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Deep Learning Based Recognition of Arabic Alphabet Sign Language ArASL: A Study with EfficientNetB3

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ABSTRACT

Sign language is a critical communication approach for the community of people with hearing and speech impairments . Humans need to be able to communicate. People who are unable to communicate verbally like the rest of humanity typically utilize sign language .The primary characteristics of signs in sign language are hand form, placement, movement, orientation, and non-manual elements. These people are facing significant obstacles in their lives, such as severe depression and unemployment as a result of these restrictions or impairments. Among the communication services they utilize is a sign language interpreter. However, the cost of hiring these interpreters makes a low-cost option necessary. As a result, society now urgently needs automatic sign language translation. The construction of image-based Arabic sign language (ArSL) identification systems has improved due to the accessibility and extensive usage of digital cameras on mobile phones. and represent an opportunity for people with hearing disabilities to participate more in their communities. Their quality of life would be significantly impacted by the creation and deployment of a new system for the recognition of (ArSL). Consequently, a method was developed to translate the visual hand data set from Arabic sign language to written data. The objective of this work is to use the EfficientNetB3 deep learning model to achieve state-of-the-art performance in the classification of Arabic Alphabet Sign Language. The suggested method achieves an impressive test accuracy of 99.84% by utilizing transfer learning, data augmentation techniques, and a well selected dataset. The outcomes show how the model can be used in practical settings for things like real-time sign language interpreters and educational resources.

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1. Introduction

Sign language is the primary means of communication for millions of persons with speech and hearing impairments worldwide. Despite the fact that numerous studies have been conducted on sign languages like American Sign Language (ASL) and Arabic Sign Language (ArSL), which represents the Arabic alphabet, remains underexplored despite its cultural and practical significance in the Arab world. People with hearing difficulties can communicate with others by using sign language. As a result, scientists, researchers, and engineers have been interested in studying and developing sign language recognition in order to provide software that can facilitate communication for those with hearing impairments.[1].

Sign language is a type of communication where meaning is expressed using recognized signs or body language. Since many people with hearing impairments are also unable to read or write, creating a sign language translation, or sign language recognition system (SLR), can greatly improve their quality of life. Because sign language recognition systems can aid in bridging the gap between the world and the community of people with hearing impairments there is a great need for them. It is among the most significant fields of computational science that addresses practical problems. The World Health Organization estimates that by 2022 Globally, more than 5% of people will have hearing loss and by 2050, this percentage is predicted to rise. The inhabitants of Arab nations, who make up about 14% of the global population, utilize the Arabic alphabet. Furthermore, a large number of people in Asia and Africa speak languages or dialects including Persian, Kurdish, Malay, Punjabi, Urdu, Balochi, Lurish, Kashmiri, Somali, and others that employ the Arabic script.[2] As a result, the Arabic script is used by about 25% of the global populace demonstrating its significance. The significance of the Arabic Sign Language alphabet is justified by the fact that 5% of people who use the Arabic alphabet have hearing impairments. The hearing-impaired community uses the (ArSL) to get around the challenge of dealing with regular Arabic letters because this is an illustration of Arabic letters in sign language. This makes it possible for them to engage in the conventional pedagogical and educational process. [3]

Fig 1– illustrates an example Images of ArSL

Even though there are obvious variations in the same sign when done by signers from diverse backgrounds or origins, the variances are minimal and only impact a small number of letters. The signer might choose to express the letters "Ra" and "H" in particular either statically or dynamically. One way to communicate the letter "Jeem," which is symbolized by a curved palm, is with a soft or sharp palm. To address these disparities, a lot of work has gone into standardizing Arabic Sign Language in order to create a language that all signers from various backgrounds can use and understand. [4] However, among Deaf Arabs, fingerspelling remains a frequent and traditional form of communication. One of the primary characteristics of the (ArSL) is the gesture's semantic significance. For instance, With the pointing finger, the number of dots in the three letters "Ba," "Ta," and "Tha" is indicated. ArSL is also distinct since it shares similarities with the alphabet of sign language. Figure 1 illustrates the letter pairings "T'a" and "Th'a," "Ayn" and "Ghayn," and "Dal" and "Thal," for instance have remarkably comparable visual characteristics. For certain letters, this further complicates the recognizing challenge. Because hearing individuals are reluctant to adopt a new language that is only spoken by a minority, deafness can be a social obstacle. Deaf people become alone and detached as a result of this refusal. Nonetheless, The advancement of systems for recognizing sign language has been aided by recent technical advancements. [5]

