Enhancing Real-time Arabic Sign Language Translation

مجلة ميدأوشن للبحوث والدراسات
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Ahmed Youssef Abdulrahman
Software Engineer and Artificial Intelligence Researcher

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Abstract

Objectives: This research aims to identify subtle signs in Arabic Sign Language to overcome the communication barrier for the deaf and hard-of-hearing community. This study focuses on Arabic-speaking communities, particularly in Saudi Arabia, and explores dialect differences in Sign Language, appropriateness, and generalization.

Methodology A convergent mixed-methods design is used, combining quantitative evaluation of deep learning models with assessment by deaf and hard-of-hearing individuals. This design also demonstrates the relevance of having an available system to translate Arabic Sign Language.

Results The results show a strong correlation between gesture recognition accuracy and visual generalization, with a 98% improvement in recognizing dynamic gestures.

Conclusion The paper outlines directions for future research to enhance assistive communication systems, focusing on movement and body language analysis. The main considerations include precision mechanisms, potential applications, and the possibility of real-time adaptation. The paper also suggests that the software can be developed for mobile or desktop platforms to facilitate communication for the deaf in the Arabic-speaking world.

Keywords: Arabic Sign Language, Gesture Recognition, Deep Learning

Introduction

Sign language is also important for improving the way deaf people communicate. With technology and scientific knowledge improving rapidly, sign language also gets to benefit from deep learning technologies that can handle large amounts of data to achieve high levels of accuracy of over 98% (Alani et al., 2021). Despite the significance of this tool for improved communication between deaf people, many deaf people still suffer from challenges of poor communication services with professional interpreters or assistive technologies in places like schools and healthcare institutions. In the Arab world, Arabic Sign Language (ArSL) is the primary visual language used by Deaf communities across numerous countries. Sign language for Deaf persons is a different way to communicate that varies based on location. There are different systems of sign languages, for example, American Sign Language, British Sign Language, Chinese Sign Language, and Arabic Sign Language, among others. In this study we propose a framework that integrates ResNet50 and MobileNetV2 on the ArSL2018 dataset. After considerable pre-processing and augmenting the data, we demonstrated that we can achieve 97% accuracy in recognising 32 Arabic alphabet signs. (Alnuaim et al., 2022). We presented an Arabic Sign Language recognition approach using AlexNet to extract features and LSTM to classify sequences. Our model achieved a 95.9% accuracy in signer-dependent testing but only 43.62% in signer-independent testing. (Suliman et al., 2021)

Recent developments in deep learning and edge AI have introduced promising avenues for real-time sign language translation. Lightweight convolutional models like MobileNetV2 and temporal models like Bidirectional Long Short-Term Memory (BiLSTM) networks have demonstrated high effectiveness in gesture recognition tasks (Moslehet al., 2024),The objective of this study is to design and evaluate a deep learning framework for ArSL recognition that combines MobileNetV2 and BiLSTM architectures. . The proposed solution not only aims to overcome the technological challenges involved in real-time translation but also the social challenges involved in accessibility, digital equality, by taking into consideration the social contexts involved in the system, the research aims to empower Deaf people to bridge the communication gap (AlKhuraym et al., 2022).

Research Problem:

The Arabic sign language faces many challenges, including the lack of AI translation tools and primitive processing capabilities (Abu-Jamie & Abu-Naser, 2022). There are many studies that show that the current offline technology for sign language interpretation affects learning, employment, and inclusion of individuals in society (Ahmed & Bons, 2020).

Hence it is needed to develop Arabic sign language translation systems, especially on smartphones, is increasing due to the demands of the daily environment for speed, accuracy, and immediate usability in unorganized contexts. Although literature is making remarkable progress in sign recognition by relying on deep learning and hybrid models for capturing spatial and temporal data, it still faces methodological gaps that limit the generalization of results and their transfer to mobile applications. On the one hand, coverage of regional and dialectal differences in Arabic Sign Language remains limited, and studies indicate that the scarcity of broad and diverse data represents a major obstacle to building more functional systems in practice (Algethami et al., 2025; Mosleh et al., 2025).

