Sign Language Detection Using Hand Landmark-Based Machine Learning

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Abstract

Communication between hearing-impaired individuals and the general public is often challenging because many people are unfamiliar with sign language. This project presents an assistive system that converts hand gestures into readable text using machine learning and computer vision techniques. The system captures hand gestures through a standard camera and processes them using real-time hand landmark detection. Instead of analyzing full images, the system extracts important hand key points and converts them into numerical features. These features are then provided to a trained machine learning classifier to recognize gestures representing common words or expressions. The predicted output is displayed as text on the screen instantly, enabling smooth and natural interaction. The proposed solution is simple, cost-effective, and user-friendly, as it requires no special hardware other than a camera. It can be effectively used in educational institutions, public service environments, and assistive communication applications. By translating visual gestures into text automatically, the system reduces dependence on human interpreters and promotes independent communication. The system is designed to operate under varying lighting conditions and different backgrounds, making it suitable for real-world scenarios. Furthermore, it can be extended in the future to support a larger vocabulary, continuous sentence formation, and integration with mobile or web-based platforms. Overall, this project demonstrates the practical potential of artificial intelligence in creating inclusive technologies and improving accessibility for the hearing-impaired community.

Keywords*— *Sign Language Recognition, Hand Gesture Recognition, Machine Learning, Computer Vision, MediaPipe, Random Forest, Assistive Technology.

I. INTRODUCTION

Communication is a fundamental part of human interaction, yet it remains a significant challenge for individuals who are hearing-impaired. Many people in the general public are not familiar with sign language, which creates barriers in daily conversations, education, healthcare, and public services. The lack of easily available interpreters further increases the communication gap, often limiting independence and social participation. With the rapid growth of artificial intelligence, there is an opportunity to design assistive technologies that can help bridge this divide and promote inclusive communication.

This project focuses on developing a real-time sign language detection system that converts hand gestures into readable text. The system uses computer vision techniques to capture hand movements through a standard camera and identify important hand landmarks. These landmarks are transformed into numerical representations, which are then processed by a machine learning classifier to determine the meaning of the gesture. The recognized output is displayed instantly on the screen, allowing users to communicate more effectively with people who do not understand sign language.

The proposed solution is designed to be simple, affordable, and practical. Since it requires only a camera and a computer, it can be deployed in classrooms, offices, and public environments without specialized equipment. By automating gesture recognition, the system reduces dependency on human interpreters and empowers users to express themselves more independently. Furthermore, the project demonstrates how artificial intelligence and vision-based techniques can be applied to create socially beneficial systems that enhance accessibility and digital inclusion.

System Components: The Sign Language Detection system integrates multiple intelligent components to ensure accurate and real-time gesture interpretation. These components work together to capture hand movements, extract meaningful features, classify the gesture, and present the output in textual form. and the wrist. These landmarks provide a compact and reliable representation of the hand structure, eliminating the influence of background noise and lighting variations. By focusing on geometric relationships rather than raw pixels, the system achieves faster and more stable recognition.

Feature Processing & Machine Learning Classification – Once landmarks are detected, their coordinates are normalized and converted into numerical feature vectors. These vectors are passed to a trained classifier implemented using Scikit-learn. The model analyzes spatial patterns in the hand structure and predicts the gesture class based on prior training. The predicted output is then mapped to a corresponding word or phrase using

a label dictionary. Finally, the recognized text is displayed on the screen along with visual cues such as landmark drawings and bounding boxes, enabling smooth and user-friendly interaction.

Output and Integration: The system generates textual output representing the recognized hand gesture in real time. Extracted landmark features are evaluated by the classifier to determine the most probable interpretation. The result is displayed with visual cues, enabling quick and clear understanding. This structured output also supports integration with assistive communication platforms.

II. RELATED WORK

Artificial Intelligence and computer vision have enabled the development of automatic sign language recognition systems to assist hearing-impaired individuals. Early research by Starner and Pentland [1] demonstrated the feasibility of vision-based gesture recognition using video input, forming the foundation for modern sign language detection systems.

Zhang et al. [2] showed that Convolutional Neural Networks (CNNs) can effectively recognize hand gestures from images. Their work proved that deep learning models automatically extract important features, improving recognition accuracy in image-based gesture systems. However, CNN-based approaches require large labeled datasets and high computational resources. Molchanov et al. [3] highlighted that

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However, CNN-based approaches require large, labelled datasets and high computational resources. Molchanov et al. [3] highlighted that deep learning-based gesture recognition systems achieve high accuracy but demand powerful hardware, which limits their suitability for lightweight real-time applications.