Transfer learning [6] has been put out as a method for overcoming this difficulty, which involves training the model on a sizable training set. The objective task is then approached using the training results as a starting point. With its reliable solutions for visual pattern recognition, transfer learning has transformed picture classification challenges and shown itself to be effective. This paper introduces a good approach for (ArSL) recognition based on EfficientNetB3, its a(CNN) known for its efficiency and performance. The study demonstrates how transfer learning, combined with appropriate data pre-processing and augmentation, can yield exceptional results in recognizing Arabic alphabet gestures. The remainder of the document is structured as follows, The literature review is covered in Section 2. The proposed method, along with its dataset, system structure, and model architecture, are covered in Section 3. Section 4 discusses comparative analysis and the outcomes of the proposed method. The study is concluded in Section 5, which also identifies areas that warrant further investigation.

2. literature review

Arabic Sign Language (ArSL) and American Sign Language (ASL) are the most widely sign languages in the world. In this research, we focused on ArSL because it lacks extensive research compared to American Sign Language. Other sign languages exist, such as Indian Sign Language (ISL), British Sign Language (BSL), and Chinese Sign Language (CSL), but their datasets are either scarce, not standardized, or not publicly available. The previous studies focused on sign language (SL) recognition In the two most common topics:

- **American Sign Language (ASL):** CNNs and deep neural networks have been used to successfully classify the ASL gestures. A useful (FFV-Bi-LSTM) approach using angle and spatiotemporal information from a 3D skeletal hand for detecting (ASL) words was created by Abdullahi, Sunusi Bala, et al. [7] The ASL was evaluated using (LMDHG and SHREC) datasets. The 98.6% accuracy on a randomly chosen ASL and accuracy 91.0% for related ASL words. Regardless, it required repeated modifications for Gaussian Mixture (GMM) Model parameters and contained problems with small alterations in hand movement rotations. A modified InceptionV3 architecture was used in Hasan, Md. Mehedi et al. [8] classify the ASL letters and numerals after augmentation, with accuracy of 98.81%. Dependence on a regulated dataset with small variability and sensitivity to unbalanced data is a weakness, which could limit generalizability to real-world circumstances. A multimodal 3D ASL identification framework utilizing hand joints (via a Leap Motion Controller) and hand form contours (through a webcam) was shown in 9-Mahdikhanlou et al [9]. A random decision forest classifier with an accuracy of 95.09% was developed using a dataset of 64,000 samples spanning 32 static gestures. Drawbacks have complications with visually similar gestures (e.g., 'M' and 'N') and decreased accuracy because of sensor restraints. The combined use of 3D and contour-based features improved recognition compared to depth-only algorithms. A wearable smart glove with resistive strain sensors and an accelerometer was introduced in DelPreto, Joseph et al. [10] in order to categorize both static and dynamic (ASL) motions. Using an LSTM neural network, the system achieved a classification accuracy of 96.3% on segmented gesticulations and 91.2% in real_time streaming testing. its generalizability was restrained by issues such as sensitivity to glove placement and user-distinct variations. The system shows how low-resource wearables could incorporate real-time gesture recognition. Charan, et al. [11] developed a model CNN for Indian Sign Language, on the ISL dataset achieving 91.7% accuracy with residual connections. To enhance synthetic data, Conditional GANs are used, resulting in a 95.5% accuracy rate.

