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[1] **Ali A. Alsaud**

[2] **Raghad Z. Yousif**

[3] **Marwan. M Aziz**

[4] **Shahab W. Kareem**

[5] **Amer J. Maho**

Kurdish Sign Language Recognition Using Pre-Trained Deep Learning Models

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Abstract: - In the tapestry of rich human communication, sign language gleams like one of the basic threads of this art, giving voice to hundreds of deaf and hard-of-hearing individuals in the region. The technology for recognizing and translating sign language fell far behind what these communities needed. Therefore, the present investigation is going to compare the performance of three top-performing deep learning algorithms in recognizing the signs created from the database of Kurdish Sign Language. The models are going to be put to a rigorous test, with a variety of signs drawn. All the 3 models give a performance that is—from all indications—good or even excellent, this is MobileNetV2, a very good candidate that manages to walk an amazing line between the requirements of high accuracy, low space complexity, and acceptable time complexity. We conclude by looking at some exciting opportunities for future research, including integrating our models into hardware devices and expanding our study to a larger variety of sign languages. And just as any good journey would, it throws up as many questions as it answers, leaving us inspired by the many possibilities that will need to be explored to enhance communication for all.

Keywords: Deep Learning, Sign language, Recognition, Pre-trained model.

I. INTRODUCTION

Sign language is a language that represents a form of communication between deaf and hard-of-hearing people with their grammar, syntax, and vocabulary, just as much as a spoken language. However, its prevalence and being understood are not that common in the larger population of the world. This has majorly been catalyzed by the various forms that it takes. Mainly, it is important to mention here that the major mode of communication for deaf individuals throughout the Kurdistan region and in neighbouring countries is through the application of Kurdish Sign Language (KSL). However, sign languages have not been in the limelight for translation technologies of spoken languages, and Kurdish Sign Language is no exception. The gap doesn't allow for an effective closing of the transmitted ideas and feelings of the deaf person, hence making them lack a gap to access the information effectively and thus participate in society. For this, the project suggests the use of deep learning techniques acting as a bridge in a convenient communication facility for easy translation of KSL into spoken language and text. There remains a difficulty in the recognition and understanding of sign languages, including KSL, because there has been little effort placed in research and technology. Even the deaf communities and the hard of hearing, especially from the Kurdish region, are highly underrepresented in scientific studies. This only adds to the gap in communication with the hearing population. However, current solutions, like machine learning applications and mechanical aids, still suffer from the lack of accuracy, affordability, and convenience of use. More so, the weaknesses of present solutions give all reasons to stress the importance of innovative approaches in sign language recognition. Hypothesis It shows that the deep learning model, essentially CNNs, attains better performance in the recognition of KSL signs compared to traditional machine learning methods. We therefore expect that ResNet50 should do particularly well in both these tasks since the abilities of the former are well known to be quite good for the two image and sequence analysis tasks. The principal motive with which this

[1] *Corresponding author: Computer Engineering Department, College of Engineering, Al-Mustansiriyah University Baghdad-Iraq

[2] *Salahaddin University-Erbil, College of science, Department of physics, Erbil-Iraq*

[2] Computer Technology Engineering *Dept.* Al-Qalam University College, Kirkuk, Iraq.

[3] Department of Computer Engineering, College of Engineering, Knowledge University, Erbil, Iraq.

[3] Department of software Engineering, College of Engineering, Salahaddin University-Erbil, Kurdistan-region, Iraq.

[4] Dept. of Technical Information Systems Engineering, Erbil Technical Engineering College, Erbil Polytechnic University, Erbil, Iraq.

[5] Department of Computer Science, College of Information Technology and Computer Science, Catholic University in Erbil, Erbil, Iraq.

research sets out is to provide a communication solution for those deaf and hard of hearing, who are, by large, impaired by the current society from effectively communicating with society at large. The scant research literature, along with the presented limitations of existing technology-based solutions, certainly underscores the push for the present study—that of applying Deep Learning techniques in the recognition and translation of KSL, such that the latter could be effectively and inclusively comprehended.

RQ1: To what extent the proposed model contribute to the effective recognition of KSL gestures through transfer learning techniques in different architectures of the neural network?

RQ2: The impact of data augmentation on the model's ability to generalize and identify KSL motions.

RQ3: The current limitations in knowledge and understanding of KSL and what further developments or activities need to be considered for its better and active functioning?

