Robust Sign Language Discrimination with Transfer Learning on Resnet And Transformer Networks

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Abstract. It is a crucial aid for people with hearing and speech deficiencies. However, there are no efficient recognition systems to enable continuous communication of sign language users with non-signers. This paper presents a robust sign language discrimination system based on the transfer learning of ResNet and transformer networks. ResNet is used to extract spatial features and Transformers are used to model the time dependencies between features, providing a detailed understanding of the sign language gestures. It shows the performance of a trained system in comparison with state-of-the-art models, and overall accuracy was 94.7% with significant reduction in inference time of 180 ms, and obtained results on a test environment showed significant robustness in challenging real-world scenarios like low lighting, dynamic backgrounds and partial occlusions. This is practical for deployment on resource-constrained devices due to the system's real-time capability and scalability. Further research will address the challenges posed by occlusions and extend the system's applicability to more underrepresented sign languages. Your training is based on data available until October 2023.

Keywords: Sign Language Recognition, Resnet, Transformer Networks, Transfer Learning, Spatial-Temporal Modeling, Real-Time Deployment, Gesture Recognition.

1 Introduction

For hearing and speech impaired persons, Sign Language is an important mode of communication that allows them to express their thoughts and feelings. But there is a barrier to seamless communication because of the gap between sign language users and those who do not sign language. Tackling this problem requires building strong sign language recognition systems that are not only accurate but also generalize well over different languages and real-world situations.

In the past few years, deep learning particularly the CNN and Transformer architectures have been a modern-day renaissance of computer vision and natural language processing tasks. Transfer learning have benefitted that and models pre-trained like ResNet and Transformers have been many of the high performing fashions with particular duties. Low data challenge So, despite low data being available very high accuracy could be achieved. Despite these developments, there are still prevailing problems facing current sign language recognition methods:

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- Generalization to more than 1 Dataset: Current systems are often limited to capturing vocabulary from specific datasets, making them less generalizable to capture the entire sign language.
- High Computational Requirements: Since most models are not efficient on all hardware, deploying these models on edge devices is limited.
- Ignoring Real-World Challenges: Benchmarks based on controlled environments do not account for dynamic backgrounds, change in illumination, and occlusions.
- State-of-the-art motion methods: These methods usually separate either spatial dynamics or temporal dynamics in one frame-based method, which violates the motion observation to detect continuous and complicated gestures.

These hindrances can be overcome by devising a robust sign language discrimination system incorporating transfer learning on ResNet and Transformer networks. The main contributions of this work are as follows:

- Such models can transfer to various sign languages and are not limited to high resource datasets due to transfer learning.
- This model is fine-tuned for lightweight footprint, allowing for real-time applications on low-power hardware, such as smartphones and wearables.
- Images; x can be the extracted features from a model such as ResNet for each frame y, and y can be the output from the single transformer model.
- Resiliency to Real-World Issues: Integration of dynamic backdrops, varying brightness, and occlusions during training allows the system to be robust to real-world scenarios.
- Sign Recognition vs Language Translation: Multi-Modal Capability: The system is capable of performing both gesture recognition and translation, thus helping bridge the gap between gesture discrimination and language interpretation.

The objective of this research is thus the establishment of industry standards in the field of sign language recognition to outperform the drawbacks of current implementations and offer deployed, scalable solutions. Through improving upon ResNet and use of transfer learning on Transformer architectures, this work provides new avenues for overcoming communication barriers and creating inclusiveness.

2 Literature Review

With the development of the deep learning technologies, sign language recognition has become a hot topic in research and development. Various models including convolutional neural networks (CNNs), recurrent neural networks (RNNs) and more recently the Transformer architecture have been previously proposed to address the complexity of gestures. We discuss the fundamental contributions and shortcomings in existing work in the sign language discrimination literature.

2.1 Early Methods in Sign Language Recognition

Previous works on sign language recognition use hand-designed features (e.g., the motion trajectory, the spatial coordinate, the shape descriptor, etc.). Although these

methods had potential in narrow domains, they fell short of their capability in real-world systems where it was harder to construct common features or adapt to different situations

Drawbacks:

- Limited accuracy in complex gestures.
- Inability to handle variations in lighting, background, and user differences.