- **Arabic Sign Language (ArSL):** There is less study and a tendency to depend on manually developed feature extraction methods in ArSL, which are less reliable. Employing deep and transfer learning, Dabwan and Basel A., et al. [12] created an (ArSL) recognition system that achieved 99% and 97.9% in test and validation accuracy on the EfficientNetB1. Using the EfficientNet(Lite), AlKhuraym, Batool Yahya, et al. [13] reported a lightweight ArSL identification system that gained 94.3% test accuracy on a custom dataset of 5,400 images. The dataset's small size and static nature are weaknesses that limit the system's to withstand a variety of real-world or dynamic movements. A vision-based system in ArSL distinction that uses CNNs to convert static hand signs into Arabic speech was proposed by Kamruzzaman et al. [14]. The model's accuracy was 90% when tested on a dataset having 3,875 pictures and an 80:20 train-test split. Small dataset size and static motions are drawbacks that could limit generalizability to dynamic, real-world situations. Using the AlexNet , Alsaadi, Zaran et al. [15] provide a real-time system with a 94.81% testing accuracy. The model was trained on a dataset of (54 049) images. Nevertheless, it is sensitive to differences in hand postures and does not generalize to backgrounds. In order to overcome the shortage of Arabic sign language interpreters, particularly in Saudi Arabia, Talal H et al. [16] propose a hybrid CNN-LSTM model. The system's accuracy rates are 94.4% for CNN and 82.7% for LSTM. Its drawbacks a lack of diversity in datasets, a dependence on certain gestures, and difficulties extrapolating dynamic motions taken from different perspectives. In a study by Elshaer, A. M. et al. [17], the ArASL system for (ArSL) recognition was created using VGG16, the classification accuracy was 96.05%. Its shortcomings include sensitivity to class disparities, dependency on static gestures, and poorer performance for specific letters like "dal" and "jeem," which restricts its use in dynamic, real-world situations. Renjith, S., Manazhy et al. [18] created a spatiotemporal model for Arabic Sign Language (ArSL) and Chinese Sign Language (CSL) detection using a Time Distributed CNN (TD-CNN), with 89.46% and 90.87% accuracies, respectively. The method improves gesture classification by utilizing temporal and spatial information from video sequences. The study demonstrates the possibility of video-based gestures in assistive technologies. A transfer learning for the ArSL recognition system using (ResNet-152) was proposed by Al Ahmadi, Saad et al. [19]. The system gained accuracies of 96.25%, 95.85%, and 97.02% on three datasets. The possibility of sophisticated CNN model to improve ArSL recognition is highlighted in this work.

In contrast to previous efforts that relied on classical feature extraction or simpler CNN architectures, our approach uses transfer learning using EfficientNetB3 -based model that it balances accuracy and computational cost.

3. Methodology

The study methodology offers an organized system for the recognition of the Arabic Alphabet Sign Language. To accomplish outstanding classification performance, it combines the benefit of a pre-processed dataset, advanced data augmentation, and the EfficientNetB3 deep learning as the base model. While prior studies have used EfficientNetB3 for image and signal classification tasks, the majority of these studies have either utilized it exactly as is or with minor fine-tuning adjustments. This paper used a series of improvements to ArSL recognition. Using a custom head based on EfficientNetB3, applying extensive augmentation techniques to improve generalization, using BatchNormalization and Dropout to improve model stability, and operating an advanced training strategy that freezes the initial layers and fine-tunes only the last 100 layers, are some of these improvements. Furthermore, we used EarlyStopping and ReduceLROnPlateau to dynamically modify the learning rate, which makes our research an untried improvement in this ArSL recognition system and the No Background RGB Arabic Alphabets Sign Language dataset. The procedures used in this study are depicted in Figure 2 below:

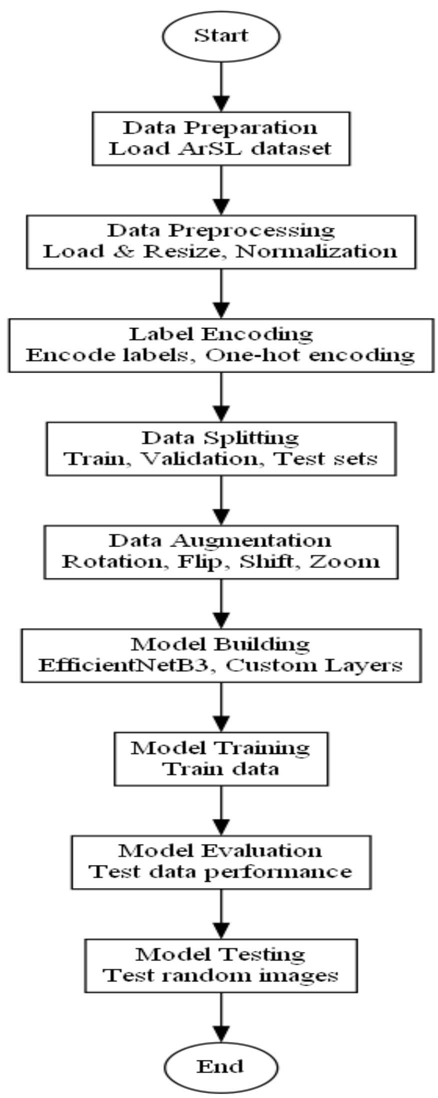

Fig. 2 – The proposed system steps

3.1. Dataset

The dataset utilized in this study was the "No Background RGB Arabic Alphabet Sign Language Dataset (AASL)". In this dataset used more than 200 participants and 6,985 images correspond to 31 classes, each of which is symbolized by an Arabic letter. As can be seen in Figure 3, the dataset was carefully chosen with an emphasis on removing backgrounds to ensure that just hand gestures were the focus. digital cameras and cellphones are utilized to take images in various lighting situations and environments. To create deep learning models for ArSL recognition, this dataset provides a strong and diverse foundation.

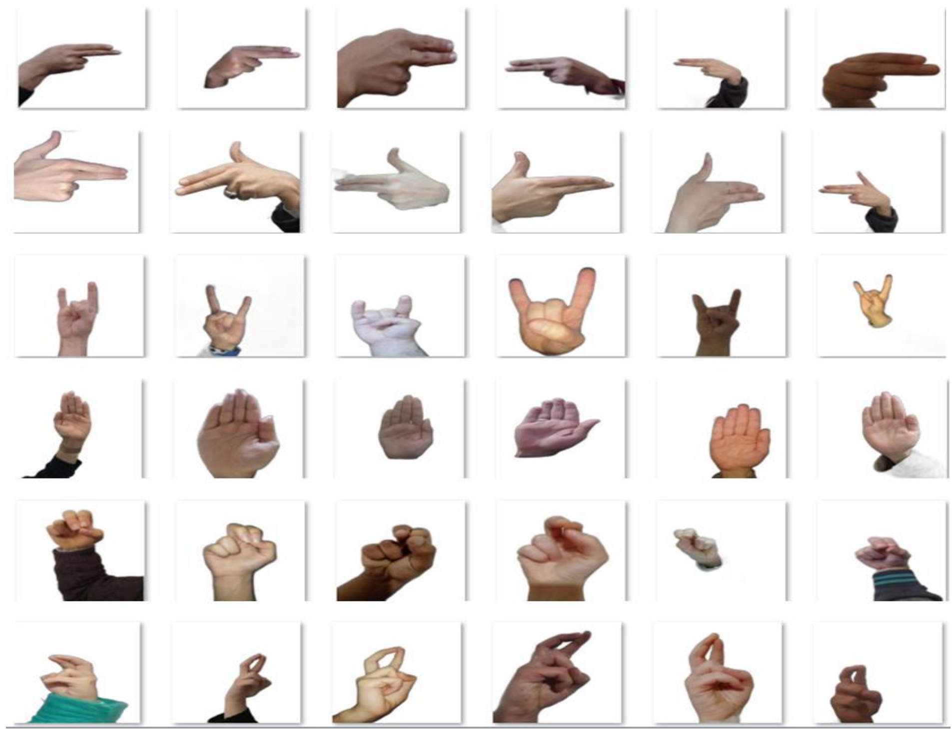

Fig. 3 – Illustrates an example of the appearance of a Arabic Alphabet Sign Language Dataset

3.2. The Model Architecture

The EfficientNetB3 [21], a member of the EfficientNet family that uses a unique compound scaling approach, was first presented by Tan and Le in 2019. A special compound scaling method balances depth, breadth, and resolution to optimize performance and efficiency. Squeeze excitation (SE) modules and lightweight-Mobile-Inverted Bottleneck Convolution (MBConv) blocks are used to decrease processing costs and parameters without surrendering heightened accuracy. the proposed method based on EfficientNetB3 achieved a test accuracy of 99.84% and strong generalization to ArSL recognition in this paper. It is also suitable for deployment on devices with limited resources, such as smartphones, due to its lightweight architecture.

