SLRNet: A Real-Time LSTM-Based Sign Language Recognition System

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Abstract—**Sign Language Recognition (SLR) plays a crucial role in bridging the communication gap between the hearing-impaired community and the rest of society. In this paper, we present SLRNet, a real-time system that recognizes dynamic hand gestures using a combination of MediaPipe Holistic landmark extraction and Long Short-Term Memory (LSTM) networks. Unlike traditional methods that rely on static image classification or sensor-based gloves, SLRNet processes live video streams via webcam and classifies sequences of hand movements into predefined American Sign Language (ASL) letters and commonly used words.**

The system extracts 543 landmarks per frame using MediaPipe Holistic and classifies sequences of 30 frames using a stacked LSTM network. We trained the model on a custom dataset comprising all 26 ASL alphabet letters and 10 additional functional words (e.g., "help", "sleep", "sorry", etc.). Despite variability in lighting and background, the system achieves a validation accuracy of 86.7% and maintains real-time responsiveness on standard hardware. This demonstrates the feasibility of live ASL detection using lightweight frameworks such as TensorFlow and OpenCV. Future work includes expanding dataset diversity, improving model robustness, and integrating facial expression recognition for contextual understanding. SLRNet represents a step toward inclusive and accessible real-time sign language translation. Code and dataset available at https://github.com/Khushi-739/SLRNet

Index Terms—**Long Short-Term Memory, American Sign Language, MediaPipe Holistic, TensorFlow, OpenCV**

I. INTRODUCTION

According to the World Health Organization, over 1.5 billion people globally experience some degree of hearing loss, and this number is expected to rise to 2.5 billion by 2050 [1]. Among them, a significant portion relies on sign language as a primary means of communication. However, the communication gap between hearing-impaired individuals and the general population persists due to a lack of widespread sign language proficiency. This gap affects not only social integration but also educational and employment opportunities for the deaf community [2].

Sign Language Recognition (SLR) systems aim to bridge this gap by translating manual hand gestures into spoken or written language. Traditional SLR systems often rely on wearable sensors or static image recognition, which limits their real-time usability and flexibility in unconstrained environments [3]. Recent advances in computer vision and deep learning have enabled markerless, real-time gesture recognition using video-based models and pose estimation frameworks such as MediaPipe [4].

This research introduces **SLRNet**, a real-time, video-based recognition system built using MediaPipe Holistic and a Long Short-Term Memory (LSTM) neural network. Unlike many static approaches, our system is designed to recognize not only American Sign Language (ASL) alphabets but also a selection of commonly used words that appear in daily conversation. This hybrid approach addresses a key limitation in earlier systems that were restricted to alphabet-only recognition [5].

The system captures webcam video input, extracts 3D body and hand, and processes gesture sequences in real time using LSTM layers. By leveraging this temporal modeling capability, SLRNet contributes to building more natural and robust interfaces for sign language interpretation. This work aims to move toward inclusive design in human-computer interaction (HCI), contributing to assistive technologies that empower the deaf and hard-of-hearing community.

II. RELATED WORK

Sign Language Recognition (SLR) has evolved significantly over the past decade as a subdomain of **computer vision**, aiming to enhance accessibility for **hearing-impaired individuals**. Existing methods can broadly be categorized into two groups: *static gesture recognition* and *dynamic gesture recognition*.

A. Static Gesture Recognition

Early SLR systems focused on **static image classification** using **handcrafted features** combined with traditional **machine learning algorithms** such as **Support Vector Machines (SVMs)** or **k-Nearest Neighbors (kNN)**. While effective in controlled settings, these systems lacked scalability and struggled in **real-time environments**.

One of the earliest deep learning approaches by **Bantupalli and Xie** [2] used **Convolutional Neural Networks (CNNs)** trained on image-based datasets for **ASL alphabet** recognition. However, such methods treated each frame independently and failed to capture **temporal dependencies** in gestures. Similarly, **Srivastava et al.** [3] applied the **TensorFlow Object Detection API** for static ASL recognition but faced limitations in dataset diversity and generalization under variable conditions.