II. LITERATURE REVIEW

The advent of such deep learning technologies, it has tremendously transformed the sign language recognition (SLR) scenario, as there are a lot of research works going on for a better kind of method to ensure a more precise and effective SLR system. In early SLR foundational studies, such as [1], it can be found that they opened with brief but essential background outlining the background inherent to the intricacies and problems characteristic to this, notably strong needs for robustness, feature extraction, and the visual-spatial character of sign language understanding. The field has highly moved towards deep learning methodologies, as very well presented by [2] with their pioneering work on Sign Language Transformers. This shift signals not only a turn away from traditional, manual feature extraction toward end-to-end models directly capable of processing raw data into interpretable results but also gives new perspectives on recognition and translation in sign language. They have furthered methodological innovations by a focus on model performance and the nuances of improved SLR. Techniques such as augmentation in the area of data and efficient architecture of MobileNetV2 proposed by [3] support very important advances towards making systems in SLR more generalizable and applicable in real time. Furthermore, multi-modal approaches to the recognition of gesture have been pointed out by [4] in their reference to studies regarding multi-modal that bring benefits from the use of diverse data sources. This helps in making more precise recognition of gestures and will become the research focus for future. On the horizon, the need for large, diverse data in SLR emerges, as well as the call for more powerful technologies to embrace the multi-meaning modalities of sign languages. Few of the more recent research works, with incorporation of innovation and critical analysis that offer promise of a solution to these barriers, may have more wide-ranging fruition for the deployment of these technologies as more inclusive and effective communication tools for the deaf and hard of hearing. In [5] introduced a novel approach to continuous sign language recognition by utilizing a correlation network, as detailed in their paper. This method emphasizes the importance of capturing temporal relationships within sign language sequences, offering a more nuanced and effective model for interpreting continuous sign language gestures, significantly enhancing the model's ability to understand the fluid dynamics of sign language communication. The study [6] provided a critical review and analysis of machine learning methods applied to sign language recognition in their work for Intelligent Systems with Applications. This review navigates from traditional machine learning techniques to contemporary deep learning advancements, addressing the challenges and necessary enhancements for accurate and reliable sign language recognition systems. The upcoming publication in the UKH Journal of Science and Engineering about the Kurdish Sign Language Recognition System signifies a considerable success, showcasing the effectiveness of machine learning techniques for specialized languages and highlighting the pressing need for additional research and data enhancement in this area. A detailed investigation into the impact of data augmentation on deep-learning-based image classification demonstrates that these methods substantially improve a model's generalization capability and performance. This insight is especially relevant for sign language recognition, suggesting promising avenues for enhancing performance. The IEEE Transactions on Multimedia review article provides a comprehensive overview of current deep learning strategies for sign language recognition, outlining effective approaches and highlighting areas necessitating further exploration. An introductory discussion on deep learning in medical image processing draws parallels to sign language recognition challenges, thereby extending the application of deep learning principles to a broad array of domains. The introduction of Sign Language Transformers emerges as a key innovation, leveraging the sequential nature of sign language to foster improved integration between recognition and translation tasks. The deployment of 3D Convolutional Neural Networks (CNNs) in sign language recognition demonstrates the potent ability of these models to capture spatial-temporal features, signifying considerable progress in this domain. The paper introduces an innovative strategy of stage-wise optimization through recurrent CNNs for continuous sign language recognition, effectively tackling the complexity of sign sequences and proposing a novel optimization approach to enhance sequence recognition. In 2016, researchers at the University of South Australia pioneered a new multimodal sign language recognition system. ModDrop: adaptive multimodal gesture recognition opens new avenues for integrating multiple data modalities into a unified, performance-enhancing framework, offering essential insights into multimodal data integration for sign language recognition [35-37]. Each of these contributions underscores the dynamic and evolving landscape of sign language recognition research, highlighting the technological advancements and methodological innovations driving progress in this crucial area of study.

Table 1 comparison for some related work

reference	Method Used	Objective	Purpose	Contribution	Achievements	Result
Cooper et al. (2011)	Visual Analysis	Understand human actions including sign language	To lay the groundwork for SLR	Early exploration of SLR challenges	Highlighted the importance of feature extraction	Paved the way for further SLR research
Camgoz et al. (2020)	Sign Language Transformers	Joint end-to-end SLR and translation	To improve SLR accuracy and efficiency	Introduced transformers to SLR	Set a new benchmark for SLR systems	Demonstrated high accuracy in SLR and translation
Sandler et al. (2018)	MobileNetV2	Efficient architecture for real-time applications	To enable real-time SLR applications	Optimization of neural network architecture for efficiency	Improved real-time processing capabilities	Enhanced performance in real-time SLR
Dolatabadi et al. (2017)	Deep Multi-Modal Fusion	Recognize static and dynamic hand gestures	To improve gesture recognition accuracy	Utilization of multi-modal data for SLR	Showcased the benefits of multi-modal integration	Increased accuracy in gesture recognition
Hu et al. (2023)	Correlation Network	Continuous SLR	To capture temporal dynamics in SLR	Novel approach for interpreting continuous SLR	Enhanced model's understanding of sign language dynamics	Significantly improved continuous SLR performance