Important characteristics of the model include:

a) **The Base Model:** The EfficientNetB3 model. The final (100 layers) were unfrozen for fine-tuning to the ArSL dataset, while the initial layers (which contain general features) were frozen.

b) **Classification:** After a GlobalAveragePooling2D layer, two fully connected layers reduced the spatial dimensions of feature maps. The first dense Layer used batch normalization and activated ReLU (512 neurons) are used. Then add the drop layer at 0.5 rate to avoid overfitting. The second dense Layer used batch normalization and activated ReLU (256 neurons). Then drop layer 0.5 rate. Finally, the result class probabilities by a final Dense Layer that contained (31) neurons (one for each class-letter) and a softmax activation function.

c)**Compile model:** Adam optimizer are used start with a slightly higher learning rate (1e-4) initially and reduce it dynamically based on Reduce LR On Plateau when validation loss plateaus), categorical cross-entropy loss, and the evaluation metric accuracy. The model was trained for 100 epochs with a batch size of 32.

d) **Data Splitting:** Three subsets of the dataset were created. The Training Set (70%), was used to optimize the model's weights. The Validation Set (15%), was used to track performance during training and adjust hyperparameters. The Test Set (15%), which was set aside for the last evaluation to determine the model's predictability.

4. Results and Discussion

In this study, the results of an experiment assessing the suggested Arabic sign language (ArSL) recognition system demonstrate its superior performance in recognizing a range of Arabic alphabet sign letters in the No Background RGB Arabic Alphabets Sign Language. For multi-class classification, it pre-processes a steps of hand gesture image by applying one-hot encoding, resizing (224×224 pixels for EfficientNetB3 compatibility), normalizing , and augmentation techniques to improve generalization.

Optimized with a custom classification head, EfficientNetB3-base model is trained with learning rate scheduling and early stopping. The model achieves high accuracy (99.67% for validation and 99.84 percent for testing), and evaluation metrics like classification reports and confusion matrices reveal how robust the model Figures 4 and Table 1. Lastly, random image testing shows how applicable it is in the real world Figure 5.

The performance of this system is assessed using a wide range of measures, including accuracy, precision, recall, and F1-score. A test's accuracy can be evaluated using the F-Score, a statistic that balances recall and precision. This metric may provide the most precise performance measurements by utilizing accuracy and recall. Importantly, a greater F-measure results with better outcomes. Recall and precision are positively correlated with less false-positives and false-negatives, respectively. An example of these metrics is as follows:

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (1)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (2)$$

$$\text{F} - \text{meature} = 2 * \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}} \quad (3)$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (4)$$

The overall result that can be achieved when applying the Proposed method displayed in Table 1.

Class	**Precision**	**Recall**	**F1-score**
Ain	1.00	1.00	1.00
Al	1.00	1.00	1.00
Alef	1.00	1.00	1.00
Beh	1.00	1.00	1.00
Dad	1.00	1.00	1.00
Dal	1.00	1.00	1.00
Feh	1.00	1.00	1.00
Ghain	1.00	1.00	1.00
Hah	1.00	1.00	1.00
Heh	1.00	1.00	1.00
Jeem	1.00	1.00	1.00
Kaf	1.00	1.00	1.00

Khah	1.00	1.00	1.00
Laa	1.00	1.00	1.00
Lam	1.00	1.00	1.00
Meem	1.00	1.00	1.00
Noon	1.00	1.00	1.00
Qaf	1.00	1.00	1.00
Reh	0.92	1.00	0.96
Sad	1.00	1.00	1.00
Seen	1.00	1.00	1.00
Sheen	1.00	1.00	1.00
Tah	1.00	1.00	1.00
Teh	1.00	1.00	1.00
Teh_Marbuta	1.00	1.00	1.00
Thal	1.00	1.00	1.00
Theh	1.00	1.00	1.00
Waw	1.00	1.00	1.00
Yeh	1.00	1.00	1.00
Zah	1.00	1.00	1.00
Zain	1.00	0.94	0.97

Table 1 – Classification Report

The confusion matrix is displayed in Figure 4, showed that all 31 classes were nearly correctly classified with a few (such "Zain") having minor misclassifications. According to the classification report, the model performed well in every class, with a weighted F1-score of 1.00.