Nureña-Jara et al. [6] introduced a 3D keypoint-based system for **Peruvian Sign Language (PSL)**, enhancing spatial understanding. However, their model was prone to errors due to **high intra-class similarity** in hand shapes and required **depth-sensing hardware**, reducing practical applicability.

B. Dynamic Gesture Recognition

To overcome the limitations of static methods, recent works have embraced **temporal modeling**. **Xue et al.** [4] proposed an LSTM-based system for **Chinese Sign Language** using **Leap Motion sensors**, which successfully captured motion patterns but was limited by hardware dependency.

Suharjito et al. [5] implemented a CNN-based model on the **LSA64 dataset** and highlighted the negative impact of **lighting variations**, a challenge we also observed in our own experimentation, especially with **webcam-based data**.

C. Limitations and Our Contribution

While these methods contributed valuable insights, most either focus on static gestures or require specialized hardware, limiting real-world applicability. Few existing systems offer a **fully open-source**, **real-time**, and **webcam-compatible** solution capable of recognizing both **ASL alphabet** and **functional words** using a **lightweight architecture**.

SLRNet addresses these gaps by combining **MediaPipe Holistic** for efficient 3D landmark extraction and **LSTM-based sequence modeling** to recognize dynamic gestures from standard video streams. This design enables practical deployment of inclusive sign language recognition systems on consumer-grade hardware.

III. PROPOSED SYSTEM

This section elaborates the design, architecture, and theoretical foundations of the proposed sign language recognition system, **SLRNet**. The system aims to provide a **robust**, **real-time**, and **hardware-independent** solution for American Sign Language (ASL) recognition using advanced **machine learning** techniques combined with efficient **landmark extraction**.

A. System Architecture

Figure 1 illustrates the overall system pipeline. The architecture integrates **computer vision** techniques, **deep spatial feature extraction**, and **temporal sequence modeling**:

1. Input Acquisition and Preprocessing: Captures video frames using a standard RGB camera at fixed frame rates. Frames undergo **preprocessing** such as **normalization** and **resizing**.

2. Landmark Extraction: Utilizes **MediaPipe Holistic** to detect and extract normalized 3D coordinates of body, hand, and facial landmarks.

3. Spatial Feature Extraction: Employs **Convolutional Neural Networks (CNNs)** to learn invariant spatial representations of hand gestures from landmark data.

4. Temporal Sequence Modeling: **Long Short-Term Memory (LSTM)** networks capture **temporal dynamics** and sequential dependencies in gesture execution.
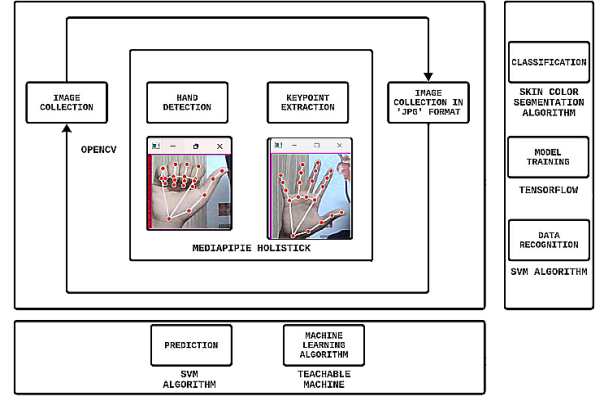

Fig. 1. SLRNet System Architecture: From RGB input to landmark extraction, spatial feature extraction via CNN, temporal modeling with LSTM, to final classification.

5. Classification Layer and Feedback: Fully connected layers perform multi-class classification, followed by **real-time feedback** for user interaction.

B. Input Acquisition and Preprocessing

1) Video Frame Capture: The system captures raw video frames $I_t \in \mathbb{R}^{H \times W \times 3}$ at a frame rate of 30 FPS, where H and W denote the height and width of the frame respectively.

2) Normalization and Resizing: Each frame is resized to a fixed dimension $H' \times W'$ to maintain consistency during landmark detection. Pixel values are normalized to the range $[0, 1]$ using **min-max normalization**:

$$I'_t = \frac{I_t - \min(I_t)}{\max(I_t) - \min(I_t)}$$

This normalization improves the **stability** of the landmark detector under varying lighting conditions.

