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AI-Driven Sign Language

Nikhil Gundlapalli*, Manoj Singh**
Department of Computer Science, S.I.E.S College of Arts, Science, and Commerce, Mumbai, Maharashtra, India
Email: nikhil09gundlapelli@gmail.com)
** (Department of Computer Science, S.I.E.S College of Arts, Science, and Commerce, Mumbai, Maharashtra, India
Email: siescsdept@gmail.com)

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Abstract:

Millions of individuals relying on sign language face communication difficulties due to the lack of widespread fluency among non-signers, leading to social exclusion. Human interpreters are often unavailable or expensive, necessitating an automated solution. This project aims to develop a robust, lightweight, and universally accessible AI system that accurately detects and translates ASL in real-time, bridging the communication gap using computer vision and efficient machine learning models.

This report details an efficient AI system for real-time American Sign Language (ASL) translation, addressing the critical communication barriers faced by millions of sign language users. The system uses a lightweight hybrid architecture: the MediaPipe framework extracts 21 key hand landmarks, which are classified by an optimized Support Vector Machine (SVM) model, chosen for superior efficiency over CNNs. Linguistic coherence is achieved using a Hidden Markov Model (HMM) for next-word prediction. This solution attained a high classification accuracy of 98%. The final system was deployed as an accessible web application featuring real-time Text-to-Speech (TTS) output.

Keywords — **Sign Language Recognition, Computer Vision, MediaPipe, Support Vector Machine (SVM), Hidden Markov Model (HMM), Real-Time Systems, Accessibility, Text-to-Speech, Feature Engineering.**

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I. INTRODUCTION

Millions of individuals relying on sign language face communication difficulties due to the lack of widespread fluency among non-signers, leading to social exclusion. Human interpreters are often unavailable or expensive, necessitating an automated solution. This project aims to develop a robust, lightweight, and universally accessible AI system that accurately detects and translates ASL in real-time, bridging the communication gap using computer vision and efficient machine learning models.

II. PROBLEM STATEMENT

Communication difficulties perpetuate social exclusion in essential settings like healthcare and workplaces. Reliance on interpreters is limited, making spontaneous interactions difficult. For an automated system to be practical, it must overcome two critical technical challenges: first, the need for true real-time performance (low latency), and second, the need to integrate linguistic context to produce coherent sentences rather than isolated words. The project's technical challenge was implementing a resource-efficient pipeline that accurately classifies 43 static hand gestures and uses a linguistic model (HMM) to produce fluent output..

III. OBJECTIVES

The project achieved five key objectives:

●O1: Custom Dataset Creation: Capture and organize a dataset covering 43 ASL classes (alphabet, numbers, and 7 common words).

●O2: Feature Engineering Pipeline: Use MediaPipe to extract 21 hand landmarks and normalize them into standardized numerical feature vectors.

●O3: Optimized Classification Model: Train and validate the Support Vector Machine (SVM) model to achieve a high classification accuracy target of 98%, prioritizing efficiency over resource-heavy deep learning.

●O4: Linguistic Integration: Integrate a Hidden Markov Model (HMM) for next-word sequence prediction to ensure conversational fluency.

●O: Accessible Deployment: Deploy the complete, low-latency system as an accessible web application (Flask) with real-time Text-to-Speech (TTS) output.

LITERATURE REVIEW

Sign language recognition evolved from costly **hardware-dependent systems** to unreliable **classical computer vision** approaches. The shift to **deep learning (CNNs/RNNs)** improved accuracy but introduced high computational costs that restrict real-world deployment. A critical development was the use of advanced feature extraction frameworks like **MediaPipe**, which provides robust, pre-trained hand tracking. This development validates the use of a **hybrid model**—pairing a fast classifier like SVM with an efficient linguistic model like HMM—to achieve high accuracy (98%) with a minimal computational load.

RESEARCH GAP & PROPOSED SOLUTION

Prevailing technologies are limited by: 1) High Computational Overhead: Heavy CNN architectures conflict with the goal of an accessible, real-time tool. 2) Generalization Failure: Simpler models like Random Forest overfit the hand geometry data. 3) Lack of Linguistic Context: Systems fail to connect isolated signs into fluent, context-aware sentences.

The conceptual solution is a "resource-aware AI" pipeline:

1.Feature-Centric Design: MediaPipe guarantees high-quality, normalized feature inputs.

2.Optimized Classification: The SVM classifier provides robust, fast, and generalizable classification (98% accuracy) on this structured input, resolving the speed constraint.