To reduce computational complexity, MediaPipe Hands introduced by Zhang et al. [4] enables real-time detection of 21 hand landmarks using a lightweight model. Landmark based representation improves efficiency by using coordinate points instead of full images, making it suitable for real-time gesture recognition.

Pugeault and Bowden [5] emphasized that feature extraction plays a crucial role in improving gesture recognition accuracy. Their research supports the use of structured hand features instead of raw image inputs for better performance.

Breiman [6] proposed the Random Forest algorithm, which provides high accuracy and robustness in classification tasks. It is particularly effective for structured numerical data such as hand landmark coordinates.

Pedregosa et al. [7] introduced the Scikit-learn library, which provides reliable tools for implementing machine learning models including Random Forest, Support Vector Machines, and Decision Trees for practical applications.

Bradski [8] introduced OpenCV, a widely used computer vision library for real-time image processing and video capture. It enables the practical implementation of live gesture detection systems.

Koller et al. [9] studied challenges in sign language recognition and emphasized the importance of efficient modeling techniques for real-time systems, especially in handling dynamic gestures.

Recent surveys by Rastgoo et al. [10] highlight that lightweight, camera-based systems combining hand landmark extraction and traditional machine learning classifiers provide a balance between accuracy and computational efficiency.

Overall, the literature supports the use of real-time hand landmark detection combined with machine learning classification for developing efficient and cost-effective sign language recognition systems. The proposed project builds on these approaches to implement a practical real-time sign language detection system.

Existing Techniques and Models: Sign language recognition systems use various techniques based on accuracy and real time requirements. Early approaches relied on traditional image processing methods such as color segmentation and contour detection combined with rule-based classification. These systems were simple and computationally lightweight but were sensitive to lighting conditions, background variations, and changes in hand orientation. With the advancement of machine learning, feature-based models such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forest were introduced. These methods classify gestures using extracted features like hand shape descriptors or landmark coordinates. Random Forest, in particular, provides good accuracy and robustness for structured numerical data, though performance depends on effective feature extraction.

Deep learning techniques, especially Convolutional Neural Networks (CNNs), further improved gesture recognition by automatically learning spatial features from images. However, CNN models require large datasets and high computational resources. To improve efficiency, modern systems use landmark-based frameworks like MediaPipe Hands, which extract 21 key hand points. Combining landmark extraction with efficient classifiers enables accurate and real-time sign language detection, forming the basis of the proposed system. These approaches help balance computational efficiency and recognition accuracy in real-time environments. The proposed project builds upon landmark-based detection and machine

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learning classification to develop a practical and cost-effective sign language recognition system.

III. PROPOSED SYSTEM

The proposed system is a real-time vision-based assistive communication tool that converts hand gestures into readable text using machine learning and computer vision techniques. System Architecture The system consists of the following major components: Input Module (Webcam Interface) Captures live video frames. Acts as the primary interaction medium. Hand Detection Module Uses MediaPipe Hands. Detects and tracks 21 hand landmarks. Provides stable real-time tracking. Feature Processing Module Extracts landmark coordinates. Converts them into structured numerical vectors. Applies normalization for improved consistency.

Classification Module Uses a trained Random Forest classifier. Maps landmark patterns to gesture labels. Produces fast and reliable predictions. Output Module Displays the predicted gesture as text. Updates continuously in real time. Avoids false outputs when no hand is detected. Working Principle User shows hand gesture in front of the camera. MediaPipe detects and extracts hand landmarks. Landmark coordinates are converted into feature vectors. The trained Random Forest model predicts the gesture.

The predicted gesture is displayed on the screen. This process repeats continuously, forming a real-time interaction loop. Advantages of Proposed System Lightweight (no raw image processing required) Real-time performance Low computational cost Robust under moderate lighting and background changes User-friendly and easy to deploy Suitable for assistive communication applications.

IV. SYSTEM ARCHITECTURE

The system architecture consists of the following modules: User Interface (Webcam Input), Frame Capture Module, Image Preprocessing (RGB Conversion), Hand Landmark Detection Module, Feature Normalization Module, Machine Learning Classification Module, Output Display Module.

This architecture ensures speed, accuracy, and real-time responsiveness.