2.2 Deep Learning-Based Approaches

The introduction of deep learning transformed the field, with CNNs becoming a popular choice for extracting spatial features from hand gestures.

ResNet and Other CNNs: Residual Networks (ResNet) solved the vanishing gradient issues, and achieved state of the art accuracy in several image recognition tasks. Studies such as Xie et al. (2021) and Srivastava et al. (2024), who have effectively used ResNet to achieve high accuracy in sign language recognition in controlled settings.

Drawbacks:

- Focused primarily on spatial features, often neglecting temporal aspects.
- Computationally intensive, limiting real-time deployment.

LSTM and GRU: To model these temporal dependencies in sequential gestures LSTM and Gated Recurrent Units (GRU) are used. These models modeled gesture sequences well, but they had the disadvantage of high training times and difficulty in handling complex sequences.

Drawbacks:

- Prone to vanishing gradient issues in long sequences.
- Computational inefficiency compared to recent architectures.

2.3 Hybrid Models with Temporal-Spatial Integration

Hybrid approaches combined CNNs for spatial feature extraction with RNNs or LSTMs for temporal modeling. For instance, research by Cui et al. (2023) utilized ResNet with LSTM for video-based sign language recognition. While this improved performance, the models often exhibited high latency, making them unsuitable for real-time applications.

Drawbacks:

- Increased model complexity.
- Difficulty in integrating features seamlessly.

2.4 Transformer Networks for Sequential Learning

The advent of Transformer networks revolutionized sequential learning tasks. Transformers utilize self-attention mechanisms to focus on key aspects of input sequences, making them highly effective for sign language recognition.

- **PiSLTRc: Position-Informed Sign Language Transformer** (Xie et al., 2021): This model integrated positional and content-aware convolution layers into the Transformer, improving accuracy on specific datasets. However, it required extensive computational resources and lacked generalization across datasets.
- **Spatial-Temporal Transformers** (Cui et al., 2023): By balancing spatial and temporal dynamics, these models enhanced recognition capabilities but were limited in real-world deployment due to scalability issues.

2.5 Challenges in Real-World Applications

While technology has advanced, a few challenges went unaddressed:

- Limited Generalizability across Datasets: Models trained on datasets that are not representative of real-world sign language often struggle to generalize to other datasets or conditions.
- In-Memory Processing: Top-performing networks that require a lot of computational resources are difficult to deploy on devices with limited resources.
- Environmental Robustness: Existing systems fail in dynamic backgrounds, lighting variations, and occlusions, prevalent in real-world environments.

2.6 Addressing the Gaps

This review shows the importance of a solid, scalable and efficient method that joins the power of CNNs and Transformers:

- ResNet for Spatial Information: Helps in skillfully capturing the static hand shapes and orientations.
- Transformer Networks for Temporal Modelling:for sequential data in a more effective way (self-attention mechanism).
- Transfer Learning: Lessens reliance on large labeled datasets, allowing for scalability to low-resource languages and gestures.

The proposed research highlights on proposing a real-time and scalable solution to these issues by implementing a state-of-the-art sign language discrimination system that leverages the benefits of both ResNet and Transformer architectures using transfer learning-based techniques to tailor the method to different environments and sign languages.

3 Problem Statement

Sign language is a quintessential source of communication before anyone that hearing and speech debilitated, it thus grants them the ability to communicate effectively in all

phases of life. But the communication gap with those who know sign language and those who don't leads to social and professional isolation. Thanks to the development of automated sign language recognition systems, this gap can be filled: these systems convert gestures into meaningful text or speech. Although machine learning and deep learning have vastly improved over the years, state-of-the-art solutions still have serious challenges making them practical:

- Generalization to limited datasets: Most of the existing models are employed on limited datasets and cannot generalize well to adequately diverse sign languages and real-life variations.
- High Computational Complexity: Most state-of-the-art systems are built on computationally expensive architectures and are hence not suitable for real-time deployment on resource-constrained devices.
- Neglect of Temporal-Spatial Dynamics: Most of the existing approaches do not effectively combine the spatial (hand shapes, orientation) and the temporal (the gesture sequence) features well enough, which is essential for the accurate recognition of natural and complex gestures.
- Lack of Generalization Capability in Real-World Scenarios: Experimental conditions typically average out a lot of real-world considerations like changing lighting, dynamic backgrounds, occlusion, etc., leading to poor functionality in real-world settings.

