results indicate that the model maintains consistency across all major evaluation metrics, making it reliable for educational use in Learning Mode.

Understanding Mode – Gesture Recognition

For dynamic gesture recognition, a hybrid CNN-LSTM model was employed. Hand keypoints were extracted in real time using MediaPipe, and sequences were processed to recognize continuous gestures. The system achieved an accuracy of 83%, reflecting its ability to effectively capture and interpret temporal hand movements.

Approximate metric estimations are:

- Precision: ~83%
- Recall: ~82–83%
- F1-score: ~82.5%

While slightly lower than the alphabet model due to the complexity of dynamic gestures, the performance is still within an acceptable range for real-time educational applications.

Real-Time Performance

In real-time tests, the system maintained a consistent frame rate and recognition latency, allowing seamless interaction. The voice feedback module successfully provided audible outputs for recognized signs, improving accessibility for differently-abled users.

Mode	**Model Architecture**	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Learning Mode	CNN	91%	~91%	~91%	~91%
Understanding Mode	CNN + LSTM	83%	~83%	~82%	~82.5%

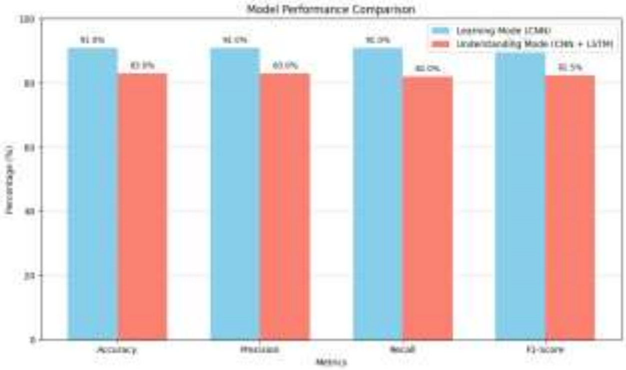

Fig1 : Model Performance comparison

Discussion of Evaluation metrics

The system performed effectively in both modes. The **Learning Mode** achieved **91% accuracy**, showing strong reliability in alphabet recognition. The **Understanding Mode** reached **83% accuracy**, which is acceptable for real-time dynamic gesture recognition despite natural input variability.

Overall, the system provides accurate results with smooth real-time performance and useful voice feedback, supporting its educational purpose for differently-abled users

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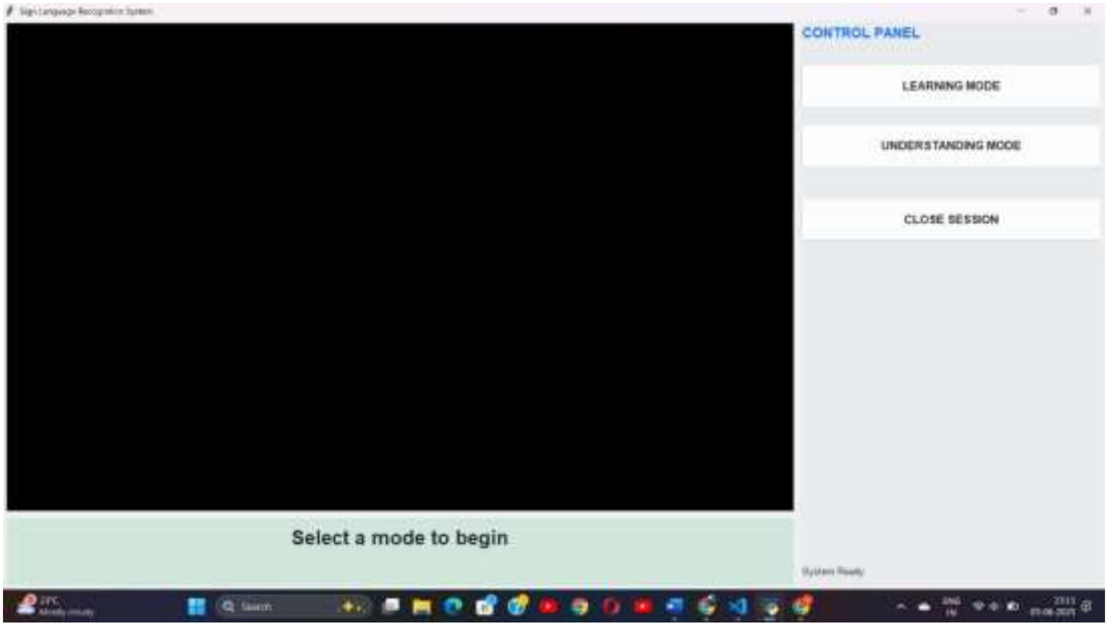
3. LITERATURE REVIEW