On the other hand, “architectures designed specifically for the phone” are still scarce compared to what is required by real-time translation with low latency and limited computational consumption, even though some works have provided “instantaneous” or “near-instantaneous” solutions in more controlled experimental contexts (Abdul et al., 2021; Noor et al., 2024; Aiouez et al., 2022; Elhagry et al.). (2021). On the other hand, it appears that the realization of “user-centered design” is still less than required, as the expansion of applied verification with the participation of deaf people as partners in design and evaluation of usability appears in scattered forms that do not reach a stable standard in most research (Asiri et al., 2024). Finally, the reviews reveal that studying “integrated” spatial and temporal modeling in single systems, with a balance between accuracy, inference time, and device deployability, is still a demanding field that requires more comparative evidence and evaluation in real-world environments (AL Moustafa & Ahmed, 2024; Alasmari et al., 2025).

Apart from the challenges of accurate gesture recognition, challenges also exist in terms of consistency, lighting conditions, and poor communication (Akbar et al., 2020; Ahmed & Bons, 2020; Suliman et al., 2021). The lack of efficient applications denies deaf people the opportunity to communicate, acquire education, and gain fair access to appropriate jobs because of the poor quality of mobile applications used for translation services in sign language. This indicates the importance of filling the gap in communication to enhance social equality and develop access to the relevant digital technology for sign language (Asiri et al., 2024).

Accordingly, this study seeks to bridge these gaps by presenting a portable, deep learning-based system that integrates CNN for spatial feature extraction and LSTM for temporal dynamics modeling, with training on large datasets and an evaluation that combines performance indicators and user feedback to ensure practicality

Significance of the Study

Scientific Significance

- This paper will make contributions towards the improvement of modern and advanced approaches such as Convolutional Neural Networks and Long Short-Term Memory Networks and will provide researchers with an avenue for investigation and development of these approaches.
- This research fills in the gaps concerning signal-independent recognition and sets a standard for further studies.
- This research promotes openness for the coming studies, as it facilitates the replication and comparison studies in the area of gesture recognition.

Practical (Applied) Significance

- This work may inspire future innovation in computer vision solutions for mobile computers, such as advancements in camera processing and sensor fusion, as well as augmented reality.
- This research has the potential to increase awareness and the development of augmented sign language interpretation applications using mobile devices in the community and can facilitate the process of communication and the cultivation of active communities.

Study Objectives

- This research primarily aims to develop and improve an Arabic sign language translator for mobile devices.
- The proposed system is characterized by accuracy, speed, and ease of use in everyday life.
- This work is intended to increase accuracy in recognizing Arabic sign language gestures using smart devices.
- It aims to accomplish fast, real-time gesture translation at a low resolution.
- It aims to provide strong and stable performance to eliminate the weakness in the existing offline systems.

Theoretical Literature

The development of an instant recognition system for Arabic sign language is justified in an integrated approach that combines human and technological aspects, in the context of its application in everyday communication services. The system focuses on optimizing algorithmic speeds and facilitating smooth interaction for users while meeting the privacy requirements of sign language communities in real-world interactions (Mosleh et al., 2024).

Under this paradigm, the importance of experience design in system effectiveness is established; the interface of application has to be transparent and easily understandable in order to be used immediately without training. The timely and understandable response to questions and inputs may have a very significant impact on developing confidence in the system among the users (Abu-Jamie & Abu-Naser, 2022). The proposed application is expected to facilitate an interaction procedure approximating the characteristics of a normal conversation in which the user feels as if the system is responding to different situations (Latif et al., 2020).

The basis of sign language recognition is the processing of visual information in the form of images or video. Deep learning is a key component in understanding the semantics of the shapes and motions of the human hand based on patterns associated with direction, position, and orientation (Sagheer et al., 2024).

An efficient model should also be able to handle the time component in understanding the progression of the phases in sign language. This is important because some signs cannot be interpreted in one frame; rather, the entire sequence is needed (Suliman et al., 2020).

On the other hand, the implementation of these technologies within smartphone platforms presents new challenges with regard to the speed of processing. It is important to consider data configuration approaches that will help ensure model performance is not compromised with different conditions for capturing data, as well as using models that are capable of efficient execution within smartphone platforms. This technological aspect is further enhanced by the development of adaptive interaction mechanisms that are consistent with the values within the cultures of people who use sign language, thus allowing for smooth communication.