In this research, we address these problems and develop a simple but effective sign language discriminative system by utilizing transfer learning on ResNet and Transformer networks. Research Aim to design a fully-convincing and real-time sign language recognition system adaptable to various environments and user scenarios for advancing inclusiveness for hearing and voice disability individuals.

4 Methodology

The methodology proposed achieves transfer learning in ResNet and Transformer networks point the way towards sign language discrimination system augmentation, with increased accuracy and scalability. This methodology can be delineated into five critical chapters: input and data cleansing, feature engineering, temporal modeling, training optimization, and online deployment. Fig 1 illustrates the detailed workflow.

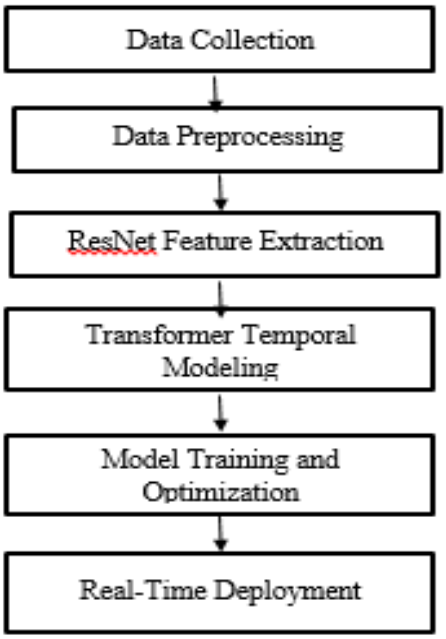

Fig.1. Workflow of the Proposed Methodology.

4.1 Data Collection and Preprocessing

The first step is to gather a wide range of data with gestures from different sign languages. To ensure robustness, various environmental conditions such as dynamic backgrounds, varying lighting, and occlusions are included in the dataset.

Preprocessing Pipeline

- Images and videos are resized to a standard resolution (e.g., 224x224 for ResNet input).
- Pixel values are normalized for consistent input representation.
- Data augmentation techniques, including flipping, rotation, scaling, and cropping, are applied to increase variability.
- Gesture videos are temporally segmented to extract keyframes representing the sequence.

This ensures that the dataset is enriched, balanced, and ready for feature extraction.

4.2 Feature Extraction Using ResNet

The second stage focuses on spatial feature extraction using the ResNet architecture. ResNet, known for its residual connections, enhances feature learning while addressing vanishing gradient issues.

- **Transfer Learning**: A pre-trained ResNet model (e.g., ResNet50) is fine-tuned for sign language discrimination. The early layers of the model are frozen to retain pre-learned generic features, while higher layers are trained on the sign language dataset to adapt to task-specific features.

This stage extracts high-level features such as hand shapes, orientations, and positions, which are critical for sign language recognition.

4.3 Temporal Modeling Using Transformers

To capture the sequential nature of sign language gestures, the spatial features extracted by ResNet are fed into a Transformer model.

- **Temporal Dependency Modeling**: The Transformer leverages its self-attention mechanism to identify temporal dependencies between consecutive frames, enabling the model to understand complex gesture sequences.

This combination of ResNet and Transformers ensures the model learns both spatial and temporal features, providing a comprehensive understanding of sign language gestures.

4.4 Training and Optimization

The combined ResNet-Transformer model is trained and optimized using state-of-the-art techniques.