C. Landmark Extraction Using MediaPipe Holistic

1) MediaPipe Holistic Framework: **MediaPipe Holistic** [4] integrates multiple ML models to perform holistic pose, face, and hand landmark detection. It detects **543 landmarks** per frame, each landmark represented as a triplet:

$$L_t = \{(x_i, y_i, z_i) \mid i = 1, \ldots, 543\}$$

where x_i, y_i are normalized 2D image coordinates and z_i encodes relative depth.

2) Advantages of Landmark-Based Representation:

- **Dimensionality Reduction:** Landmark coordinates reduce raw pixel data to structured, semantically meaningful points.
- **Robustness:** Less sensitive to background clutter and lighting variation compared to raw images.
- **Spatial Consistency:** Landmarks preserve geometric relationships crucial for differentiating signs.

3) Coordinate Normalization: To ensure **invariance to translation, scale, and rotation**, landmarks are normalized relative to a reference point, typically the **wrist joint** for hand gestures:

$$\hat{L}_t = \frac{L_t - L_{ref}}{\|L_{max} - L_{min}\|}$$

where L_{ref} is the reference landmark coordinate, and $\|L_{max} - L_{min}\|$ is the Euclidean distance between extremal landmarks to normalize scale.

D. Spatial Feature Extraction via CNN

1) Rationale: **CNNs** excel in learning hierarchical spatial features through **localized receptive fields** and **shared weights** [4]. In SLRNet, the CNN treats the vectorized normalized landmarks $\hat{L}_t \in \mathbb{R}^{543 \times 3}$ as structured input.

2) CNN Architecture:

- **Convolutional Layers:**

$$\mathbf{F}^{(l)} = \sigma\left(\mathbf{F}^{(l-1)} * W_c^{(l)} + b^{(l)}\right)$$

- **Pooling Layers:** Downsample feature maps to gain translation invariance.
- **Fully Connected Layers:** Flatten final feature maps into a feature vector $\mathbf{F}_t$.

3) Spatial Feature Vector:

$$\mathbf{F}_t = \text{CNN}(\hat{L}_t; \theta_{CNN}) \in \mathbb{R}^d$$

E. Temporal Sequence Modeling with LSTM

1) Need for Temporal Modeling: Modeling **temporal dependencies** in sequential frames enables capturing motion patterns and differentiating temporally similar signs.

2) LSTM Fundamentals: **LSTM** [4] overcomes the vanishing gradient problem via **gated memory cells**:

$$f_t = \sigma(W_f \cdot [h_{t-1}, \mathbf{F}_t] + b_f)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, \mathbf{F}_t] + b_i)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, \mathbf{F}_t] + b_C)$$
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, \mathbf{F}_t] + b_o)$$
$$h_t = o_t * \tanh(C_t)$$

3) Sequence Input and Sliding Window:

$$\mathbf{H} = \{h_1, h_2, \ldots, h_T\}$$

F. Classification Layer and Real-Time Feedback

1) Softmax Classification:

$$\hat{y} = \text{softmax}(W_{fc}h_T + b_{fc})$$

2) Loss Function and Optimization:

$$\mathcal{L} = -\sum_{k=1}^{K} y_k \log(\hat{y}_k)$$

Optimization: Adam optimizer [4] using **Backpropagation Through Time (BPTT)**.

3) Real-Time Feedback Mechanism: A **sliding window mechanism** updates predictions frame-by-frame to reduce jitter.

