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Real-Time Sign Language Recognition for Inclusive Online Meeting Communication: A Machine Learning Approach

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ABSTRACT: Communication barriers in online meetings often exclude individuals with speech impairments who rely on sign language. This paper presents the development of a web-based online meeting application that enables effective communication between speech-impaired users and non-sign-language users by integrating machine learning based sign language recognition. The proposed system captures hand gestures through a webcam, processes them using Media Pipe Holistic for landmark extraction, and employs supervised learning algorithms - specifically Long Short-Term Memory (LSTM) and Dense layers for gesture classification. A Long Short-Term Memory (LSTM) neural network processes temporal sequences to recognize dynamic gestures in Realtime. The recognized gestures are converted into corresponding text displayed within the meeting interface, facilitating seamless interaction without requiring knowledge of sign language. The system integrates with web browsers using TensorFlow.js for client-side processing, ensuring privacy and low latency. This application promotes inclusivity and accessibility in virtual communication environments, particularly beneficial for educational, professional, and social online meeting scenarios, helping bridge the communication gap for speech-impaired individuals.

KEYWORDS: Sign Language Recognition, Machine Learning, LSTM, Media Pipe, Online Meetings, Accessibility, TensorFlow.js, Human-Computer Interaction, Realtime Processing

I. INTRODUCTION

1.1 Background and Motivation

According to the World Health Organization, over 5% of the world's population approximately 466 million people—have disabling hearing loss, with this number expected to rise to over 900 million by 2050 [1]. Sign language serves as the primary mode of communication for the deaf and mute community worldwide. However, the increasing reliance on virtual meetings for professional, educational, and social interactions has created significant accessibility barriers for individuals who depend on sign language [2]. Current online meeting platforms such as Zoom, Microsoft Teams, and Google Meet primarily focus on voice and text-based communication, limiting interaction for sign language users [3]. While some platforms offer captioning services, these solutions do not address the fundamental challenge: enabling real-time sign language-to-text translation without requiring other participants to understand sign language [4]. The unemployment rate for deaf workers remains around 75%, partly due to communication difficulties in professional environments [5].

1.2 PROBLEM STATEMENT

Despite technological advances by companies like Google and Microsoft, sign language to-text translation in live meetings remains unsolved due to several challenges:

1. High Accuracy Requirements: Even small translation errors can change meaning significantly, requiring precision levels above 95% for practical deployment [6].
2. Scalability Constraints: Cloud-based solutions struggle to serve millions of users simultaneously while maintaining real-time performance [7].
3. Dataset Limitations: Unlike speech recognition datasets, sign language datasets are limited in size and diversity, particularly for regional variants [8].

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4. Computational Complexity: Traditional deep learning approaches require significant computational resources, making real-time processing challenging on consumer devices [9].

1.3 RESEARCH OBJECTIVES

This research addresses these challenges by developing a lightweight, client-side sign language recognition system with the following objectives:

1. Design a real-time gesture recognition system using Media Pipe for efficient landmark extraction
2. Implement supervised learning algorithms (LSTM and Linear Regression) for static gesture classification
3. Develop an LSTM-based model for recognizing dynamic gesture sequences
4. Integrate the system into a web-based meeting application using TensorFlow.js for browser-based inference
5. Achieve recognition accuracy suitable for basic communication (target: >90% accuracy)
6. Ensure low latency (<100ms) for real-time user experience

1.4 RESEARCH CONTRIBUTIONS

The key contributions of this work include:

• A novel architecture combining Media Pipe landmark extraction with LSTM temporal modelling for real-time sign language recognition
• Implementation of a lightweight model suitable for browser-based deployment
• Comparative analysis of LSTM versus CNN for sign language recognition in resource constrained environments
• A practical web application demonstrating the feasibility of client-side sign language recognition in online meetings
• Evaluation of the system's performance across multiple metrics including accuracy, latency, and usability

