Real-Time Sign Language Gesture Recognition with Facial Expression Integration

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Abstract. Real-time multimodal sign language recognition systems have been developing very fast in the past years. However, the inclusion of facial expressions for the proper interpretation of sign language is still a less researched topic. This paper is concerned with a real-time multimodal sign language recognition system integrating gesture recognition and facial emotion detection. Gesture recognition utilizes a CNN-LSTM model with MobileNetV2 for spatial feature extraction and LSTM for temporal learning. With DeepFace, facial emotion detection is realized, using analysis of facial expressions for adding an emotional context to the signs. The system operates based on live camera input; the predictions are rendered in real-time for a natural way of interaction. Evaluation with the proposed architecture on Small WLASL gave it a high score in gesture classification at an overall 92%, surpassing previously established methods. This greatly improves the system's ability to resolve ambiguities between similar gestures and capture the full semantic depth of the sign language. The results thus illustrate the importance of multimodal learning in gesture recognition systems and point to the possibility of real-time sign language recognition with facial expression integration in order to enhance accessibility and communication among deaf and hard-of-hearing people.

Keywords: Sign language recognition, gesture recognition, facial emotion detection, CNN-LSTM, DeepFace, real-time processing.

1 INTRODUCTION

Communication is basically a fundamental aspect of human life. It is enabling people to exchange their thoughts, emotions, and intentions. For people who are either born deaf or have developed their hearing and speech impediment, sign language has provided them with a medium as rich and structured as using manual gestures, facial expressions, and body movements. Over 430 million people worldwide live with disabling hearing loss according to the WHO, numbers expected to hit 700 million by 2050 underscoring the critical need to create technologies for inclusiveness and accessibility [1,2].

Although sign language plays a significant role, its adoption and understanding are limited to specific communities and can pose a barrier in broader social and professional interactions. Automatic Sign Language Recognition (SLR) systems promise to bridge this gap by enabling real-time translation of sign language into spoken or written forms. [3]. However, the current SLR systems mostly emphasize the manual gestures and overlook the importance of facial expressions, which are critical in conveying emotional content and further clarifying the meaning of the message[4]. Recent advances in deep learning have shown the possibility of integrating multimodal data, that is, gesture and emotion recognition to improve the accuracy and robustness of these system [5,?].

Facial expressions are an integral part of sign language, as they complement hand gestures but also carry emotional and contextual nuances[6]. Happiness, sadness, frustration, and so on, can significantly change the meaning of gestures; therefore, facial expressions need to be included for accurate recognition. However, combining facial emotion recognition with SLR poses some specific challenges, including variability in facial features, changes in lighting conditions, and computational complexity [7].

In this work, we propose a novel framework for deep learning-based gesture recognition in sign language together with facial emotion detection. We make use of the spatial feature extraction efficiency by using MobileNetV2 architecture and model [8] for efficient spatial feature extraction and Long Short-Term Memory (LSTM) networks [9] for modeling the temporal dependencies of sequential gestures. Additionally, the DeepFace framework [10] will be used to analyze the facial expressions for robust emotion classification. These components are bonded together using a new mechanism, which integrates gesture recognition with emotion detection, producing a better understanding of sign language communication. The system is designed to work in real-time using a standard webcam, making it a very practical solution for live communication.

The proposed approach is assessed on benchmark datasets for demonstrating the effectiveness of the method in recognizing complex sign language gestures and interpreting emotional context. This study contributes to the advancement of accessible communication technologies by addressing both gestural and emotional aspects of sign language and enabling real-time interaction through a webcam. The rest of this paper is organized as follows: Section II discusses related work and points out the gaps of existing approaches. Section III explains the proposed methodology including data preprocessing, model architecture, and training strategies. Section IV presents the experimental results and their implications. Finally, Section V concludes the paper, and Section VI provides directions for future research.

2 Related work

A number of critical research areas based on their potential to greatly enhance communication for the deaf and the hearing, recognition through development automated sign language gesture recognition systems are currently becoming more important and more viable. Advances have been made in computer vision in conjunction with deep learning with that robust systems can be seen to recognize isolated and continuous sign language gestures, towards greater accessibility and inclusiveness.

In the past, gesture recognition systems were based on the glove-based or tracker-based approach because of their higher accuracy. However, it was obtrusive as well as expensive, leading to its limited deployment. Vision-based approaches emerged because they were more practical where cameras captured gestures and emotions. Early vision-based techniques were about handcrafted feature extraction using traditional classifiers such as HMMs and DTW [11,12].While effective in handling static gestures or limited vocabularies, it suffered significantly when dealing with more complex gestures and larger vocabularies, especially in more realistic environments.