Architecture Flow:

Gesture Input Flow: User → Webcam Interface → Frame Capture → RGB Conversion → Hand Landmark Detection → Feature Normalization → Random Forest Classifier → Display Predicted Gesture → User

Image-Based Gesture Flow:

User → Webcam → Capture Frame → Convert BGR to RGB → Detect Hand Landmarks → Create Feature Vector → Predict Gesture → Display Text → User

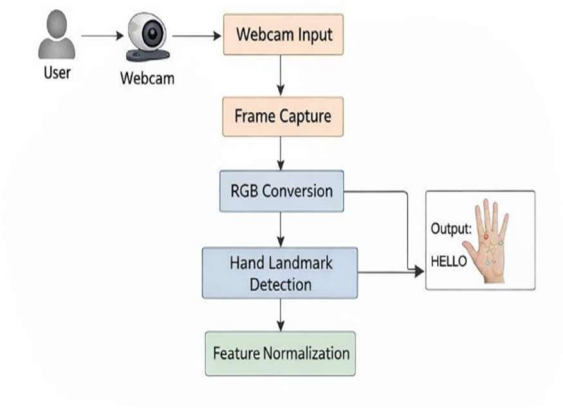

Fig: Overall System Architecture of the Hand Gesture Recognition System

UML DIAGRAM:

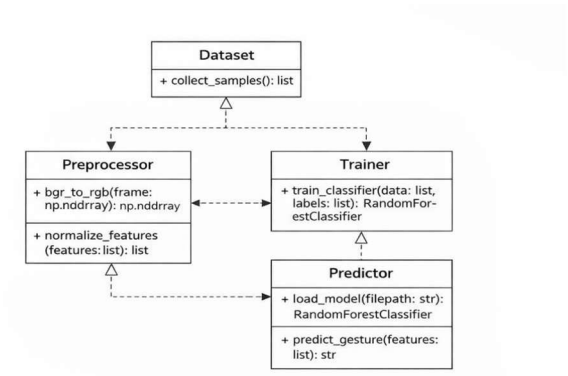

Fig: UML Diagram of the Gesture Recognition Modules

USE CASE:

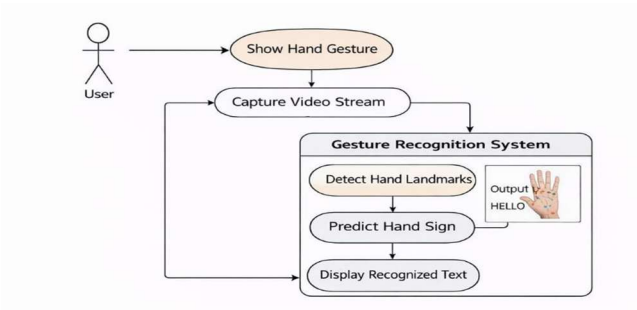

Fig: Use Case Diagram of the Gesture Recognition System

CLASS DIAGRAM:

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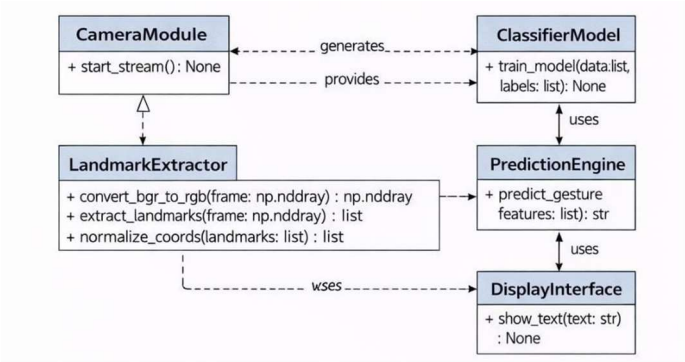

Fig: Class Diagram of the Gesture Recognition System

SEQUENCE DIAGRAM:

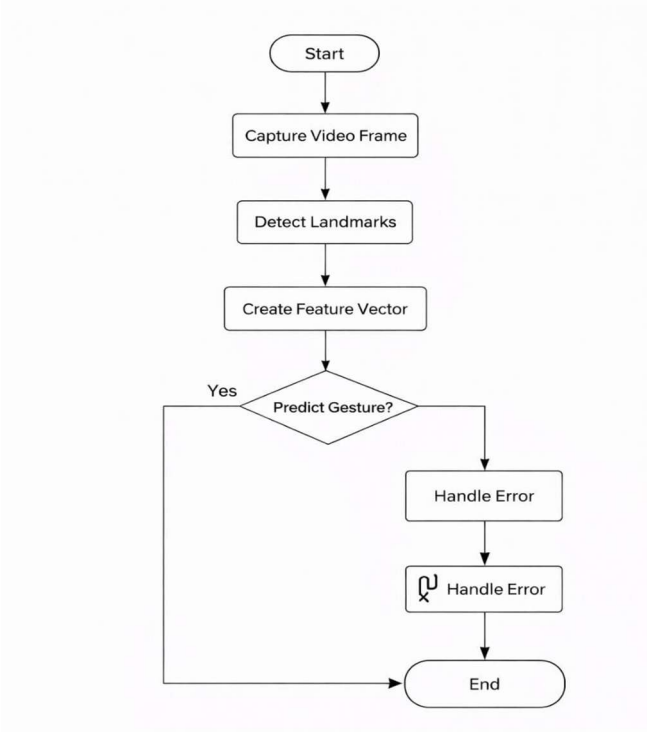

Fig: Activity Diagram of the Gesture Recognition System

V. METHODOLOGY

The proposed Sign Language Detection system follows a structured machine learning pipeline consisting of data collection, preprocessing, feature extraction, model training, and real-time prediction.

1. Data Collection
Gesture samples were collected using a webcam. For each gesture class (Sorry, Good, Bad, Ok, Hi, Thanks, Love u), multiple samples were captured under different lighting conditions and backgrounds. This ensured diversity and improved model generalization.

2. Hand Landmark Detection
MediaPipe Hands was used to detect and track 21 hand landmarks in real time. Instead of processing full images, the system extracts only the landmark coordinates (x, y, z), which represent the geometric structure of the hand.

3. Feature Extraction
The detected landmark coordinates were converted into structured numerical feature vectors. Normalization techniques were applied to reduce variations due to hand position and scale differences.

4. Dataset Preparation
The collected feature vectors were labeled according to their corresponding gestures. The dataset was divided into training and testing sets using a stratified train-test split method to ensure balanced class distribution.

5. Model Training
A Random Forest classifier was selected due to its robustness, ability to handle non-linear relationships, and strong performance with medium-sized datasets. The model was trained using the landmark-based feature vectors.

6. Model Evaluation
The trained model was evaluated using metrics such as:
Accuracy, Misclassification rate, Out-of-Bag (OOB) error
Real-time response performance.
The system achieved high classification accuracy with stable predictions.

7. Real-Time Prediction
During live operation: The webcam captures frames continuously. MediaPipe detects hand landmarks. Extracted features are passed to the trained Random Forest model.

The predicted gesture label is displayed instantly on the screen. Failure-handling mechanisms prevent predictions when no hand is detected.

VI. RESULTS

The Sign Language Detection system was implemented entirely in Python and executed in a local environment using a standard webcam. The experimental setup focused on validating real-time hand tracking, landmark extraction, and machine learning–based gesture classification. MediaPipe was used to detect 21 hand landmarks from each video frame, and these coordinates were converted into normalized feature vectors. The dataset for training consisted of multiple samples collected for each predefined gesture, captured from different angles and slight variations to improve robustness.

The trained Random Forest classifier was evaluated using both stored test samples and live demonstrations. During experiments, users performed gestures in front of the camera while the system continuously detected the hand, extracted features, and generated predictions. Testing covered variations in lighting, background conditions, hand distance from the

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camera, and differences between users. This helped verify whether the model could generalize beyond the training data.

Additional tests were conducted to observe system behavior in challenging scenarios, such as partial visibility of the hand, quick motion, and temporary loss of detection. The application was also monitored for response time to ensure that predictions appeared instantly and supported natural interaction. These experiments confirmed that the integrated pipeline of detection and classification functions effectively in real-time environments.

Evaluation Metrics: The performance of the proposed Sign Language Detection system was evaluated using both quantitative metrics and real-time testing. The dataset of hand landmark feature vectors was divided into training and testing subsets using stratified sampling to ensure equal representation of all gesture classes. After training the Random Forest classifier, the model was tested on unseen data. The overall classification accuracy achieved was 94%, indicating that the system correctly recognized most gestures in the test dataset. This demonstrates that landmark-based geometric features are effective for gesture classification.