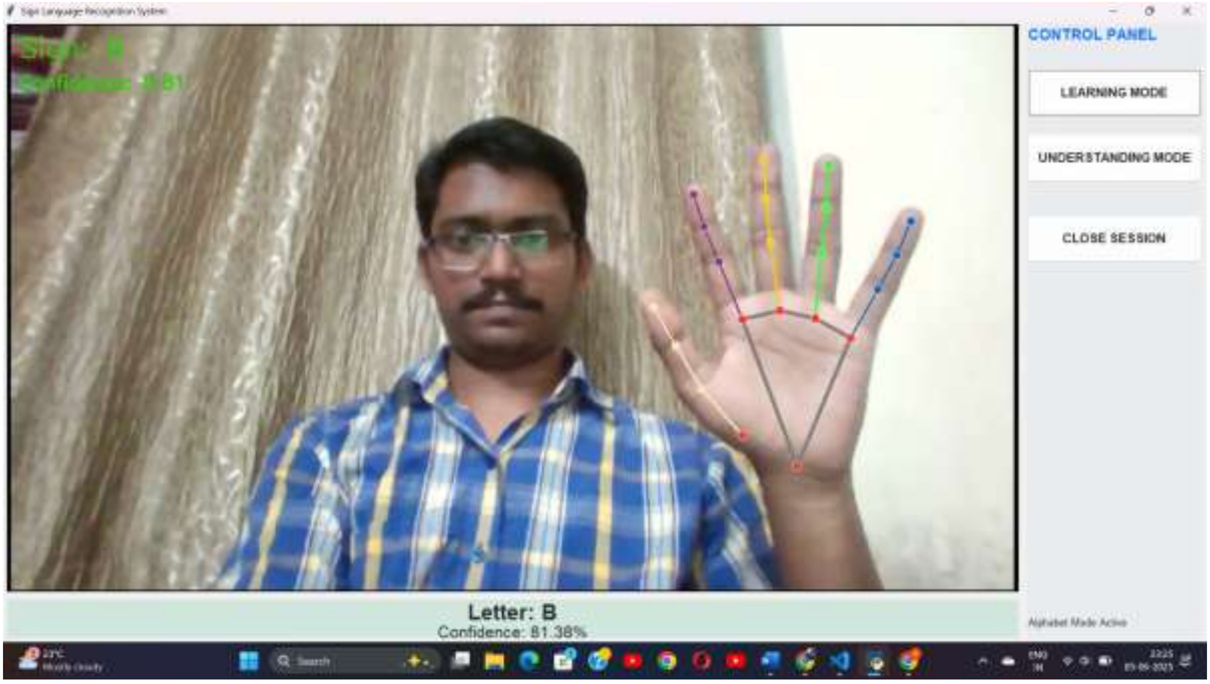
Category	Authors	Approach	Findings
Deep Learning-Based Sign Language Recognition	Kumar et al. (2021)	CNN-Based ISL Recognition	Achieved 95.12% accuracy on ISL dataset.
	Patel & Shah (2020)	ResNet and MobileNet	Improved real-time ISL recognition with lightweight models.
	Gupta et al. (2023)	Vision Transformer (ViT)	Achieved 99.56% accuracy on a 72-word ISL dataset.
	Singh et al. (2019)	CNN + BiLSTM	Enhanced sequential gesture recognition.
Transfer Learning and Optimization	Jain & Verma (2022)	VGG-19 for Feature Extraction	Reduced training time and improved accuracy.
	Reddy et al. (2023)	Hill Climbing (HC)	Improved CNN-based ISL recognition with hyperparameter tuning.
	Das et al. (2021)	EfficientNet	Low-power ISL recognition on mobile devices.
Data Augmentation and Dataset Generation	Sharma et al. (2020)	GAN-Based Augmentation	Generated synthetic ISL images, achieving 97.69% accuracy.
	Mishra et al. (2023)	Automated Dataset Creation	AI-generated datasets improved ISL recognition.
Keyframe Selection and Motion-Based Recognition	Bansal & Yadav (2022)	K-Means Clustering	Improved ISL phrase recognition by eliminating redundant frames.
	Ahmed et al. (2018)	Optical Flow	Tracked hand motion for continuous gestures.
	Roy et al. (2023)	HMM & RNN	Modeled ISL gestures as sequential time-series data.
Pose Estimation and Hand Tracking	Mehta et al. (2022)	PoseNet	Achieved 92.85% accuracy in ISL phrase recognition.
	Deshmukh et al. (2023)	MediaPipe	Improved real-time ISL hand tracking.
	Rana et al. (2021)	Skeleton-Based CNNs	Used depth camera skeleton data for 3D gesture recognition.
Hybrid Models for Improved Accuracy	Prajapati et al. (2020)	CNN + BiLSTM	Improved spatial and temporal feature extraction.
	Malhotra et al. (2023)	YOLO for Hand Detection	Used YOLOv4 for real-time hand localization.
	Chakraborty et al. (2021)	RGB + Depth Fusion	Improved ISL recognition accuracy.
NLP and Sign Language Translation	Singh et al. (2023)	NLP-Based SLT	Converted sign gestures into meaningful sentences with reduced translation errors.