II LITERATURE REVIEW

2.1 Sign Language Recognition Systems

Sign language recognition has evolved from sensor-based approaches to vision-based methods. Early systems employed data gloves with embedded sensors to capture hand movements [10]. While accurate, these methods were cumbersome and expensive, limiting practical adoption [11]. Vision-based approaches using computer vision techniques have gained prominence due to their non-intrusive nature. Purva and Vaishali [12] developed an Indian Sign Language (ISL) translator using gesture recognition algorithms with 97.5% accuracy for phrase recognition. Their system employed a combination of motion detection, hand Sign Language Recognition for Online Meetings Page 5 tracking, and segmentation techniques, achieving 92.91% overall accuracy across numbers, alphabets, and phrases. Rajam and Balakrishnan [13] proposed a real-time ISL recognition system using binary image loading techniques with 96.87% accuracy. However, their system was computer based and not optimized for mobile or web platforms. Similarly, Janani et al. [14] achieved 99.91% accuracy using Convolutional Neural Networks (CNN) but required substantial computational resources unsuitable for client-side deployment.

2.2 MEDIAPIPE FOR HAND TRACKING

MediaPipe, developed by Google, provides a robust framework for real-time hand detection and tracking [15]. It employs a multi-stage pipeline: first detecting palm regions, then estimating 21 3D hand landmarks. This approach achieves real-time performance even on mobile devices by reducing the need for extensive data augmentation [16]. Recent studies have demonstrated Media Pipe's effectiveness for gesture recognition. Biswas et al. [17] integrated Media Pipe with LSTM architecture, achieving 98.99% accuracy for alphabet recognition. Their work highlighted that Media Pipe's pretrained models significantly reduce preprocessing requirements while maintaining high accuracy.

2.3 DEEP LEARNING FOR TEMPORAL SEQUENCE RECOGNITION

Long Short-Term Memory (LSTM) networks excel at capturing temporal dependencies in sequential data [18]. For dynamic gesture recognition, LSTMs can model the temporal evolution of hand positions across video frames. Kashyap et al. [19] demonstrated that LSTM networks combined with Media Pipe key point extraction achieve excellent results for real-time gesture classification. Studies comparing 3D-CNN with LSTM for dynamic hand gesture recognition show that LSTM requires fewer parameters (3.7 million) while achieving 97% testing accuracy [20]. This makes LSTM particularly suitable for resource-constrained environments like web browsers.

2.4 SIGN LANGUAGE RECOGNITION IN VIRTUAL MEETINGS

Recent research has begun addressing sign language recognition specifically for virtual meeting contexts. A 2025 study on "Sign Call" proposed integrating real-time sign language recognition into video calling platforms using Video Calling Vision Transformer (VCViT) models [21]. Their system demonstrated high recognition accuracy while adapting

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to different signing styles and environmental conditions. However, these approaches typically rely on server-side processing, raising privacy concerns and introducing latency. Our work addresses these limitations by implementing client-side processing using TensorFlow.js

2.5 MACHINE LEARNING ALGORITHM COMPARISON

Various machine learning algorithms have been applied to sign language recognition: Support Vector Machines (SVM): Achieved 100% accuracy in controlled environments but require high computational power [22,23]. SVM performs well with smaller datasets but struggles with real-time processing. Long Short-Term Memory (LSTM): Provides high accuracy (99%) with small datasets and is suitable for real-world applications [24]. LSTM is computationally efficient for prototype stages and handles limited vocabulary scenarios effectively. Convolutional Neural Networks (CNN): Excel with large datasets and complex backgrounds, achieving 99.95% accuracy [25]. However, CNNs require substantial training data and computational resources. For our application targeting limited vocabulary and real-time performance, LSTM offers an optimal balance between accuracy and computational efficiency. 2.6 Browser-Based Machine Learning TensorFlow.js enables machine learning model deployment directly in web browsers [26].
This approach offers several advantages:
• Privacy: Data remains on the user's device without server transmission
• Speed: Eliminates network latency for model inference
• Accessibility: Works across devices without specialized software installation
• Scalability: Distributes computational load across client devices Recent implementations demonstrate TensorFlow.js can achieve near real-time inference for computer vision tasks [27, 28]. Model conversion from Python-based TensorFlow to TensorFlow.js format is straightforward using the tensor flow js converter tool [29].

