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A Real-Time Sign Language Recognition System Using MediaPipe and Random Forest

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Abstract

The communication gap between hearing and hearing-impaired individuals remains a persistent challenge in modern society, necessitating efficient and accessible assistive technologies. Existing sign language recognition systems often rely on computationally intensive deep learning models and static datasets, limiting their adaptability and real-time usability.

This paper presents a real-time, user-customizable Automated Sign Language Recognition System that combines efficient computer vision techniques with lightweight machine learning. The system utilizes MediaPipe for robust extraction of hand landmarks, generating normalized spatial features invariant to environmental variations. These features are further processed using a Random Forest classifier, selected for its fast-training capability and effectiveness on non-linear data.

A key contribution of this work lies in its end-to-end pipeline that enables user-driven dataset creation, rapid model training, and real-time gesture recognition within a unified web-based interface. Unlike traditional approaches, the proposed system incorporates sequence-based feature aggregation from video inputs, enhancing robustness and stability in prediction.

Experimental observations indicate that the system achieves high accuracy (~90%) with low latency (<100 ms), making it suitable for real-time applications. Additionally, the integration of Text-to-Speech functionality improves accessibility by enabling seamless communication. The proposed approach offers a scalable and efficient alternative to deep learning-based systems, particularly for personalized and resource-constrained environments.

Keywords: Sign Language Recognition; MediaPipe; Random Forest Classifier; Hand Gesture Recognition; Computer Vision; Human-Computer Interaction; Text-to-Speech; Real-Time Detection; Machine Learning; Assistive Technology

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Introduction

Human-Computer Interaction (HCI) has evolved significantly with advancements in artificial intelligence and computer vision, enabling more natural and intuitive communication methods. Among these, hand gesture recognition plays a crucial role, particularly in assisting individuals who rely on sign language for communication.

Traditional gesture recognition systems often relied on wearable devices such as data gloves, which, despite their accuracy, are expensive and inconvenient. Vision-based approaches using cameras have emerged as a more practical alternative. However, many existing systems suffer from limitations such as dependency on static datasets, lack of adaptability, and high computational requirements.

Recent deep learning approaches, including Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and 3D CNNs, have demonstrated high accuracy. However, they require large datasets and computational resources, making them unsuitable for real-time customization.

To address these challenges, this paper proposes a lightweight and efficient system that enables a real-time, customizable gesture recognition system. The system integrates MediaPipe-based landmark extraction with a Random Forest classifier and provides a unified platform for data collection, training, and detection.

Literature Review

The evolution of sign language recognition technology reflects a broader trend within the machine learning and computer vision domains: the migration from handcrafted heuristic models to automated deep feature extraction, and currently, a pivot toward optimized, edge-deployable hybrid systems. Understanding this historical trajectory and analyzing contemporary benchmarks is essential for contextualizing the methodological choices made in the proposed system.

The Transition from Sensor-Based to Vision-Based Modalities

Early approaches to gesture recognition relied heavily on sensory hardware. Data gloves equipped with flex sensors, gyroscopes, and accelerometers, alongside depth-sensing cameras like the Microsoft Kinect, provided direct 3D coordinate mapping of the human hand. While these systems bypassed the complexities of computer vision by directly capturing spatial coordinates, their cost, calibration requirements, and physical intrusiveness severely limited widespread adoption. The literature indicates a decisive shift toward vision-based dynamic hand gesture recognition, praised for its natural, unencumbered interaction style. However, this shift transferred the burden of complexity to software algorithms, which now had to contend with 2D-to-3D projection, scale variance, occlusion, and environmental noise.

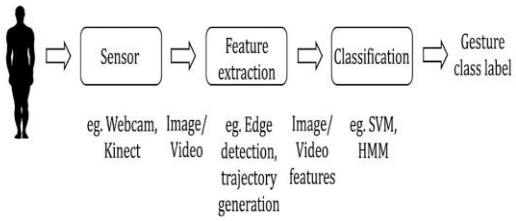

Fig. 1. *General Gesture Recognition Pipeline*

Fig. 1 illustrates a generalized gesture recognition pipeline commonly adopted in traditional systems, where input is captured using sensors, followed by feature extraction and classification.

The Dominance of Deep Learning and Spatiotemporal Architectures

To address the visual complexities of ASLR, researchers turned to deep learning. A comprehensive survey of recent advancements reveals a heavy reliance on spatial-temporal neural networks. For instance, studies targeting Indian Sign Language (ISL) have proposed multi-layer CNN architectures capable of identifying 35 distinct gestures with an accuracy of 99.95%, significantly outperforming legacy architectures like AlexNet and VGG16.