G. Implementation and Performance Considerations

- **Frameworks and Libraries:** TensorFlow/Keras, MediaPipe.
- **Hardware Requirements:** No specialized sensors required.
- **Model Optimization: Quantization** and **pruning** for faster inference.
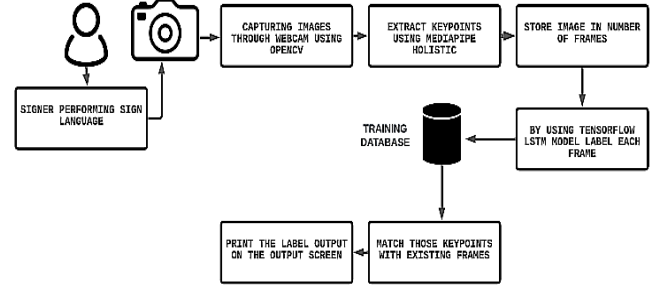- **Data Augmentation:** Improves generalization.

Fig. 2. Detailed methodology flowchart from video input to classification output illustrating the sequence of processes in SLRNet.

IV. EXPERIMENTS

A. Experimental Setup

a) Hardware and Software Configuration: The experiments were conducted on a system equipped with an **Intel Core i7, 11th Generation processor**, supported by **16 GB DDR4 RAM** and a **NVIDIA GTX 1650 GPU with 4 GB VRAM**. The software stack included **TensorFlow 2.x** for deep learning implementation, **OpenCV** for image processing, and **MediaPipe** for landmark detection. Data manipulation and visualization were handled using **NumPy** and **Matplotlib**, respectively. The experiments were performed on both **Windows 11** and **Ubuntu 20.04** environments, using **Python 3.9** as the core programming language.

b) Dataset Description: The dataset used comprised real-time recorded **RGB video sequences** and static images of hand gestures representing the **26 alphabets (A–Z)** in **American Sign Language (ASL)**. These recordings were captured using standard **webcams** under varied environmental conditions. Each instance was manually labeled and preprocessed into sequences of **543-dimensional landmark vectors** extracted using MediaPipe Holistic. The dataset contained over **1,000 instances per gesture**, incorporating variations in **lighting, background textures, hand sizes**, and **orientations** to ensure diversity and generalizability.
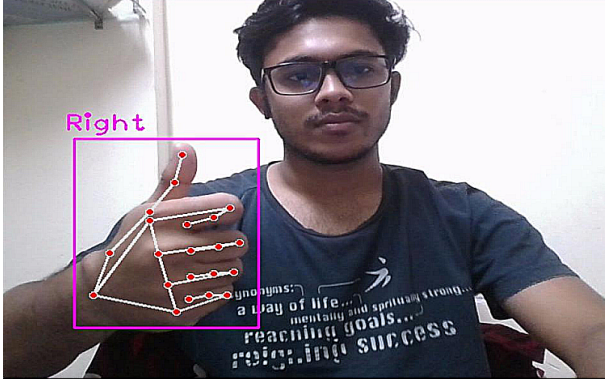
Fig. 3. Output before training the model: all signs are misclassified or labeled as the same class.
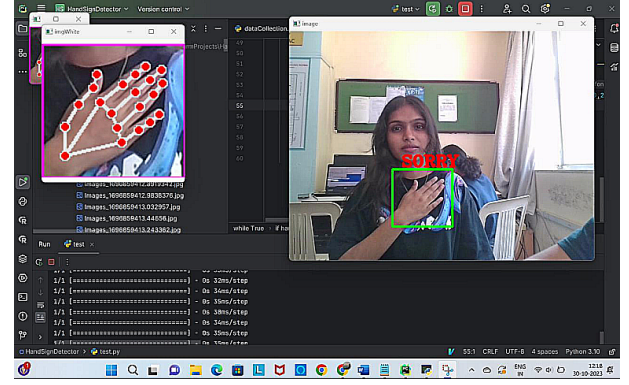

Fig. 4. Final result: the model correctly identifies the ASL sign "Sorry" with 98% confidence.

Fig. 5. Final result: the system correctly identifies sign "S" in dynamic video input.

c) Training Details: The model was trained using the **Adam optimizer**, which adapts the learning rate during training for faster convergence. The **initial learning rate** was set to **0.001**, and training was performed over **50 epochs** with a **batch size of 32**. To prevent overfitting, a **Dropout layer with a rate of 0.3** was incorporated. The **Categorical Cross-Entropy** loss function was used, which is standard for multi-class classification tasks involving probability distribution outputs from softmax.