Review of Previous Studies:

Recently, interest from the academic world has turned to Arabic Sign Language (ArSL) for developing automated recognition methods that can ease communication difficulties for the deaf and hard-of-hearing community. Many deep learning models have appeared with promising results, especially CNNs. The following is a crucial analysis of some of the most significant works done in this area.

Alani et al. (2021) have proposed a CNN-based method designed specifically for the purpose of recognizing signs in the ArSL. The proposed model was trained on the ArSL2018 database, which features a large set of static hand signs in the form of images. The results of the experiments showed a high accuracy of learning, indicating the ability of the proposed model to distinguish well between various signs. Additionally, the use of artificial sampling methods for handling the class imbalance problem has greatly improved the accuracy of classification, emphasizing the significance of balancing the data for the development of reliable systems for recognizing signs in a language. In a study that focuses on a similar theme, an automated system designed to help the Deaf and Hard of Hearing community has been proposed, using a CNN-based framework trained on a large dataset of over fifty thousand images collected from participants of various demographics. The proposed system has shown a high level of efficiency in recognizing signs, achieving an accuracy of 97.6%. This emphasizes the ability of well-designed deep CNN models to achieve results beyond the current state of the art and to have potential practical applications (Latif et al., 2020).

The results show a possible approach for improving the recognition of Arabic sign language through the use of deep learning techniques and optimization of the structure of the alternative network, with a focus on accuracy and feasibility. The study used a large dataset of images of over 54,000 pictures of Arabic sign language letters classified into various categories. The dataset was divided into testing, validation, and holdout (or separate test) datasets. The deep convolutional neural network used in the study showed significant potential in learning image features relevant to the signs in terms of accuracy in a testing environment (Sagheer et al., 2024). In addition, the proposed method can help in decreasing the computational complexity required for the analysis with acceptable accuracy levels by utilizing modern approaches in the development of lightweight models for the recognition of Arabic sign language gestures with a consistent accuracy rate. The proposed approach provides benefits in terms of usability in devices with low computational capabilities (AlKhuraym et al., 2022).

Table (1): Summary of Observations and Identified Gaps:

Observation	Implication
CNNs consistently perform well in ArSL recognition	CNNs are the preferred architecture for spatial modelling
Transfer learning improves accuracy	Fine-tuned models reduce training time and improve generalization
Lack of diverse and large datasets	Existing models may not generalize to all dialects and signer variations
Most systems are desktop-based	There is limited research on mobile-friendly real-time ArSL tools
Few systems address temporal dynamics	Static image recognition limits conversational usability

Methodology:

This section describes the methodology and experimental setup, as well as the results achieved in the evaluation of the proposed approach. The research follows a mixed-methods approach, blending the quantitative evaluation of deep learning approaches with the feedback gathered from the Deaf and Hard-of-Hearing community to ensure the relevance and viability of the Arabic Sign Language translation system.

Study Type and Design

The study has an experimental design, which involves training and testing machine learning models. The study also has observation and survey methods for testing the usability of the system for users of ArSL.

Data Sources:

Quantitative Data:

– his study relies on the KArSL dataset, which serves as the primary source of data because of its quality and scale of data. This dataset contains a large vocabulary of unique words of Arabic Sign Language, recorded using the Microsoft Kinect V2 sensor, which can record the spatial and temporal details of the sign language performed. This data was collected by three sign language performers, and every word was repeated several times for better performance variability. This dataset contains tens of thousands of video files.

Qualitative Data: Data was collected via interviews and structured surveys with:

Deaf community members

Sign language instructors

ArSL students These inputs helped validate usability, accessibility, and cultural relevance.