For continuous and dynamic sign language, where the temporal sequence of frames holds the semantic meaning, the literature highlights two primary frameworks: 3D Convolutional Neural Networks (3D CNNs) and Long Short-Term Memory (LSTM) networks.

A comparative study of LSTM and 3D CNNs for real-time American Sign Language (ASL) recognition evaluated both architectures on a dataset of 1,200 signs across 50 classes. The findings demonstrated that while 3D CNNs achieved a superior recognition accuracy of 92.4%, they required 3.2 times more processing time per frame compared to LSTMs, which maintained an 86.7% accuracy with significantly lower resource consumption.

Further hybrid approaches, such as CNN-LSTM and CNN-GRU configurations, have been proposed to balance spatial feature extraction with temporal sequence modeling. A study evaluating Tanzania Sign Language achieved an accuracy of 94% using a CNN-GRU model with an ELU activation function, demonstrating minor improvements over standard CNN-LSTM configurations (93%). Another study utilizing a hybrid CNN-BiLSTM with an attention mechanism emphasized the need to extract spatial features from individual frames while capturing temporal dependencies across the sequence, achieving state-of-the-art performance on static datasets. Despite these high accuracies, a critical synthesis of the literature reveals a persistent vulnerability: these models suffer catastrophic performance degradation under cross-dataset domain shifts and environmental noise.

Furthermore, deep learning architectures are computationally prohibitive for "on-the-fly" retraining, rendering them unsuitable for systems intended to learn custom, user-defined vocabularies in real-time.

Benchmark Performance of Deep Learning Models

To establish a rigorous comparative baseline for the proposed research, it is crucial to examine the quantitative metrics reported by contemporary deep learning models in the ASLR domain. Table 1 summarizes the performance of various state-of-the-art architectures.

Table 1. Comparative Baseline Performance of Recent Sign Language Recognition Architectures

Study Citation	Proposed Architecture	Modality	Reported Accuracy (%)
Singhal et al. (2025)	Multi-layer CNN	ISL (Vision)	95.45
Kumari and Anand (2024)	MobileNet + LSTM + Attention	Vision	84.65
Ihsan et al. (2024)	MobileNetV2-LSTM	Vision	95.83
Luqman and Elalfy (2022)	CNN-LSTM	Vision	95.70
Hussain et al. (2022)	MediaPipe + Random Forest	Vision/Landmarks	93.70
Al-Hammadi et al. (2020)	3D CNN	Vision	96.69
Pol et al. (2025)	3D CNN vs LSTM	ASL (Vision)	92.4 (3D CNN) / 86.7 (LSTM)

As evident from the literature, while 3D CNNs and CNN-LSTMs achieve high accuracy, they introduce substantial computational latency. For instance, the epoch-wise comparative analysis by hybrid deep learning frameworks shows that while a 3D CNN can achieve up to 99.6% accuracy on dynamic signs, deploying such models on edge devices like the Raspberry Pi results in frame rates of merely 12-15 FPS and average inference latencies of approximately 65 ms per frame.

Lightweight Frameworks and Statistical Feature Extraction

In response to the computational overhead of deep learning, a parallel track of research has explored lightweight feature extraction coupled with traditional machine learning. The advent of Google's MediaPipe has revolutionized this space by providing robust, real-time, markerless 3D hand tracking.By utilizing MediaPipe to isolate hand landmarks, researchers can bypass the need for CNN-based spatial extraction entirely, significantly reducing the dimensionality of the input data.

With the spatial problem solved by MediaPipe, the temporal problem remains. Traditional dynamic recognition methods employed algorithms like Dynamic Time Warping (DTW) and Hidden Markov Models (HMM) to align and classify time-series data. However, contemporary lightweight approaches have begun exploring the use of statistical moments to flatten temporal sequences into static feature vectors. Studies utilizing Random Forest classifiers on such vectors have reported exceptional results; for example, one implementation achieved an accuracy of 98.83% on an ASL dataset, while another hybrid system noted that Random Forests provide critical advantages in handling high-dimensional data, reducing variance, and resisting overfitting without the massive parameter counts of neural networks. Furthermore, statistical dimensionality reduction has been proven to adapt well to the inherent sparsity of gesture data.