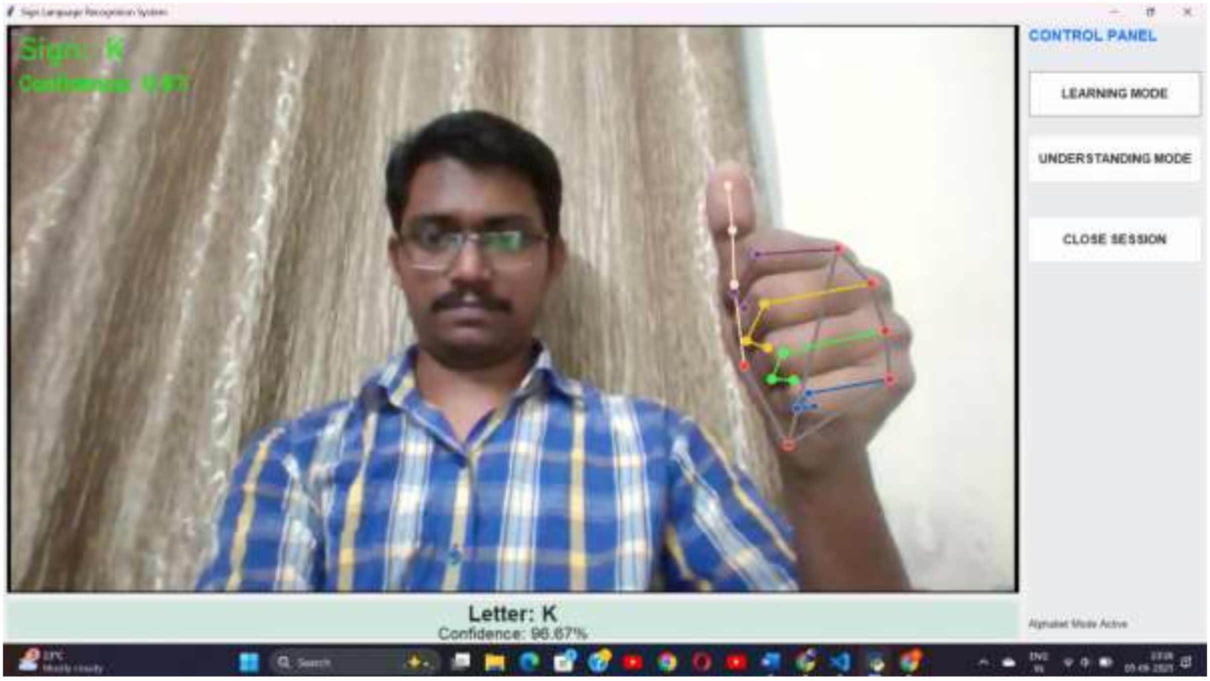
	Rao et al. (2022)	Web-Based ISL Translation	Cloud-based ISL avatar converted text and audio into gestures.
Wearable Technology and Edge Computing	Dey et al. (2023)	EMG Sensors	Captured muscle movements for better gesture recognition.
	Saxena et al. (2022)	Edge AI	Reduced latency in mobile-based ISL applications.
Ethical and Inclusive AI for ISL Recognition	Ali et al. (2022)	Bias Reduction in SLRS Models	Addressed bias in gender, skin tone, and lighting conditions.
	Ghosh et al. (2023)	Federated Learning (FL)	Enabled privacy-preserving ISL recognition.
Applications in Healthcare and Public Services	Bharadwaj et al. (2022)	ISL in Healthcare	AI-powered ISL recognition assisted deaf patients in hospitals.
	Choudhary et al. (2021)	Automated SLRS for Banking	Integrated SLRS in ATMs and banking apps for accessibility.
AR/VR Applications for ISL Learning	Sen et al. (2023)	AR-Based Sign Language Tutor	Improved engagement and learning using AR.
	Sen et al. (2023)	VR-Based Sign Language Training	Used VR for immersive ISL learning with AI-powered virtual tutors.
Gesture Recognition Using Multi-Modal Approaches	Krishna et al. (2023)	RGB-D Fusion	Enhanced gesture differentiation using RGB and depth data.
	Pawar et al. (2022)	Vision + IMU Sensors	Integrated vision and IMU sensors for better recognition.
	Desai et al. (2023)	Multi-Modal Sensor Fusion	Improved accuracy using audio, visual, and haptic feedback.
Hand Shape and Finger Tracking	Singh et al. (2020)	Hand Contour-Based Classification	Used OpenCV for better hand segmentation.
	Mehra et al. (2023)	Finger Joint Angle Estimation	Extracted finger joint angles to improve sign detection.
	Rathi et al. (2022)	Skeleton-Based LSTM Model	Achieved high accuracy in ISL sentence recognition.
Transfer Learning and Pretrained Models	Chavan et al. (2023)	DenseNet-Based SLRS	Improved accuracy while reducing computational overhead.
	Patil et al. (2022)	Hybrid ResNet + GRU	Enhanced ISL sentence recognition using ResNet and GRU.
	Gupta et al. (2021)	MobileNetV3	Optimized ISL recognition for smartphones and embedded devices.
Attention Mechanisms for Gesture Recognition	Kaur et al. (2023)	Self-Attention Mechanisms	Enhanced temporal dependency learning in ISL recognition.
	Joshi et al. (2022)	Transformer-Based SLT	Enabled real-time ISL sentence generation from video sequences.