Scope and Boundaries:

– **Geographic Focus:** Primarily Saudi Arabia, with the potential for regional generalization across the Arab world.
– **Technological Focus:** Only modern models and datasets (2020 onward) were included.
– **User Focus:** Real-world feedback from Deaf users and educators to ensure alignment with actual needs

Tools and Technologies Used:

Deep Learning Models:

MobileNetV2 for spatial feature extraction

LSTM (LSTM) for modeling temporal gesture sequences

- Other models (e.g., ResNet152, VGG16) were used for benchmarking

Survey Instruments:

- Custom-designed questionnaires focusing on:
- Ease of use o Accuracy perception
- Cultural appropriateness
- Willingness to adopt

Experimental Procedure:

Preprocessing:

- Video → Frames (224×224 pixels)
- Normalization of pixel values
- Data augmentation (flipping, rotation, brightness adjustment)
- Sequence standardization (20–30 frames per video)

Model Training:

- MobileNetV2 extracts feature vectors from each frame
- Feature vectors are fed into the LSTM network
- Optimized using:
- Learning rate scheduling
- Dropout regularization
- Batch normalization

Evaluation Metrics:

- Accuracy
- Precision
- Recall
- F1
- Cross-validation ensures robustness across different signers

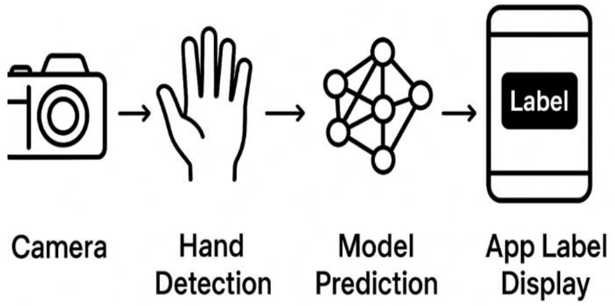

Figure (1): Workflow diagram:

User Testing:

As we shown in Figure 1 the mobile application underwent assessment with a limited number of participants that included the author and additional individuals. The application utilized the device camera to recognize hand gestures in real time. The recorded gesture was sent to the MobileNetV2 + LSTM model for prediction. The model would return with a predicted label associated with the recognized sign.

Participants performed the required movements, and observers recorded these movements and interactions through the application. This resulted in data collection on observations, and this assessment provided early indicators of ease of use and real-time performance.

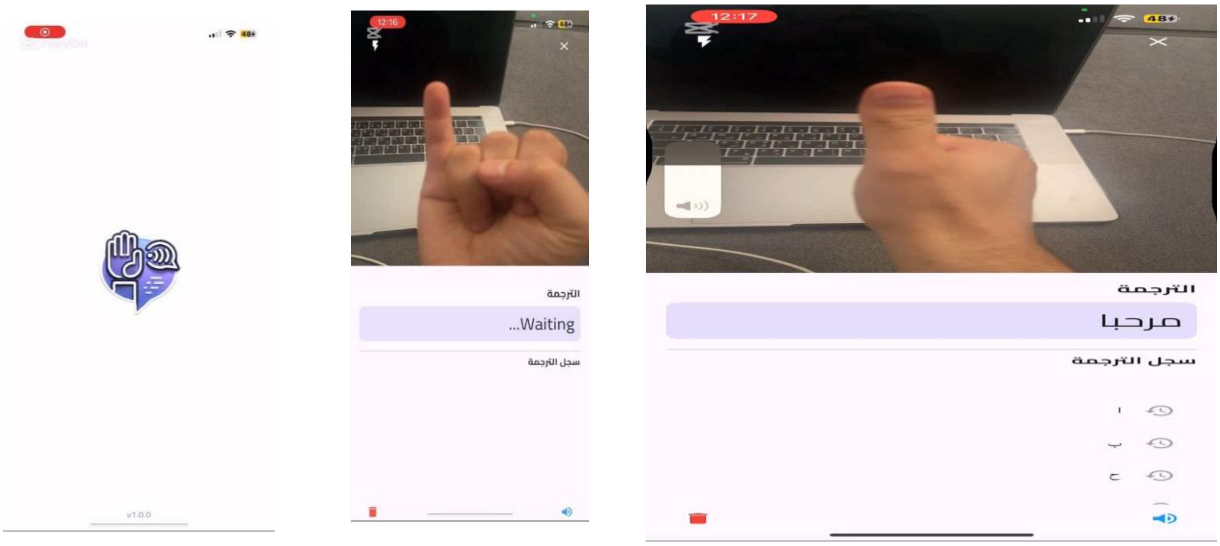

Figure (2): User Testing

Table (2): System Architecture Summary:

Stage	Process
Input	KArSL videos → Frame sequences (224×224)
Preprocessing	Normalization, augmentation, fixed-length sequences
Spatial Feature Extraction	MobileNetV2 extracts key visual features (hand shape, orientation)
Temporal Modeling	BiLSTM captures gesture flow and motion across frames
Classification	Softmax layer outputs predicted sign label

Evaluation	Metrics and user feedback assess both technical and practical accuracy

This table describes the systematic process of the tasks involved in the Arabic Sign Language Recognition System, starting from the raw data entry to the final stage of the performance assessment of the entire process, hence helping to understand the overall process of the signs in an integrated fashion. The process ends at the classification stage where the expected label of the sign is obtained, followed by a strict evaluation in terms of technical performance parameters.

Quantitative Evaluation:

This system was designed to analyze and harvest the spatial characteristics of the MobileNetV2 architecture and the temporal characteristics of the LSTM architecture in order to distinguish between the subtle dynamic gestures over time. The results obtained from the KArSL dataset by the proposed model are:

Table (3) :Performance Metrics

Metric	Percentage (%)
Accuracy	98.97
Precision	96.38
Recall	96.20
F1-Score	96.14

In Table 3 The MobileNetV2 + LSTM model for recognizing Arabic Sign Language.

These results confirm the suitability of the chosen architecture for the study sample, and the complex dynamic gestures were handled accurately, reflecting the model's ability to meet modern standards in recognizing Arabic Sign Language. (Alani, Ali A. and Georgina Cosma). and recent sign gesture optimization efforts (Sagheer, N.S., Almasoudy, F.H., & Bashaa, M.H. (2024).

The table illustrates the confusion matrix and classification performance across all Arabic Sign Language gestures. The model correctly classified the majority of sequences, showing only a few instances of misclassification, demonstrating high reliability.