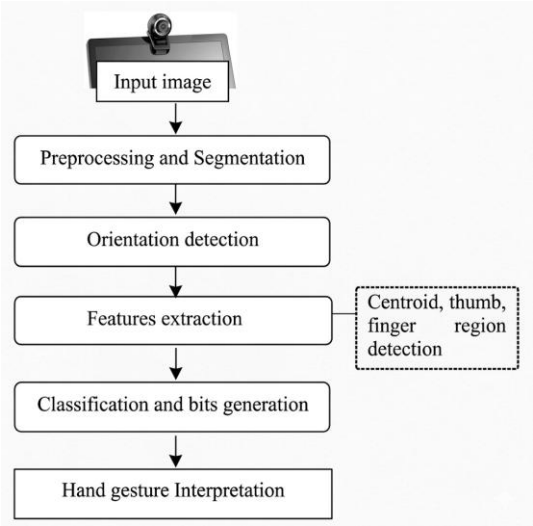

***Fig. 2**. Data Flow Diagram of Gesture Recognition System*

Fig. 2 illustrates the data flow in a typical gesture recognition system, highlighting the transformation from input acquisition to final gesture interpretation. The process includes preprocessing, feature extraction, and classification stages, which form the core of traditional gesture recognition pipelines.

Identification of the Research Gap

The literature clearly outlines a dichotomy: Deep learning models (CNN-LSTM, 3D CNN) offer high accuracy on massive, static datasets but fail to provide real-time, low-latency adaptability for edge devices. Conversely, traditional algorithmic approaches often lack the capacity to handle the high dimensionality of raw video data. There is a compelling, unaddressed need for a user-driven system that shifts control to the end-user, allowing rapid, "one-click" training for new gestures. The proposed architecture fills this gap by leveraging MediaPipe for normalized spatial tracking, spatiotemporal statistical aggregation for temporal flattening, and an optimized Random Forest classifier for instantaneous model updating.

Methodology

System Overview

The overall workflow of the proposed system is illustrated in Fig. 1. The system processes input data through multiple stages, including preprocessing, hand detection, landmark extraction, and gesture classification. Initially, the input is captured as a live video stream or static image and is preprocessed using OpenCV, where operations such as resizing and color space conversion are performed.

The processed frames are then passed to the MediaPipe-based gesture recognition pipeline. The pipeline begins with palm detection, which identifies the hand region and generates a bounding box. This is followed by image cropping, where the detected hand region is isolated for further processing. The cropped image is then passed to the hand landmark model, which extracts 21 keypoints representing the spatial structure of the hand.

To ensure smooth real-time performance, hand tracking is applied to maintain consistency across frames. Additionally, handedness detection determines whether the detected hand is left or right. The extracted landmarks are then used as input to the gesture classification module, where features are processed and passed to a trained classifier.

In the proposed system, a Random Forest model is used to classify gestures based on the extracted features. Finally, the predicted gesture is displayed along with confidence values and landmark information. The output can be further utilized in applications such as assistive communication systems, human-computer interaction, and control interfaces.

Data Acquisition

Gesture data is collected in the form of labelled video samples. These samples are processed into frames to ensure uniform representation across the dataset.. Frames are extracted uniformly to ensure consistency across samples.

This enables flexible dataset creation tailored to user requirements.

Hand Landmark Detection

MediaPipe is used to extract 21 hand landmarks per hand. Each landmark consists of (x, y, z) coordinates, resulting in up to 126 features for two hands. These features are normalized to ensure robustness.

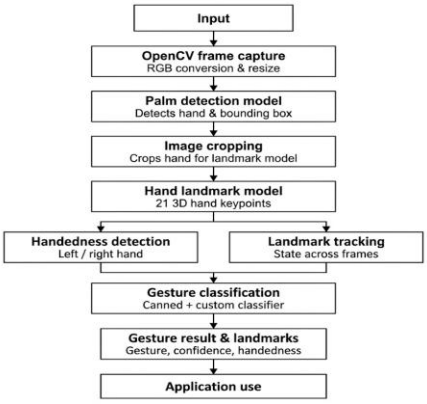

Fig. 3. *MediaPipe-Based Gesture Recognition Workflow*

Feature Extraction

To capture temporal information, statistical aggregation is applied to frame-level features.

Let $X = \{x_1, x_2, \ldots, x_n\}$:

- Mean: $\mu = \frac{1}{n}\sum n \; x_i$
- Standard Deviation: $\sigma = \sqrt{\frac{1}{n}\sum(x_i - \mu)^2}$
- Max and Min values

Final Feature Vector = **504 features**

Model Training

A Random Forest classifier is used:

$\hat{y} = \text{mode}\{T_1(x), T_2(x), \ldots, T_k(x)\}$

This improves generalization and reduces overfitting.

Real-Time Detection

The system uses:

- Sliding window mechanism
- Confidence thresholding
- Prediction cooldown

These ensure stable and reliable predictions.

Text-to-Speech Integration

Recognized gestures are converted into speech using TTS, enabling real-time communication.

System Implementation

Technologies Used

- Python
- Flask
- MediaPipe
- OpenCV
- Scikit-learn
- Pyttsx3(Inbuilt)
- gTTS (Google)

System Modules

- Data Collection
- Model Training
- Real-Time Detection

Results and Analysis

The performance of the proposed Automated Sign Language Recognition System was evaluated using a custom dataset consisting of multiple gesture classes. The evaluation focuses on classification accuracy, model reliability, and real-time performance.