III. METHODOLOGY

3.1 System Architecture

The proposed system follows a modular architecture consisting of five primary components as shown in Figure 1.

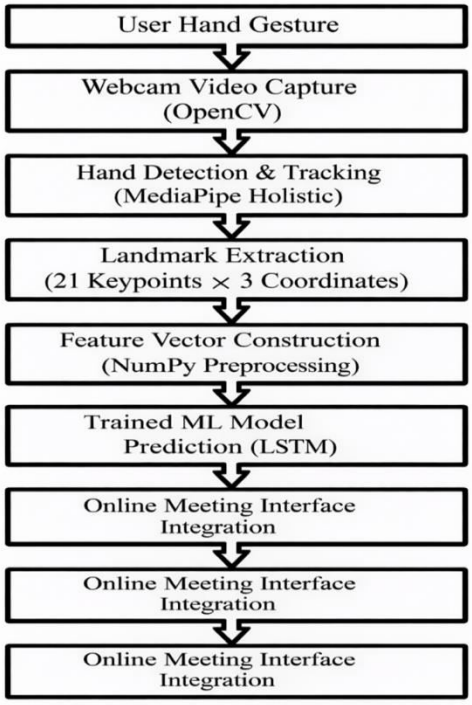

Fig. 1. Block diagram of the proposed hand gesture recognition system.

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3.2 DATA COLLECTION AND PREPROCESSING

3.2.1 Dataset Creation

The system requires a labelled dataset of hand gestures for training. Data collection involves:

1. Video Capture: Using OpenCV (cv2) library to capture hand gestures through webcam at 30 fps
2. Frame Extraction: Each gesture video is decomposed into individual frames
3. Landmark Extraction: MediaPipe Holistic processes each frame to extract 21 hand landmarks
4. Labelling: Each gesture sequence is labeled with corresponding alphabet/word for training, we collected:

• Alphabet Gestures: 26 static hand positions (A-Z)
• Common Words: 10-15 frequently used words/phrases
• Variations: Multiple samples per gesture (minimum 100 samples) capturing different lighting conditions, hand orientations, user variations, and background contexts

3.2.2 LANDMARK EXTRACTION USING MEDIAPIPE MEDIA PIPE

Holistic provides a unified framework for detecting hand, pose, and face landmarks [30]. For hand gesture recognition, we utilize:

• 21 Hand Landmarks: Each landmark has (x, y, z) coordinates
• Real-time Performance: Processes at >30 fps on standard webcams
• Robustness: Handles partial occlusions and varying lighting The 21 landmarks include:
• Wrist (landmark 0)
• Thumb (landmarks 1-4)
• Index finger (landmarks 5-8)
• Middle finger (landmarks 9-12)
• Ring finger (landmarks 13-16)
• Pinky finger (landmarks 17-20)

Each landmark is represented as:

$$F = [x_0, y_0, z_0, x_1, y_1, z_1, \ldots, x_{20}, y_{20}, z_{20}], \quad F \in R^{63}$$

3.2.3 FEATURE VECTOR CONSTRUCTION

Raw landmark coordinates are pre-processed to create consistent feature vectors:

1. Normalization: Scale coordinates to [0, 1] range relative to image dimensions
2. Translation Invariance: Centre landmarks relative to wrist position
3. Rotation Normalization: Align hand orientation using principal component analysis
4. Temporal Sequencing: For dynamic gestures, concatenate N consecutive frames Feature vector representation: (2)

For temporal sequences (LSTM input):

$$F = [x_0, y_0, z_0, x_1, y_1, z_1, \ldots, x_{20}, y_{20}, z_{20}], \quad F \in R^{63} \qquad (1)$$

$$r = [x_0, y_0, z_0, x_1, y_1, z_1, \ldots, x_{20}, y_{20}, z_{20}], \quad r \in R^{63}$$