S.No	Parameter	Description / Value
1	Model Used	Random Forest Classifier
2	Feature Extraction	MediaPipe (21 Hand Landmarks)
3	Dataset Split	Train-Test Split (Stratified Sampling)
4	Number of Gesture Classes	7
5	Overall Accuracy	94%
6	Misclassification Rate	6%
7	Out-of-Bag (OOB) Error	Low and Stable
8	Real-Time Response Time	Less than 1 second
9	Generalization Across Users	Good
10	Performance Under Lighting Change	Stable with minor variation
11	Major Error Cause	Similar finger configurations
12	Failure Handling	No prediction when hand not detecet

Fig: Performance Evaluation of the Proposed Sign Language Detection System

Gesture	Correctly Classified	Minor Misclassification With
Sorry	High	Rare confusion with Hi
Good	High	Occasionally Ok
Bad	High	Minimal confusion
Ok	High	Good
Hi	Very High	Rare confusion
Thanks	High	Love u (minor cases)
Thanks	High	Love u (minor cases)
Love u	Very High	Thanks (minor cases)

Fig: Class-wise Performance Summary

A confusion matrix was generated to analyze class-wise performance. The matrix showed that most gestures were correctly classified along the diagonal elements, confirming strong prediction capability. Minor misclassifications were observed between visually similar gestures such as “Good” and “Ok,” where finger positions are closely related. However, these errors were minimal and did not significantly affect overall performance.

The Out-of-Bag (OOB) error was also evaluated as part of Random Forest validation. The OOB error remained stable as the number of trees increased, confirming that the model does not overfit and generalizes well to unseen data. In real-time testing using webcam input, the system demonstrated fast response time with predictions generated almost instantly after landmark extraction. The model maintained stable outputs under moderate lighting variations and different user hand orientations. Minor fluctuations occurred during rapid movement or partial hand visibility, but predictions stabilized once landmarks were clearly detected.

Overall, the evaluation confirms that the system achieves high accuracy, stable real-time performance, and good generalization ability, making it suitable for practical sign language assistance applications.

Analysis:

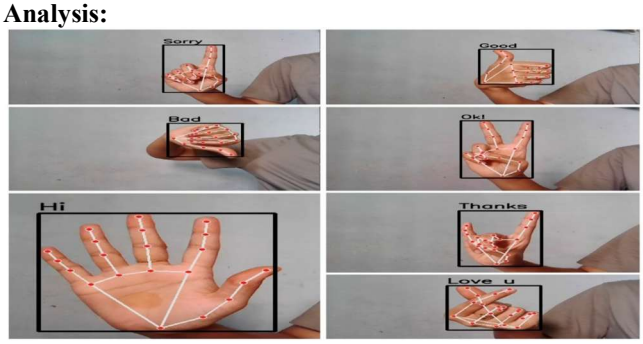

Fig: Recognized Sign Language Gestures with Extracted Hand Landmarks

The experimental results demonstrate that the proposed Sign Language Detection system successfully performs real-time gesture recognition with high responsiveness and stability. As shown in the output samples (e.g., Sorry, Good, Bad, Ok, Hi, Thanks, Love u), the system accurately detects hand landmarks and correctly classifies the gestures into their respective text labels. When users performed gestures that were included in the training dataset, the trained Random Forest classifier efficiently mapped the extracted 21 hand landmark coordinates to the correct gesture class. The predictions were displayed instantly on the screen, confirming that the integration of MediaPipe and machine learning provides smooth real-time interaction.

The landmark-based feature extraction significantly improved the system’s reliability. Since the model uses geometric relationships between key points instead of raw image pixels, it is less affected by background noise, wall color, or minor lighting variations. During testing, the system maintained consistent predictions across multiple trials and different users, demonstrating good generalization capability. The bounding box and landmark visualization also confirm that MediaPipe accurately tracks finger positions and hand structure in real time.

VI . CONCLUSION

This project successfully developed a real-time Sign Language Detection System that recognizes hand gestures using computer vision and machine learning techniques. The system uses a webcam to capture live video, and MediaPipe is employed to detect and track 21 hand landmarks for each frame. These landmarks are converted into numerical feature vectors, which are then used by a trained classifier to predict the corresponding sign or gesture. By focusing on geometric hand representations instead of raw images, the system remains lightweight, fast, and computationally efficient.

The project implemented a supervised learning approach where gesture samples were collected, labeled, and divided into training and testing datasets. A Random Forest classifier was trained to learn the mapping between landmark patterns and gesture classes. After training, the model was integrated into a real-time pipeline capable of continuously detecting hands, extracting features, and displaying predictions instantly.

The developed system demonstrates that accurate and responsive gesture recognition can be achieved without complex deep learning architectures. It works effectively under different lighting conditions and backgrounds while maintaining low hardware requirements. Overall, the project provides a practical, user-friendly, and affordable solution that can support communication assistance, human-computer interaction, and accessibility technologies.

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