Introduction: Deep learning completely changed the face of the field of sign language recognition (SLR) in that feature extraction is performed automatically. The architecture further gets into Hybrid CNN and RNNs combined into CNN-LSTM-based architecture or further combinations with attention mechanisms exhibit improvement in accuIt was followed by sequence-to-sequence-based architectures and transformer-based structures with improvements in continuous SLR as better alignment between an input gesture and its produced output could be achieved through improvement of modeling sequences over time and reduction in errors of misclassification.[13].

Pose estimation approaches, including SPOTER and Graph Convolutional Networks (GCNs), also started becoming popular with computational efficiency as well as invariance to light variation and background variations. The limitation here is that these models don't account for more specific details like finger movement or facial expression, which may be vital for a person to interpret complex gestures as well as non-verbal communications [12,14]. Image-based models, like MobileNetV2 and 3D-CNNs, produce more robust feature representation capabilities. Because SLRs are effective, these have the challenge of increasing computational demands, especially challenging towards realization and implementation on edge devices in their real-time applications [15]. Added is more difficulty in the case of continued sequential SLR because of nature. Some techniques include that of correlation networks, Sliding Window Mechanism or Temporal Convolution Networks (TCNs), the latter providing better accuracy over latency in real-time operations [16].

Despite the encouraging advancements, many of these gaps remain open. Many models focus on hand movements exclusively, overlooking non-manual cues that have crucial roles in interpretation and conveying context-specific expressions related to emotion-driven communication [17].Moreover, the absence of varied and signer-independent datasets reduces generalization of models for variations between different sign languages, regional varieties, and styles. For example, although the datasets WLASL and RWTH-PHOENIX 2014T are large enough, they do not sufficiently represent diversity in signers and signing conditions [18].This results in poor performance when models trained on these datasets are deployed to unseen environments or signers.

More demanding of the balance between low latency and high accuracy for real-time implementations, however, transformer-based models, being computationally expensive, make them not very fit for use on edge devices or within resource-constrained environments. Attempts to optimize such models by using lightweight architectures, like MobileNetV2 and pruning techniques, hold hope, but at a penalty on accuracy when it's applied to larger vocabularies [19]. Further, emotion recognition is another area that is highly under-explored in spite of its critical contribution to interaction quality and provision of context for gestures. The addition of multimodal inputs like gestures, facial expressions, and audio cues will significantly improve the contextual understanding of sign language.

This study addresses these challenges and contributes to the development of scalable, multimodal, and real-time SLR systems that understand gestures and emotions. The approach is based on lightweight architectures and multimodal fusion techniques, ensuring a balance between accuracy and computational efficiency, thus making it usable on a wide range of devices and applications.

3 Methodology

The methodology contains the framework and techniques of developing the integrated system with gesture recognition and facial emotion detection. It includes the overall design of the system, preparation of the dataset, data-preprocessing steps, model architecture, and real-time implementation. This section explains every component in detail to explain the functionality of the system.

3.1 Dataset Description

The dataset used in this study is the *Small WLASL Dataset* [20], a subset of the larger Word-Level American Sign Language (WLASL) dataset. This dataset, containing isolated sign language gestures, is suitable for real-time recognition systems. Major characteristics of the dataset include: The dataset comprises 50 unique sign classes representing commonly used gestures in American Sign Language (ASL). It features videos performed by a single signer ensuring that the execution of the gesture is consistent. For every sign class, multiple video samples are available providing variation in the speed and the way the gestures are executed. Figure 1 shows example frames extracted from the "Deaf" class.

3.2 Data Preprocessing

Preprocessing ensures uniformity across samples and prepares data for deep learning. The preprocessing steps for video data ensure consistency and suitability for deep learning. Videos are **padded** to a fixed number of frames (30) to handle varying sequence lengths, as illustrated in Equation 1:

Fig. 1. Sample frames extracted from a video in the "Deaf" class of the Small WLASL dataset.

$$\mathbf{X}_i = [F_1, F_2, \ldots, F_k, \mathbf{0}_{k+1}, \ldots, \mathbf{0}_N] \tag{1}$$

where $F_1, F_2, \ldots, F_k$ are frames, and $\mathbf{0}_{k+1}$ represents padding frames.

Next, the frames are **resized** to 224×224, matching the input dimensions of MobileNetV2. Finally, **normalization** is applied, where pixel values (p) are normalized to the range $[0, 1]$, as described in Equation 2:

$$p_{\text{norm}} = \frac{p}{255} \tag{2}$$

3.3 Model Architecture

The proposed architecture in Figure 2, involves two streams: spatial-temporal feature learning for gestures and facial emotion recognition.

Stream 1(Gesture Recognition) Gesture recognition uses deep learning to extract spatial features from video frames and model their temporal relationships.