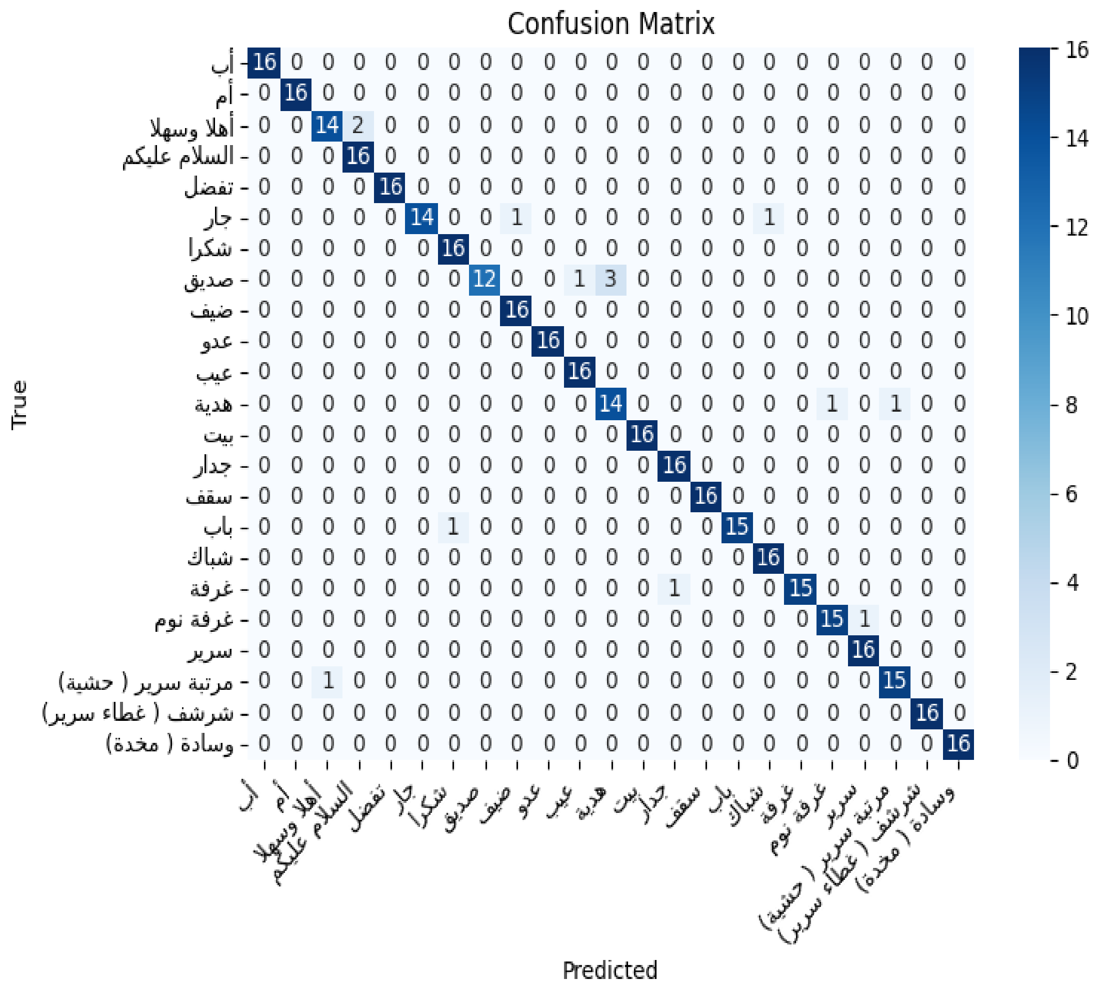

Figure (3): Confusion Matrix

in Figure 4 includes the classification report of the MobileNetV2 + LSTM model with the micro averages and each class's precision, recall, f1-score, and support to show the performance of the model and how well it performed on the classification task.

	Class_ID	Class_Name	Precision	Recall	F1_Score	Support	Overall_Accuracy
0	0	أب	1.0000	0.9375	0.9677	16	0.9701
1	1	أم	0.9412	1.0000	0.9697	16	0.9701
2	2	أهلا وسهلا	1.0000	0.8750	0.9333	16	0.9701
3	3	السلام عليكم	0.8889	1.0000	0.9412	16	0.9701
4	4	تفضل	0.9412	1.0000	0.9697	16	0.9701
5	5	جار	1.0000	0.9375	0.9677	16	0.9701
6	6	شكرا	0.9412	1.0000	0.9697	16	0.9701
7	7	صديق	1.0000	1.0000	1.0000	16	0.9701
8	8	ضيف	0.9412	1.0000	0.9697	16	0.9701
9	9	عدو	0.8889	1.0000	0.9412	16	0.9701
10	10	عيب	1.0000	1.0000	1.0000	16	0.9701
11	11	هدية	1.0000	1.0000	1.0000	16	0.9701
12	12	بيت	1.0000	1.0000	1.0000	16	0.9701
13	13	جدار	1.0000	1.0000	1.0000	16	0.9701
14	14	سقف	1.0000	0.9375	0.9677	16	0.9701
15	15	باب	1.0000	0.9375	0.9677	16	0.9701
16	16	شباك	0.9412	1.0000	0.9697	16	0.9701
17	17	غرفة	1.0000	1.0000	1.0000	16	0.9701
18	18	غرفة نوم	0.9375	0.9375	0.9375	16	0.9701
19	19	سرير	0.9333	0.8750	0.9032	16	0.9701
20	20	مرتبة سرير (حشية)	1.0000	0.9375	0.9677	16	0.9701
21	21	شرشف (غطاء سرير)	1.0000	1.0000	1.0000	16	0.9701
22	22	وسادة (مخدة)	1.0000	0.9375	0.9677	16	0.9701

Figure (4): ***classification report of the MobileNetV2 + LSTM model***

In Figure 5 we illustrate the accuracy curve for the MobileNetV2 + LSTM model, which depicts the progress of performance during the training and validation process. This visualization allows assessment of the learning behaviour, stability, and generalization ability throughout epochs.