3..3.Fluency Engine: The integration of the lightweight HMM ensures linguistic sequence prediction, overcoming the isolated sign barrier.-and-white hardcopy

METHODOLOGY

Data Acquisition and Feature Engineering

A custom dataset was captured covering 43 distinct gesture classes (A-Z, 0-9, and 7 common words). The MediaPipe framework was used to identify and extract 21 key hand landmarks (wrist, knuckles, fingertips). These coordinates were rigorously normalized relative to the hand's bounding box. This normalization ensures the 42-dimension feature vector is invariant to position or size, directly supporting the system's 98% accuracy and robustness.

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Model Selection and Training: Why SVM Over CNN?

A. *Initial testing showed the Random Forest model suffered from overfitting on the landmark geometry. The Convolutional Neural Network (CNN) was rejected because it is computationally heavy, demands long training times, and is unsuitable for the project's real-time, lightweight goal. The final choice was the Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel. SVM was selected because it is computationally lightweight, handles the high-dimensional features effectively, avoids overfitting, and achieves a validated accuracy of 98%.*

Model Comparison: Performance and Efficiency Analysis

Model	**Observed Accuracy**	**Computational Load**	**Decision Rationale**
Random Forest	High (Prone to Overfitting)	Moderate	Discarded due to poor generalization on landmark data.

Convolutional Neural Network (CNN)	High (Theoretical)	Heavy	Discarded, unsuitable for real-time, low-resource deployment.
Support Vector Machine (SVM)	98%	Lightweight	Selected: superior accuracy, efficiency, and robustness on structured features.

B. System Architecture and Natural Language Integration and Bookmarks

- AllThe workflow captures the hand movements via a webcam, extracts 21 landmarks via MediaPipe, uses SVM to classify the gesture, and then passes the result to the linguistic engine.
- The Hidden Markov Model (HMM) serves to predict the next word or phrase in a sentence based on the sequence of signs already recognized. This contextual analysis substantially enhances linguistic coherence and reduces the signing effort required from the user, leading to smoother, faster communication.
- The translated output is immediately processed by the integrated Text-to-Speech (TTS) module, providing real-time audible verbal output. This is crucial for enabling direct dialogue with non-signers in public settings, fulfilling the project's goal of seamless interaction.

Results and Performance Evaluation

The hybrid architecture was successfully validated. The SVM classifier achieved a robust and validated classification accuracy of 98%.

Real-Time Validation: The lightweight pipeline ensured low latency and fast, efficient translation speeds, satisfying the crucial real-time performance requirement essential for live communication.

Functional Outcomes: The system was successfully implemented as a functioning web application, confirming technical feasibility and high user accessibility. The integrated pipeline—encompassing SVM classification, HMM prediction, and TTS conversion—was functionally validated, successfully producing coherent sentences and audible speech in real time.

Unique Contribution / Deployment

The primary contribution is the development of a highly optimized, lightweight, and deployable hybrid pipeline. This solution is based on a "resource-aware AI" philosophy, ensuring that the entire system can function efficiently on standard, non-specialized consumer hardware (bypassing the need for heavy GPUs).

The system was successfully deployed as a low-latency web application using the Flask framework. This deployment strategy ensures the system is universally accessible as a browser extension, maximizing its reach and utility for the hearing- and speech-impaired community

IV. Conclusions

The The project successfully designed and implemented a real-time American Sign Language (ASL) recognition system, achieving a validated classification accuracy of 98%. The hybrid methodology, which leverages MediaPipe, SVM, and HMM, effectively balanced accuracy, speed, and computational efficiency. By providing both real-time textual subtitles and instantaneous verbal output via a universally accessible web interface, the project fulfills its purpose of significantly enhancing communication accessibility.

FUTURE WORK

While robust for static gestures, the system has significant potential for expansion:

●Dynamic Gesture Recognition: Incorporate temporal modeling techniques (e.g., RNNs or LSTMs) to detect complex, continuous motions essential for conversational signing accurately.

●Mobile Application Development: Optimize the architecture for deployment as a native application on mobile platforms (Android/iOS) to enable on-the-go communication.

●Multi-Language Support: Expand the dataset to include other regional sign languages, such as Indian Sign Language (ISL) or British Sign Language (BSL), to achieve a global reach.

●Vocabulary Expansion: Continuously expand the core vocabulary to support richer, more detailed professional and social conversations.

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