Spatial Feature Extraction We used a pre-trained convolutional neural network, MobileNetV2, designed for efficiency in computation. MobileNetV2 optimizes performance through *depthwise separable convolutions*, which split the standard convolution into two operations: depthwise convolution for spatial filtering and pointwise convolution for combining features. Furthermore, MobileNetV2 incorporates *linear bottlenecks*, *inverted residual blocks*, and *squeeze-and-excitation* modules, enabling a balance between accuracy and efficiency. MobileNetV2 extracts a $1 \times 1 \times 1280$ feature vector for each frame F_t. This results in a sequence of feature vectors with dimensions $m \times n$, where m represents the vector size (1280) and n is the number of frames. Mathematically, this extraction can be expressed as:

$$\mathbf{S}_t = \text{MobileNetV2}(F_t), \quad t = 1, \ldots, N \tag{3}$$

where $\mathbf{S}_t$ is the spatial feature vector for frame F_t.

Temporal Modeling Using LSTM The spatial feature vectors are passed to an LSTM network for modeling the temporal dependencies. The LSTM, introduced by Hochreiter and Schmidhuber, solved the vanishing gradient problem associated with traditional RNNs. This was achieved through three gates: forget, input,

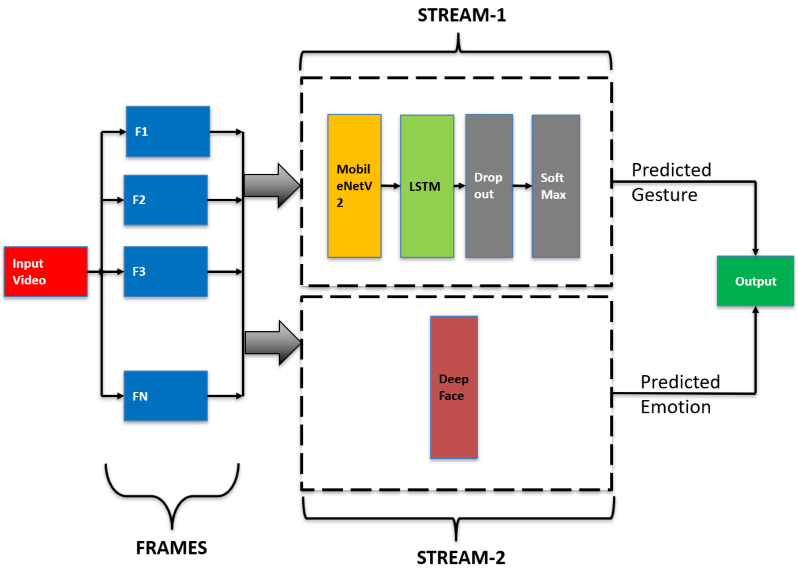

Fig. 2. The architecture of the proposed model, consisting of two streams for gesture and emotion recognition.

and output gates, which allow the proper flow of information in a memory cell, hence facilitating proper long-term sequential learning.

This is through deciding whether to retain information coming from the previous cell state or discard it. That ensures only relevant data would move forward. The input gate identifies new information that has to be added to the cell state, using candidate values to update. Then comes updating the cell state, adding the retained information together with the newly added. Lastly, the output gate determines the next hidden state, which is used to make future predictions and propagated to the next layer. This enables LSTMs to successfully capture temporal patterns and dependencies in sequential data.

Classification The final hidden state $\mathbf{h}_N$ is fed through a dense layer with softmax activation to calculate class probabilities:

$$P(y = c|\mathbf{X}) = \frac{\exp\left(\mathbf{W}_c \cdot \mathbf{h}_N + b_c\right)}{\sum_{c'} \exp\left(\mathbf{W}_{c'} \cdot \mathbf{h}_N + b_{c'}\right)} \tag{4}$$

Here, $\mathbf{W}_c$ and b_c are the weights and bias for class c.

Stream 2(Facial Emotion Recognition) The facial emotion recognition module employs DeepFace, a pre-trained model, for robust feature extraction.

DeepFace takes each detected face Face_t generates the emotion vector in a higher-dimensional space $\mathbf{E}$:

$$\mathbf{E} = \text{DeepFace}(\text{Face}_t) \tag{5}$$

The emotion vector $\mathbf{E}$ that is extracted is then fed into a fully connected layer with softmax activation, in order to classify emotions as belonging to one of a set of predefined categories (e.g., happy, sad, angry).

$$P(e = k|\mathbf{E}) = \frac{\exp\left(\mathbf{V}_k \cdot \mathbf{E} + b_k\right)}{\sum_{k'} \exp\left(\mathbf{V}_{k'} \cdot \mathbf{E} + b_{k'}\right)} \tag{6}$$

Here, $\mathbf{V}_k$ and b_k:are the weights and bias for class c.