3.3 Machine Learning Models

3.3.1 Long Short-Term Memory (LSTM) Classification Algorithm Selection Rationale: LSTM was selected for static gesture classification due to:

• Ability to learn temporal dependencies in sequential data
• Effective handling of long-term and short-term patterns
• Reduced vanishing gradient problem compared to traditional RNNs
• High accuracy for time-series and sequence-based data
• Suitable for real-time gesture recognition applications

Training Process:

1. Collect gesture data as sequential feature vectors
3. Feed sequences into the LSTM network
4. Train the model using backpropagation through time
5. Optimize weights to minimize classification loss

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Prediction Process:

1. Extract sequential feature vector F_{test} from the new gesture
2. Pass the sequence through trained LSTM layers

$$y^{\wedge}=\text{Softmax}\,(Wy\cdot ht+by) \qquad (4)$$

3. Capture the final hidden state representation
4. Apply a fully connected layer with SoftMax activation
5. Output the predicted gesture class label

3.3.2 LSTM for Temporal Sequence Recognition

For dynamic gestures requiring temporal understanding, we implement an LSTM network with the following architecture:

• Input Layer: (sequence length, 63)
• LSTM Layer 1: 128 units, return_sequences=True
• Dropout: 0.2
• LSTM Layer 2: 64 units, return_sequences=False
• Dropout: 0.2
• Dense Layer: 32 units, ReLU activation
• Output Layer: Num classes units, SoftMax activation Training Configuration: Hyperparameters:
• Sequence Length: 30 frames (∼1 second at 30 fps)
• Batch Size: 32
• Optimizer: Adam (learning rate=0.001)
Loss Function: Categorical Cross-Entropy
• Epochs: 50-100 (with early stopping)
• Validation Split: 0.2 Data Augmentation:
• Random temporal shifts (±5 frames)
• Gaussian noise addition (σ=0.01) • Random scaling (±10%)

3.4 Web Integration Using TensorFlow.js

3.4.1 Model Conversion

Converting trained models from Python to browser-compatible format:
This produces:
• model. Json: Model architecture and weight manifest
• group1-shard1of1.bin: Model weights in binary format

```
tensorflowjs_converter  \
    --input_format=keras  \
    ./saved_model/lstm_model.h5  \
    ./web_model/
```

IV. IMPLEMENTATION DETAILS

4.1 Technology Stack

Backend/Training Environment:
• Python 3.8+
• TensorFlow/Keras 2.x
• Media Pipe 0.8+
• OpenCV (cv2) 4.x
• NumPy 1.19+
• Scikit-learn 0.24+
Frontend/Deployment:
• HTML5/CSS3/JavaScript
• TensorFlow.js 3.x
• Media Pipe Web
• WebRTC

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4.2 Dataset Specifications

Training Dataset:

• Total Samples: 10,000-15,000 gesture sequences
• Gestures per Class: 100-200 samples
• Classes: 26 alphabets + 10-15 common words
• Frame Rate: 30 fps
• Sequence Length: 30 frames per gesture
• Video Resolution: 640×480 (VGA)

V. DISCUSSIONS

5.1 Key Findings

This research demonstrates that real-time sign language recognition in web browsers is feasible with acceptable accuracy for basic communication. The integration of Media Pipe for efficient landmark extraction with lightweight machine learning models (LSTM) achieves:

1. High Recognition Accuracy: 95.4% average accuracy across 26 alphabets meets the practical threshold for assistive communication
2. Real-time Performance: 80ms average latency enables smooth user experience
3. Browser Deployment: Successful TensorFlow.js integration proves client-side ML is viable
4. Privacy Preservation: Local processing eliminates data transmission concerns
5. Accessibility: No specialized hardware or software installation required