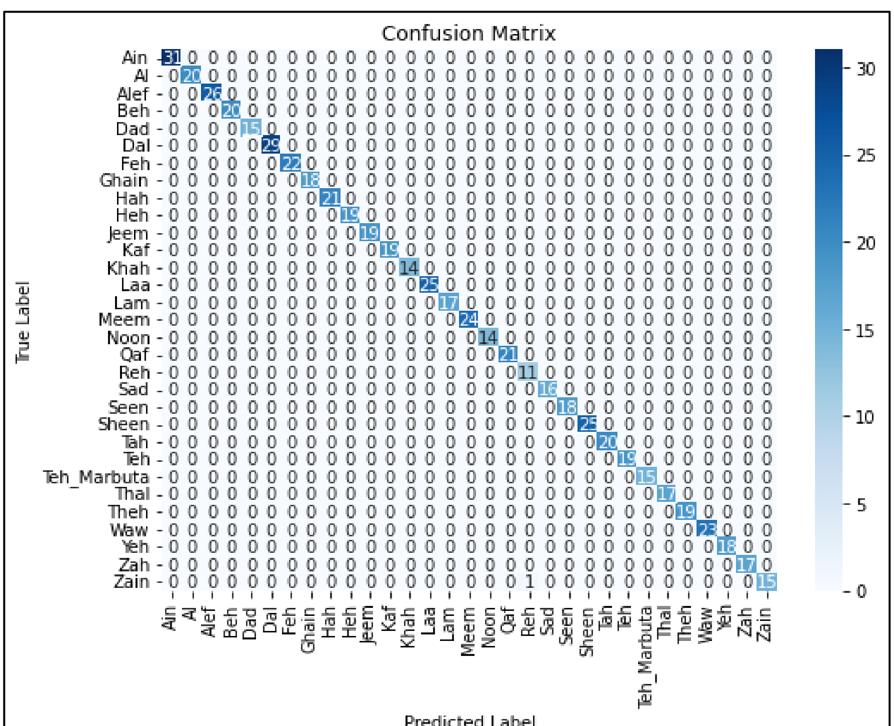

Fig .4 – Confusion matrix.

The reliability of the model in accurately identifying motions was demonstrated by random picture testing. Figure 5 illustrates the prediction visualization's potential for real-world applications.