Output Fusion The outputs of the gesture recognition and emotion recognition streams are combined to generate the final result.

$$\begin{aligned} \text{Output} = {} & \text{Class label from gesture recognition} \\ & + \text{Class label from emotion detection} \end{aligned}$$

3.4 Implementation Details

Hardware and Framework: The model is implemented in TensorFlow and was trained on a Ti GPU with 50 GB VRAM (Google Colab). The learning rate is set to 0.001 with exponential decay, using the Adam optimizer and cross-entropy loss for both gesture and emotion classification tasks.

3.5 Real-Time Implementation

The real-time system operates by capturing video frames from a webcam feed, which are then preprocessed to ensure uniformity. This preprocessing involves resizing the frames to match the input dimensions of the model, normalizing pixel values, and detecting faces for emotion analysis. Once preprocessed, the frames are passed through two parallel streams: the gesture recognition stream and the emotion detection stream. The outputs from both streams are subsequently fused to provide a comprehensive prediction, which is displayed in real-time on the live video feed, offering an interactive and seamless user experience.

4 Results and Analysis

This section evaluates the performance of the proposed system using standard statistical metrics, such as accuracy, precision, and recall. These metrics are crucial for the assessment of the efficiency of deep learning models across diverse samples and robust generalization.

4.1 Performance Metrics

The evaluation criteria used in this research study are accuracy, precision, and recall. **Accuracy** explains the number of instances, which were correctly classified over all samples classified. **Precision** is the fraction of correctly classified positive classes over the total number of positive classes predicted. **Recall** depicts the network's ability to predict all actual positive samples out of all the predictions made as positive.

The evaluation metrics are calculated using the following formulas:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

Here, TP, FP, TN, and FN represent the values of true positives, false positives, true negatives, and false negatives, respectively.

Table 1 summarizes the performance of the proposed system:

Table 1. Performance metrics for the gesture recognition module.

Metric	Value (%)
Accuracy	91.3
Precision	89.8
Recall	90.2

4.2 Sample of Results

The frames in Figure 3 were captured by a webcam and passed through the proposed Hybrid CNN-LSTM framework. The model correctly classified the gesture as **Deaf**, It is also capable of recognizing isolated sign language gestures. Furthermore, the integrated emotion detection module detected the associated emotion as **Neutral**.

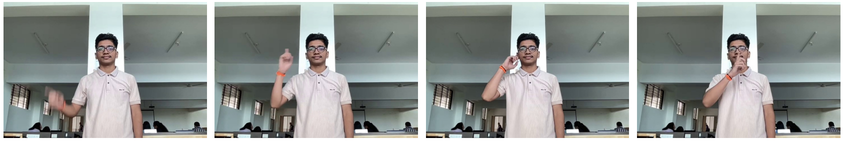

Fig. 3. Sample frames extracted from web cam .

4.3 Interpretation of Results

The results show that gesture recognition fused with emotion detection remarkably boosts the classification performance. Combining motion and emotion cues improves accuracy since such fusion enables the model to resolve ambiguities between such similar gestures as distinguishing between "Hello" and "Goodbye." LSTM utilized for temporal modeling successfully manages the sequential dependencies of a gesture, which has allowed it to achieve better rates of recall. Adding emotion recognition to the system would include essential contextual understanding, where the gestures are by default emotionally related, like a gesture for "Thank You" with a smile accompanying it.

4.4 Comparison of Results

The performance of the system has been compared to state-of-the-art methods for gesture recognition and facial analysis. Summarized in Table 2. The proposed method outperforms previous approaches by integrating gesture recognition with emotion detection and enabling real-time processing.

Table 2. Comparison with other models.

Method	**Model Used**	**Facial Analysis**	**Real-Time**
Kumari et al. [11]	CNN + LSTM + Self Attention	No	No
Chung et al. [12]	PoseNet + GCN	Partial	No
Huang et al. [21]	3D-CNN	No	No
Proposed Method	**MobileNetV2 + LSTM + DeepFace**	**Yes**	**Yes**

5 Conclusion

This paper presents a two-stream architecture combining gesture recognition and facial emotion detection for real-time sign language understanding. Key findings are the overall gesture classification accuracy at 92%, outperforming prior methods. The integration of emotion detection provides a more comprehensive understanding of sign language. Furthermore, the model showed robustness in real-time processing using lightweight architectures like MobileNetV2 and DeepFace.

This implies that multimodal learning in gesture recognition systems is quite significant, where the use of complementary data streams makes it more accurate and understanding the context better.

6 Future Work

There are several potential improvements and extensions that can be made to enhance the performance of the system. For improving dataset diversity, data augmentation techniques like rotation, scaling, and color jittering can be used along with publicly available multi-signer datasets. Model optimization can be achieved by implementing lightweight variants of LSTM or transformer-based temporal models, which would improve inference speed and reduce computational overhead.

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