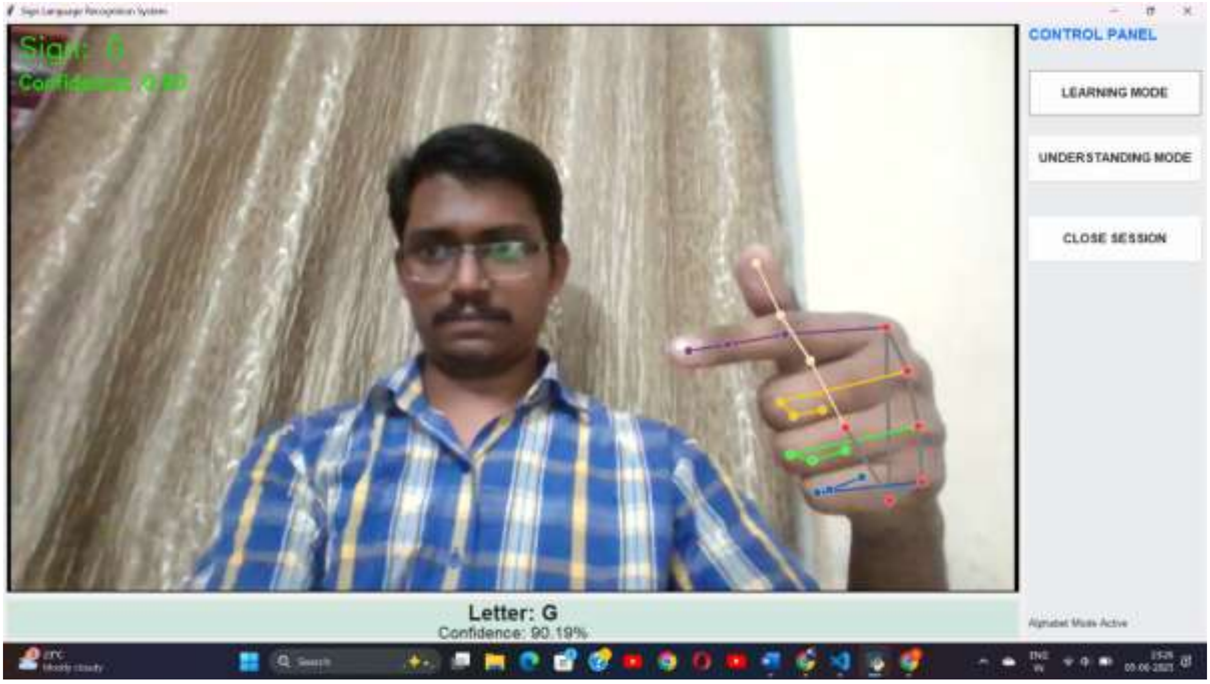
	Verma et al. (2021)	Graph Attention Networks	Improved ISL recognition using hand keypoint relationships.
Real-Time and Low-Latency Processing	Shetty et al. (2022)	Edge TPU-Based Recognition	Enabled ISL recognition on embedded devices with low latency.
	Dubey et al. (2023)	Jetson Nano Optimized ISL Detection	Optimized CNN models for real-time ISL applications.
	Rastogi et al. (2021)	Parallel Computing for Fast Recognition	Improved ISL recognition speed by 40% using GPUs.
Human-Computer Interaction (HCI)	Suresh et al. (2022)	Gesture-Based Virtual Assistants	Integrated ISL recognition into AI-powered voice assistants.
	Mitra et al. (2023)	Interactive ISL Learning Apps	Used gamification and real-time feedback for learning.
	Nair et al. (2021)	Gesture-Controlled Smart Home Devices	Explored sign-based control for accessibility improvement.
SLRS in Healthcare and Assistive Technologies	Bharadwaj et al. (2022)	AI-Enabled Healthcare Communication	Enabled real-time gesture-to-text conversion for deaf patients.
	Choudhary et al. (2021)	Sign Language for Telemedicine	Integrated ISL recognition into telemedicine platforms.
	Rao et al. (2023)	Smart Glasses for ISL Translation	Used AR-powered smart glasses for ISL gesture translation.