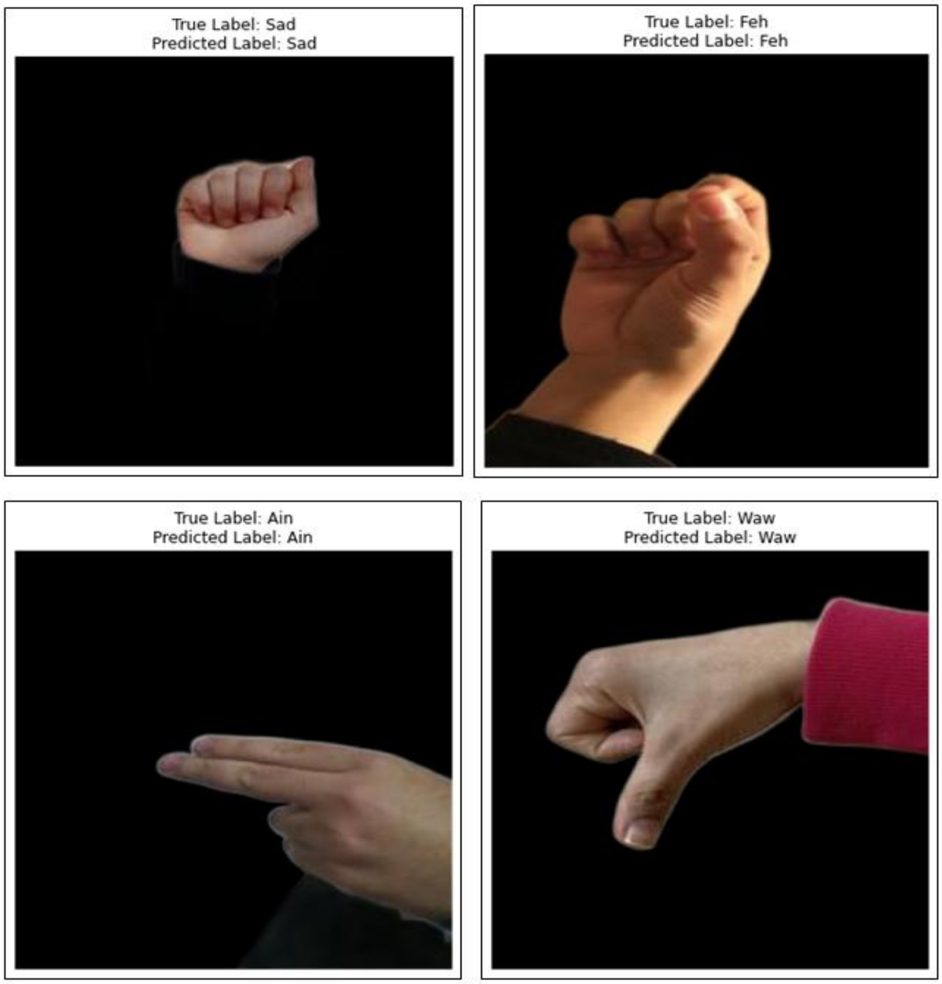

Fig 5 – Sample Test Image with Predicted and True Labels

To evaluate how well the earlier efforts performed when using this dataset. One article was utilized and examined [20] that used and introduced the dataset used in our study. This work showed the first CNN-based ArASL recognition model with a validation accuracy of 97.4% using a cleaned and enhanced version of the AASL dataset. The durability of the model was enhanced by specific pre-processing techniques like dynamic dropout and backdrop reduction. Important progress in ArASL identification is highlighted in this article, along with possibilities for dynamic gesture recognition and scalability. Any other prior published studies had not used this data until this paper was finished. The models in Table 2 that used the ArSAL dataset used in this study and comparison with the proposed method:

Ref.	Accuracy %
[20]	97.4%
Proposed model	99.8%

Table 2 – Our system's performance in comparison with other recent models

5. Conclusion

Hearing-impaired people are deficient in communicating with others in a simple method as they have to learn sign language, which is identified as their formal language to communicate with the community. The total success of image-based solutions for this challenge depends on the segmentation quality and the choosing of the features that should convey the major visual elements of the sign language motion. The present solutions reveal great space for improvement for the ArSL language recognition solutions which usually depend on deep learning models. Using transfer learning with EfficientNetB3, this paper presents a reliable and effective model for Arabic Alphabet Sign Language recognition. The presented model showed the possibility for use in real-time interpreters and instructional aids by achieving a test accuracy of 99.8% on the test dataset. Future studies will be focused on adding dynamic movements by incorporating real-time video-based recognition to the dataset. Also integrating gesture recognition into interactive hearing-impaired systems. The results of this research make a substantial contribution to the field of assistive communication technologies for the Deaf community, paving the way for their real-world application.

References

[1] M. Mustafa, "A study on Arabic sign language recognition for differently abled using advanced machine learning classifiers", J. of Ambient Intelligence and Humanized Computing 12, 4101–4115, Mar. 2020.

[2] Mirdehghan, M. Persian, Urdu, and Pashto: A comparative orthographic analysis. Writ. Syst. Res. 2010, 2, 9–23.

[3] El-Bendary, N.; Zawbaa, H.M.; Daoud, M.S.; Hassanien, A.E.; Nakamatsu, K. ArSLAT: Arabic Sign Language Alphabets Translator. In Proceedings of the 2010 International Conference on Computer Information Systems and Industrial Management Applications (CISIM), Krakow, Poland, 8–10 October 2010; pp. 590–595.

[4] Adam R. 2015. Standardization of Sign Languages. Sign Language Studies 15:432–445. DOI: 10.1353/sls.2015.0015.

[5] Alawwad, Rahaf Abdulaziz, Ouiem Bchir, and Mohamed Maher Ben Ismail. "Arabic sign language recognition using Faster R-CNN." International Journal of Advanced Computer Science and Applications 12, no. 3 (2021).

[6] Zhuang, Fuzhen, Zhiyuan Qi, Keyu Duan, Dongbo Xi, Yongchun Zhu, Hengshu Zhu, Hui Xiong, and Qing He. "A comprehensive survey on transfer learning." Proceedings of the IEEE 109, no. 1 (2020): 43-76.

[7] Abdullahi, Sunusi Bala, and Kosin Chamnongthai. "American sign language words recognition using spatio-temporal prosodic and angle features: A sequential learning approach." IEEE Access 10 (2022): 15911-15923.