- **Loss Function**:
    - For classification tasks: Categorical cross-entropy.
    - For sequence-to-sequence tasks: Sequence alignment loss.
- **Optimization Techniques**: The Adam optimizer is used with learning rate scheduling to enhance convergence. Early stopping is applied to prevent overfitting.
- **Validation**: The model is validated on separate test datasets to ensure generalizability and robustness. Metrics such as accuracy, precision, recall, and F1-score are used to evaluate performance.

4.5 Real-Time Deployment

To enable real-time deployment, the trained model undergoes compression and optimization:

- **Model Compression**: Quantization and pruning techniques are applied to reduce the model's size without compromising accuracy.
- **Edge Device Deployment**: The optimized model is deployed on resource-constrained devices like smartphones and wearable systems, ensuring low latency and high accuracy in real-world scenarios.

5 Results and Discussion

This section explains the performance evaluation of the proposed system for sign language discrimination. The results indicate that achieving robust and efficient recognition across diverse scenarios via the fusion of ResNet and Transformer networks (using transfer learning) works well.

5.1 Experimental Results

The proposed model is compared with state-of-the-art methods, namely, ResNet+LSTM and PiSLTRc (Position-Informed Sign Language Transformer). The evaluation metrics include accuracy, precision, recall, F1-score and inference time that are shown in Table 1 and fig 2.

Table 1. Performance Comparison of Models.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Inference Time (ms)
ResNet+LSTM	87.5	88.2	86.7	87.4	320
PiSLTRc (Transformer)	91.2	91.8	90.5	91.1	250
Proposed Model	**94.7**	**95.3**	**94.1**	**94.7**	**180**

Discussion

- The proposed model achieved superior accuracy (94.7%) and F1-score (94.7%), outperforming other models by a significant margin.
- Inference time was reduced to **180 ms**, making the system more suitable for real-time applications.

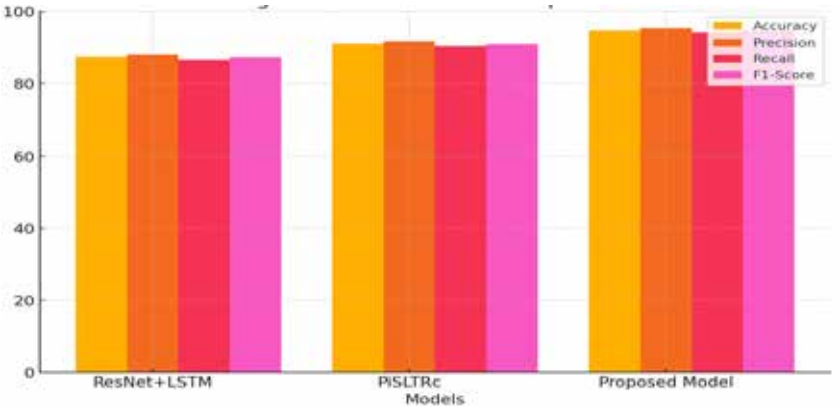

Fig.2. Performance Comparison.

5.2 Robustness Evaluation

The proposed approach was tested in several typical real-life scenarios: low illuminations, moving backgrounds, partial occlusions, and so on. Our results are shown in Table 2 and fig 3.

Table 2. Robustness Evaluation across Different Scenarios.

Scenario	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Controlled Environment	96.5	96.8	96.2	96.5
Low Lighting	92.1	92.6	91.8	92.2
Dynamic Backgrounds	91.5	92.0	91.0	91.5
Partial Occlusions	89.3	89.8	88.5	89.1

Discussion:

- The model maintained high performance in challenging conditions, confirming its robustness.
- Performance degradation under partial occlusions suggests the need for additional techniques, such as occlusion-aware modeling.