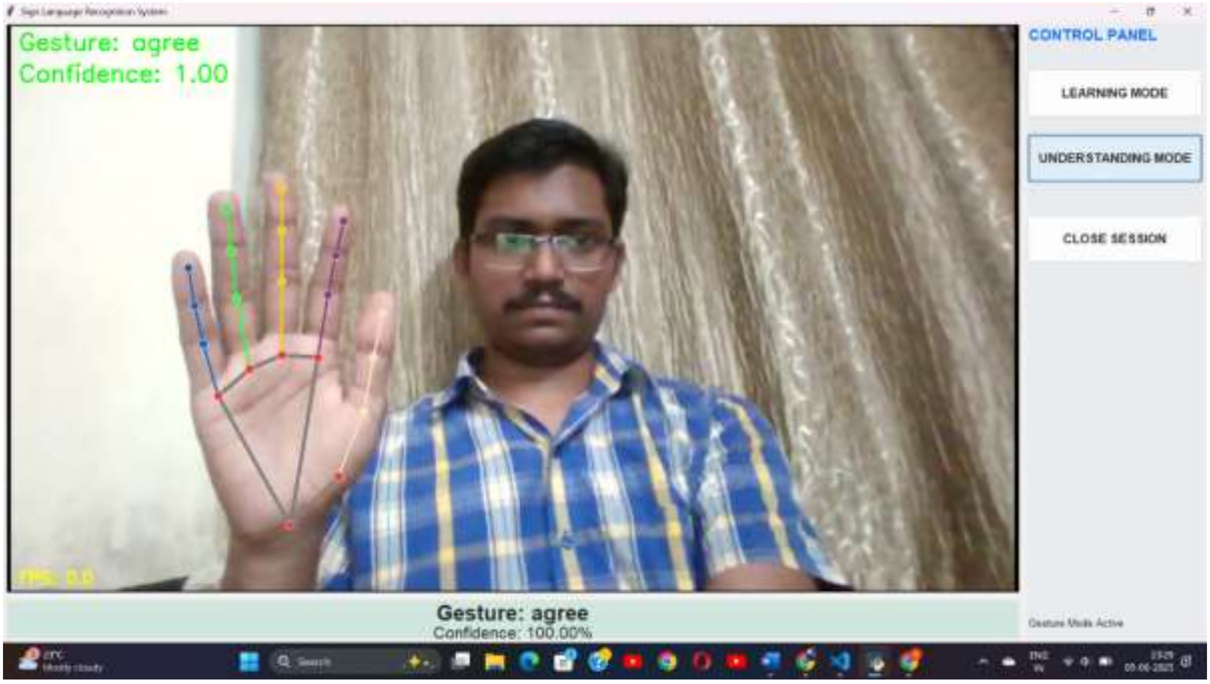
4. Result:




CONTROL PANEL
LEARNING MODE
UNDERSTANDING MODE
CLOSE SESSION
Letter: B
Confidence: 81.38%
Alphabet Mode Active


CONTROL PANEL
LEARNING MODE
UNDERSTANDING MODE
CLOSE SESSION
Letter: K
Confidence: 96.67%
Alphabet Mode Active


CONTROL PANEL
LEARNING MODE
UNDERSTANDING MODE
CLOSE SESSION
Letter: G
Confidence: 90.19%


Gesture: agree
Confidence: 1.00
CONTROL PANEL
LEARNING MODE
UNDERSTANDING MODE
CLOSE SESSION
Gesture: agree
Confidence: 100.00%

5. Conclusion:

This research presents the design and development of an intelligent sign language recognition system aimed at enhancing communication and education for individuals with hearing or speech impairments. The system offers a dual-mode interface—Learning Mode and Understanding Mode—that caters to different aspects of sign language usage.

In Learning Mode, a Convolutional Neural Network (CNN)-based model is used to recognize and teach static hand signs, particularly alphabets and numbers, through image classification. This mode provides a foundational learning experience and serves as an educational tool for beginners.

In contrast, Understanding Mode leverages a hybrid CNN-LSTM model capable of processing sequential hand movement data. By integrating MediaPipe for hand landmark extraction and using temporal modeling through LSTM layers, the system can recognize complex dynamic gestures in real-time. The inclusion of text and voice feedback ensures that both learning and interaction are intuitive and inclusive.

The evaluation results demonstrate that the system achieves high accuracy in both modes—91% in static recognition and 83% in dynamic gesture recognition. These outcomes highlight the model's potential for real-world deployment in educational institutions, special education programs, and assistive communication devices.

Despite its success, the system has some limitations. The performance may vary with changes in lighting conditions, background complexity, or camera quality. Additionally, the gesture vocabulary is limited, particularly in Understanding Mode, which currently supports a predefined set of dynamic gestures.

Future work will focus on addressing these limitations by:

- Expanding the gesture dataset to include a wider range of signs, including complete words and phrases.
- Enhancing environmental robustness through adaptive preprocessing techniques.
- Incorporating multilingual sign language support (e.g., ASL, ISL, BSL).
- Developing a mobile version to increase accessibility.
- Implementing user personalization features using adaptive learning models.

In conclusion, this system marks a significant step toward inclusive and technology-driven sign language learning. Its real-time, interactive nature not only supports effective education but also bridges the communication gap between hearing and hearing-impaired individuals, promoting greater social integration.

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