[8] Hasan, Md Mehedi, Azmain Yakin Srizon, Abu Sayeed, and Md Al Mehedi Hasan. "Classification of American sign language by applying a transfer learned deep convolutional neural network." In 2020 23rd International Conference on Computer and Information Technology (ICCIT), pp. 1-6. IEEE, 2020.

[9] Mahdikhanlou, Khadijeh, and Hossein Ebrahimnezhad. "Multimodal 3D American sign language recognition for static alphabet and numbers using hand joints and shape coding." Multimedia tools and applications 79, no. 31 (2020): 22235-22259.

[10] DelPreto, Joseph, Josie Hughes, Matteo D'Aria, Marco De Fazio, and Daniela Rus. "A wearable smart glove and its application of pose and gesture detection to sign language classification." IEEE Robotics and Automation Letters 7, no. 4 (2022): 10589-10596.

[11] Charan, Marrivada Gopala Krishna Sai, S. S. Poorna, K. Anuraj, Choragudi Sai Praneeth, PG Sai Sumanth, Chekka Venkata Sai Phaneendra Gupta, and Kota Srikar. "Sign language recognition using cnn and cgan." In Inventive Systems and Control: Proceedings of ICISC 2022, pp. 489-502. Singapore: Springer Nature Singapore, 2022.

[12] Dabwan, Basel A., Mukti E. Jadhav, Yahya A. Ali, and Fekry A. Olayah. "Arabic Sign Language Recognition Using EfficientnetB1 and Transfer Learning Technique." In 2023 International Conference on IT Innovation and Knowledge Discovery (ITIKD), pp. 1-5. IEEE, 2023.

[13] AlKhuraym, Batool Yahya, Mohamed Maher Ben Ismail, and Ouiem Bchir. "Arabic sign language recognition using lightweight cnn-based architecture." International Journal of Advanced Computer Science and Applications 13, no. 4 (2022).

[14] Kamruzzaman, M. M. "Arabic sign language recognition and generating Arabic speech using convolutional neural network." Wireless Communications and Mobile Computing 2020, no. 1 (2020): 3685614.

[15] Alsaadi, Zaran, Easa Alshamani, Mohammed Alrehaili, Abdulmajeed Ayesh D. Alrashdi, Saleh Albelwi, and Abdelrahman Osman Elfaki. "A real time Arabic sign language alphabets (ArSLA) recognition model using deep learning architecture." Computers 11, no. 5 (2022): 78.

[16] Noor, Talal H., Ayman Noor, Ahmed F. Alharbi, Ahmed Faisal, Rakan Alrashidi, Ahmed S. Alsaedi, Ghada Alharbi, Tawfeeq Alsanoosy, and Abdullah Alsaeedi. "Real-Time Arabic Sign Language Recognition Using a Hybrid Deep Learning Model." Sensors 24, no. 11 (2024): 3683.

[17] Elshaer, A. M., Yousef Ambioh, Ziad Soliman, Omar Ahmed, Miral Elnakib, Mohamed Safwat, Salma M. Elsayed, and Mahmoud Khalid. "Enhancing Arabic Alphabet Sign Language Recognition with VGG16 Deep Learning Investigation." In 2024 14th International Conference on Electrical Engineering (ICEENG), pp. 184-186. IEEE, 2024.

[18] Renjith, S., Manazhy Rashmi, and Sumi Suresh. "Sign language recognition by using spatio-temporal features." Procedia Computer Science 233 (2024): 353-362.

[19] Al Ahmadi, Saad, Farah Muhammad, and Haya Al Dawsari. "Enhancing Arabic Sign Language Interpretation: Leveraging Convolutional Neural Networks and Transfer Learning." Mathematics 12, no. 6 (2024): 823.

[20] El Kharoua, R., & Jiang, X.M. (2024). Deep Learning Recognition for Arabic Alphabet Sign Language RGB Dataset. Journal of Computer and Communications, 12, 32-51. https://doi.org/10.4236/jcc.2024.123003

[21] Tan, Mingxing, and Quoc Le. "Efficientnet: Rethinking model scaling for convolutional neural networks." In International conference on machine learning, pp. 6105-6114. PMLR, 2019.