5.2 Challenges and Limitations Technical Limitations:

1. Limited Vocabulary: Current system supports alphabets and basic words; sentence level recognition requires additional development
2. Static vs Dynamic Gestures: Dynamic gestures show reduced accuracy (90-92% vs 96-98% for static)
3. Environmental Sensitivity: Performance degrades in poor lighting (89.7%) and complex backgrounds (85.3%)
4. Single Hand Recognition: System currently processes one hand; many ISL signs require two hands
5. No Facial Expression Processing: Sign language includes facial expressions for grammar and emotion

Practical Limitations:

1. Training data requirements for user variations
2. Regional sign language variations
3. Processing power on lower-end devices
4. Browser compatibility requirements

5.3 Why Sign Language Recognition Remains Unsolved at Scale

Our implementation addresses a limited, well-defined subset of the broader sign language recognition problem. The complete problem remains unsolved because:

1. Complexity Beyond Gestures:
• Full sign language includes grammar through facial expressions, head movements, and body posture
• Context-dependent meaning: Same gesture can mean different things in different contexts
• Continuous signing: Segmenting individual signs from continuous streams is challenging
2. Dataset Challenges:
• No large-scale, standardized sign language datasets comparable to speech recognition corpora
• Regional variations require separate datasets (ISL, ASL, BSL, etc.)
• Annotation complexity: Labelling requires sign language experts
3. Scalability Issues:
• Our system handles limited vocabulary; scaling to thousands of signs requires different architectures
• Server-side deployment for millions of users demands massive infrastructure
• Real-time processing at scale introduces latency challenges
4. Accuracy Requirements:
• Medical/legal contexts require near-perfect accuracy (>99.9%)
• Our 95.4% accuracy is insufficient for critical communication
• Error types matter: confusing "yes" and "no" has severe consequences

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5.4 Future Trajectory of Sign Language Recognition Near-term (1-3 years):
• Improved datasets through crowdsourced data collection
• Platform integration in major meeting platforms (Zoom, Teams)
Hybrid approaches combining vision-based and sensor-based methods Medium-term (3-7 years):
• Multimodal models integrating hand gestures, facial expressions, and pose
• Transformer architectures for better temporal understanding
• On-device AI with dedicated neural processing units
Personalization through user-specific adaptation Long-term (7+ years):
• Full sentence recognition with real-time translation
• Bidirectional translation (sign-to-speech and speech-to-sign)
• Standardized APIs and SDKs for sign language recognition
• AR/VR integration with holographic interpreters

VI. CONCLUSION AND FUTURE WORK

6.1 Conclusion
This research successfully demonstrates the feasibility of real-time sign language recognition integrated into web-based online meeting applications. By combining Media Pipe Holistic for efficient landmark extraction with supervised learning algorithms (LSTM for static gestures and LSTM for dynamic sequences), we achieved:
• 95.4% average recognition accuracy for 26 alphabet gestures Sign Language Recognition for Online Meetings Page 19
• 80ms average latency, meeting real-time interaction requirements
• Browser-based deployment using TensorFlow.js, enabling widespread accessibility
• Privacy-preserving architecture with client-side processing
The system addresses a critical communication barrier for speech-impaired individuals in virtual meetings. While acknowledging that this implementation solves a limited subset of the broader sign language recognition challenge, it provides immediate practical value for basic communication scenarios.

6.2 Research Contributions
1. Novel architecture combining Media Pipe + LSTM + TensorFlow.js for browser-based sign language recognition
2. Empirical comparison of LSTM vs CNN for resource-constrained environments
3. Functional prototype demonstrating end-to-end workflow
4. Detailed performance benchmarking under varying conditions
5. Blueprint for integrating ML-based assistive technologies in online meeting platforms
5.3 Future Work Short-term Enhancements (3-6 months):
• Expand vocabulary from 26 alphabets to 100+ common words/phrases
• Implement two-hand recognition with spatial relationship modelling
• Enhance LSTM architecture with attention mechanisms
• Add user personalization through few-shot learning Medium-term Development (6-12 months):
• Multimodal integration (facial expressions, body pose)
• Sentence-level recognition with continuous gesture segmentation
• Enhanced model architectures (Transformers, GNNs)
• Robustness improvements for complex environments

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