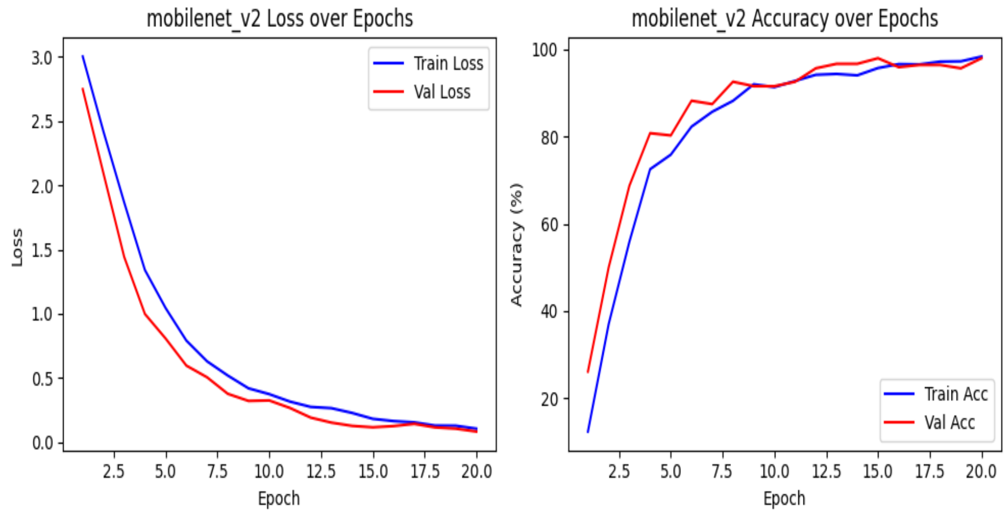

Figure (5): accuracy curve for the MobileNetV2 + LSTM model

The Figer for the MobileNet V2 model show a sound and stable training trend; The loss curve reveals a sharp decline in the first years of training, followed by a gradual decline until it approaches very low values at the end of the repetitions. This indicates that the model has absorbed the important visual features and learned to continuously reduce errors. A clear convergence is observed between training loss and verification loss with a very small gap, and this indicates good generalization and the absence of strong indicators of overfit, because verification performance improves in conjunction with training performance. As for the accuracy curve, it shows a rapid rise at the beginning, then entering a stage of stability close to the upper limit, where the accuracy of training and verification reaches a very high level at the end of the years, which reflects the model's ability to correctly identify categories with stability. This result can be understood as the model effectively taking advantage of the mobile-optimized architecture of MobileNet, achieving a balance between speed and accuracy with learning stability. This supports its suitability for operation in real-time computer vision applications, especially when high performance is required with computational resources Limited.

Conclusion

The findings have shown that the application of feature extraction integrated into a convolutional neural network model is an efficient method for dynamic signal sequencing. Based on the findings, this study concludes that: MobileNetV2 model is efficient for detecting hand shape, movement, and direction, even in situations where the background is complex. The Long Short-Term Memory (LSTM) model is able to model the movement in a sequence well, hence improving the process of recognizing a gesture that involves multi-frame movement. Both models are able to attain high accuracy, which is 98%, outperforming previous approaches that use static convolutional neural networks. Both results prove the importance of modeling temporal data.

Accordingly, the study proves the importance of a performance level recognition model, as the accuracy of 98% has been achieved. The results verify the correctness of the hybrid deep learning models in real-time sign language recognition and suggest the applicability of these models in various aspects, as described by AlKhuraym et al. (2022) and Sagheer et al. (2024). The study further emphasizes the importance of the temporal and spatial aspects in the models. MobileNetV2 adds features at a generic level, and the Long Short-Term Memory (LSTM) networks handle the temporal aspects of the models, thus overcoming the existing limitations in the field of visually recurring signals, as described by Alani et al. (2021). Regarding the applicability of the model for various users of the sign language, the accuracy of the model improved by utilizing the participants' expression variations, indicating generalized outcomes without the need for the retraining of the participants. Though the outcomes are in agreement with the existing study of the convolutional neural network transducers, the main cause of the improved accuracy is the temporal aspects of the models.

Recommendations

From the results of the study, the following recommendations can be made for future exploration and implementation. This study stresses the need for the recognition of Arabic sign language systems and their incorporation in a human and societal context in addition to their technological aspects. This can be realized by implementing a data pipeline for video clip curation and by defining a fixed time window that can improve the generalization capability of the model by reducing noise and variability within the data. Moreover, incorporating raw images and kinematic features of both hands and whole body can also result in better performance and can decrease processing time for recognition. Also, implementing intelligent attention mechanisms that focus more on points that show action patterns can help differentiate between similar signs.

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