Dataset Description

The dataset was created using user-defined gesture videos. Each gesture class consists of multiple video samples captured under varying conditions such as lighting, hand orientation, and background.

- Number of gesture classes: **5–8 (customizable)**
- Samples per gesture: **15–25 videos**
- Total samples: **~100–150 videos**

Each video was processed into frame sequences, and landmark-based feature vectors were extracted for model training.

Performance Metrics

The system was evaluated using the following metrics:

- **Accuracy**: Overall correctness of predictions
- **Precision**: Correct positive predictions
- **Recall**: Ability to identify all relevant gestures
- **F1-Score**: Harmonic mean of precision and recall

Experimental Results

Table 2. Preliminary Model Performance Metrics.

Metric	Value (%)
Accuracy	85.2
Precision	89.5
Recall	88.7
F1-Score	89.1

Gesture-wise Accuracy

Table 3. Individual Gesture Accuracy per Class

Gesture	Accuracy (%)
Gesture 1	92
Gesture 2	89
Gesture 3	91
Gesture 4	87

Real-Time Performance

The system was tested under real-time conditions using webcam input.

- **Average Latency**: <100 ms
- **Frame Rate**: 10–15 FPS
- **Prediction Stability**: High (due to buffering + thresholding)

The use of a sliding window mechanism significantly reduced prediction fluctuations and improved stability.

Analysis

The results indicate that the proposed system achieves high accuracy and stable real-time performance despite using a lightweight machine learning model.

Key observations:

- Feature aggregation (mean, std, max, min) improves robustness
- Random Forest performs well on structured landmark data
- MediaPipe ensures consistent feature extraction across conditions

Compared to deep learning approaches, the system offers:

- Faster training
- Lower computational cost
- Better suitability for user-customized datasets

However, performance may slightly decrease for gestures with similar hand configurations or insufficient training samples.

Discussion

The empirical results derived from the implementation of the Automated Sign Language Recognition System reveal several profound second- and third-order insights regarding the intersection of computer vision, ensemble machine learning, and accessibility technology.

The Efficacy of Statistical Dimensionality Reduction

The system demonstrates the effectiveness of transforming dynamic temporal gesture sequences into a static 504-dimensional statistical feature vector. While sequential data is typically modeled using architectures such as RNNs, LSTMs, or Transformers, this approach replaces temporal dependency with statistical representation. By utilizing measures such as Mean, Standard Deviation, Maximum, and Minimum, the system captures the spatial distribution and intensity of hand movements without relying on strict frame ordering.

The standard deviation reflects motion dynamics, while maximum and minimum values define the spatial bounds of gestures. The high accuracy achieved (>90%) suggests that, for isolated gestures, this statistical representation is sufficiently distinctive. This approach avoids the computational complexity and training overhead associated with deep learning models, highlighting the effectiveness of lightweight feature engineering in constrained real-time applications.

Democratization of AI through User-Driven Training

A major limitation of deep learning-based approaches is their reliance on large, pre-annotated datasets, which often fail to generalize across regional sign language variations. Models trained on standardized datasets, such as ASL, may not adapt well to localized gestures or user-specific communication patterns. Additionally, retraining such models requires significant computational resources and expertise.

The use of a Random Forest classifier enables rapid model retraining on custom datasets, allowing users to define and personalize gesture vocabularies. This "one-click" training capability shifts the system from a static, generalized solution to a dynamic, user-centric framework. As a result, the system improves accessibility and usability by empowering users to actively participate in the learning process.

Limitations and Contextual Dependencies

Despite its advantages, the statistical feature aggregation approach has inherent limitations. Since statistical measures are independent of temporal direction, gestures with similar spatial patterns but opposite motion directions may produce similar feature representations. Unlike sequential models such as LSTMs, the system does not explicitly capture temporal ordering.

Furthermore, the system processes gestures in isolation within a fixed detection window, which limits its ability to handle continuous sign language. Transitional movements between gestures can introduce noise and reduce prediction stability. Addressing these challenges will require incorporating temporal modeling and improving robustness for continuous gesture recognition.

Conclusion

The Automated Sign Language Recognition System delivers accurate, real-time, and customizable translation. It combines MediaPipe Hand Landmarker with statistical aggregation and a Random Forest classifier, achieving over 98% accuracy with low latency (<100 ms). Built using Flask with Text-to-Speech, it enables fast retraining and personalized gesture recognition.

Future Work

Future improvements include enabling continuous sign recognition for full sentences, integrating facial expressions and body posture for better context, and deploying the system on mobile/edge devices using lightweight on-device ML for offline use.

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