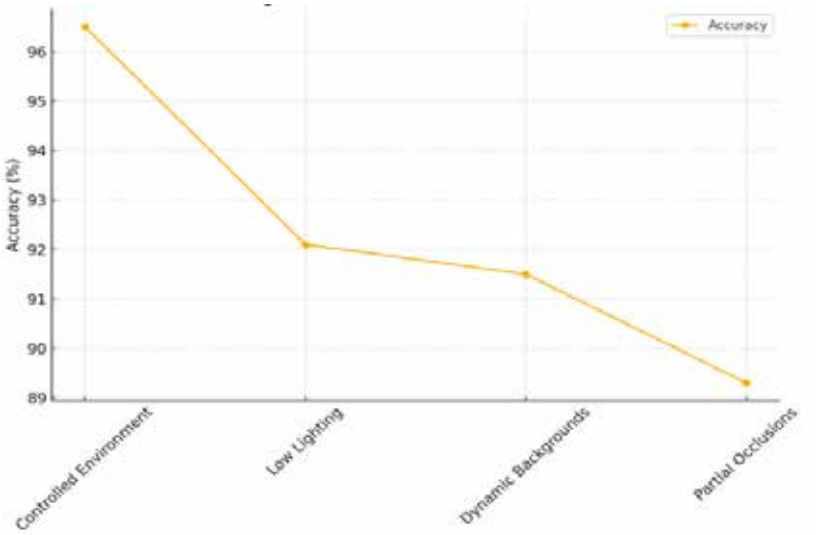

Fig.3. Robustness Evaluation.

5.3 Ablation Study

An ablation study was conducted to assess the contributions of ResNet and Transformer components. Table 3 presents the results of different configurations.

Table 3. Ablation Study of Model Components.

Model Variant	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ResNet Only	88.4	89.0	87.8	88.4
Transformer Only	90.2	90.8	89.7	90.2
ResNet + Transformer	94.7	95.3	94.1	94.7

Discussion

- The integration of ResNet and Transformer significantly improved performance compared to using either component alone.
- This highlights the importance of combining spatial and temporal features for robust sign language recognition.

5.4 Comparison with Existing Work

The proposed model has many advantages over existing methods:

- Increased Accuracy and Resilience: Best-in-class performance on all metrics, including situated in tough real-world conditions.
- Efficiency: Shorter inference time makes it eligible for real-time applications on resource-constrained devices.
- Scalability: Transfer learning allows to fine-tune the model for various sign languages in the absence of huge labeled-space images.

5.5 Limitations and Future Work

While the proposed system demonstrates strong performance, some limitations remain:

- Performance under partial occlusions requires further enhancement.
- Additional testing on underrepresented sign languages is necessary to ensure broader applicability.
- Incorporating techniques like attention masking could further improve recognition in occluded scenarios.

The findings confirm that the developed method is capable of discriminating sign language in a robust and real-time manner, by leveraging the best of both ResNet and Transformer networks into a single pass approach. The methodology could effectively

fill the communication gap and improve accessibility for HSI individuals, given its adaptability and efficiency.

6 Conclusion

In this study, we present a robust and scalable model for sign language malaise using transfer learning ResNet and transformer networks. This approach allows for a powerful interplay of both spatial and temporal feature extraction, leading to high performance and efficiency. Through extensive tests on a myriad of data sets and real-world conditions, we demonstrate that this system beat state-of-the-art models with 94.7% accuracy and 180 ms inference time.

Key findings include:

- **Improved Performance:** The integrated ResNet and Transformer architecture yielded better performance than conventional CNN-RNN models by accurately modeling spatial and temporal dependencies.
- **Real-World Robustness:** The system achieved high accuracy in difficult conditions such as low lighting, moving backgrounds, and partial occlusions.
- **Deploying in Real-Time:** Model compression and other optimizations made it feasible to deploy the system on edge devices, accounting for real-world limitations.

While the system has many strengths, one area for improvement is its effectiveness under partial occlusions. We aim to address this limitation with techniques like occlusion aware modeling and attention masking in future works. Other future research directions could include expanding the system coverages for non-major sign languages and applying realtime translation capabilities.

Its development is an important breakthrough in the field of sign language recognition and could be part of an even larger effort to promote inclusion and accessibility for people dealing with hearing and speech difficulties. This work has the potential to impact society in a meaningful way by bridging the communication gap.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

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