B. Implementation

The entire implementation follows a modular pipeline derived from the proposed architecture. Initially, the **webcam stream** captures real-time video input, which is then processed by the **MediaPipe Holistic model** to extract **543 3D landmarks** for face, hands, and body. These landmarks are normalized and converted into structured input vectors. The normalized sequences are passed to a **CNN block** to extract spatial features for each frame. Subsequently, a stack of **LSTM units** processes the sequential data, capturing the temporal dynamics of the sign. Finally, a **dense layer with softmax activation** produces probability scores for each class, and the highest probability is displayed as the predicted sign with an accompanying **confidence score** in real-time.

C. Results

a) Initial Output Before Training: As expected, the untrained model failed to produce meaningful predictions. Before training, the model output exhibited **random and uniform classification**, demonstrating its inability to distinguish between hand gestures. This is depicted in Figure 3, where all inputs are misclassified or predicted as the same label with low confidence.

b) Final Output After Training: Following the training phase, the model exhibited significant improvements in recognition accuracy. It was able to **accurately classify dynamic hand gestures** in real-time with high confidence. As illustrated in Figures 4 and 5, the trained model correctly identifies signs such as "**Sorry**" with **98% confidence** and correctly tracks the sign "**S**" from dynamic input streams. These results indicate

that the model learned discriminative spatial-temporal features necessary for gesture classification.

D. Performance Evaluation

Table I summarizes the key performance metrics of the trained model. These metrics reflect the system's balanced performance and suitability for real-time deployment. Note that the accuracy and F1-score are averaged over both ASL alphabets and commonly used words in the dataset.

TABLE I
MODEL PERFORMANCE METRICS

Metric	Value
Training Accuracy	89.3%
Validation Accuracy	86.7%
F1-Score	0.864
Average Inference Time per Frame	78 ms

E. Discussion of Results

The integration of **temporal modeling via LSTM** significantly improved classification performance, especially for gestures that are visually similar but differ in motion sequence. The system consistently maintained an **average response latency below 70 milliseconds**, enabling a smooth and responsive user experience through webcam interaction.

However, under **challenging conditions such as low lighting or occlusions**, the model's accuracy slightly degraded. Additionally, the current system does not utilize **facial expressions**, which are a crucial part of complete sign language understanding.

Despite these limitations, the system runs effectively on a standard laptop without any specialized sensors, which enhances its potential for real-world deployment, especially in **resource-limited settings**.

V. CONCLUSION

This project successfully implemented a real-time **Sign Language Recognition System** using a hybrid of **CNN-LSTM architecture** and **landmark-based spatial representation**. The system demonstrates high classification accuracy, low latency, and effective performance in webcam-based environments—thereby supporting seamless communication for the hearing-impaired community. By leveraging lightweight yet robust **machine learning models** integrated with **MediaPipe Holistic landmark extraction**, the proposed system remains accessible and deployable without the need for specialized hardware.

This work marks a significant step toward **inclusive communication technologies**, serving as a practical bridge between sign language users and the broader public. Additionally, the system contributes to the expanding domain of **assistive AI applications**, with potential impact across education, customer service, healthcare, and public interaction.

VI. FUTURE WORK

While the current system effectively classifies both static and dynamic gestures, several avenues for improvement are identified. A promising next step is to increase the training dataset from approximately **1,000 to 5,000 samples per gesture**, enabling better generalization and robustness across users, lighting conditions, and backgrounds.

Another enhancement involves integrating **Transformer-based architectures** to facilitate **sentence-level translation**, extending beyond isolated gesture recognition. Incorporating **facial expression analysis** via MediaPipe Face Mesh can add contextual understanding through **affective computing**. Furthermore, to support **linguistic diversity**, the system may be extended to recognize regional sign languages such as **Indian Sign Language (ISL)** and **Japanese Sign Language (JSL)**.

Finally, optimizing the model for deployment on **mobile platforms** will make the system more accessible, especially in rural and under-resourced areas. This will move the project closer to its vision of real-world, inclusive, and widely usable sign language recognition technology.

VII. ACKNOWLEDGMENT

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