III. METHODOLOGY

The deep learning technique applied in this study—based on the model developed—is proposed to base the research framework. In this case, the deep learning technique applies in the development of the recognition system for Kurdish Sign Language (KSL) gestures. This part is related to preprocessing, the part related to the training of the model and evaluation by confronting it with the traditional machine learning method and another model of deep learning trained with the same database. From the background research, one can say that out of these three algorithms (InceptionV3, MobileNetV2, and ResNet50), it would be ResNet50 that would perform the best for hand gesture recognition, as proven by previous studies. This study can be termed as the following: Data

Collection: Collect the dataset of the people who can perform the gestures of Kurdish Sign Language (KSL) from the region of Kurdistan in Iraq. In this work, we have taken the dataset that contains different varieties of the form of images related to the hand gestures. The dataset contained both static and dynamic signs; it included a very wide range of hand signs to make the model performance valid in multiple scenarios. Then it was augmented, and the resulting sample had more than 17,000 samples for the 5 classes, which should bring high accuracy when training models on this data. Data Preparation—Background Removal: At the data preparation phase, removal of background from images using the rembg library in Python was applied to get some samples for training. The loop was looping the images, and each time it had a different background, so the sample was more diverse. This aims at focusing on hand signs by getting rid of the background from the captured images first, leaving the hand gesture without any other thing around. This is all-important so that the model may learn critical features of hand movement without unwanted influences.

Figure (1) dataset before background removal

Figure (2) dataset after background removal

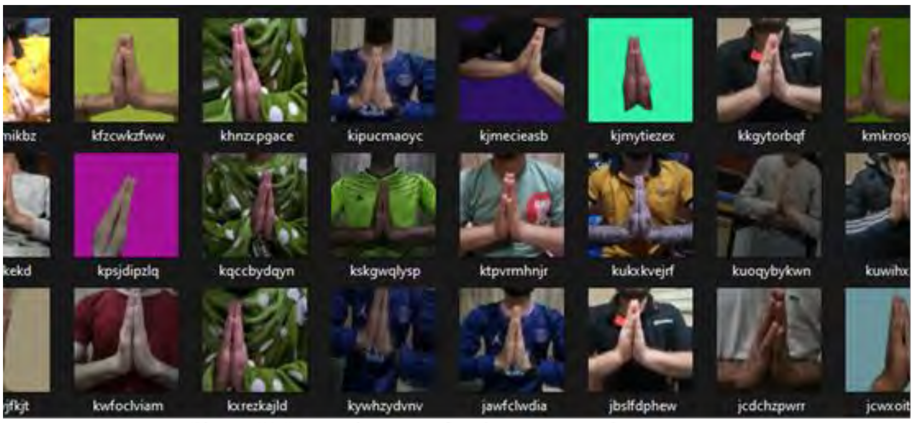


Figure (3) Dataset increase after data augmentation process

Data Augmentation: several augmentation techniques were employed, aimed at simulating diverse real-world situations and boosting the model's ability to recognize unseen data. The implemented transformations encompass a variety of adjustments: rotating images up to a maximum of 20 degrees, shifting images along both horizontal and vertical axes up to 20% of their dimensions, applying a shear transformation with a factor of 0.2, zooming into or out of images by 20% at random, altering brightness levels between 50-150% of the original image, and similarly adjusting contrast within the same range. Additionally, missing pixels were filled using the nearest neighbor method. These augmentation methods are designed to enhance model training and testing by significantly expanding the volume and diversity of the dataset.

Data Preprocessing: First, data preparation—that is, "data preprocessing"—is quite essential in the line of computer vision processes, as the foundation is laid for model performance. The Kurdish Sign Language dataset has a large amount of rich visual data and needed very subtle handling to derive maximum model performance. This further saw these images undergoing an important preprocessing step—resizing—before being presented to the deep learning models, namely MobileNetV2, InceptionV3, and ResNet50.

Feature Extraction: The concept of feature extraction, when applied in the domain of deep learning, hence, is, in a way, a little different from the manner in which it is used and discussed in conventional machine learning techniques. Traditional machine learning approaches would require us to hand-engineer and extract relevant features from data, but in deep learning models, they could actually on their own learn the features right from data (LeCun, Bengio, & Hinton, 2015). It has become one of the key enablers to the massive success of deep learning across a range of applications. Image recognition works like an effort to recognize Kurdish sign language. The present investigation was based on three of the popular CNN architectures: MobileNetV2, InceptionV3, and ResNet50. As noted by Sandler et al. (2018), Szegedy et al. (2016), and He et al. (2016), the fact that these models are pre-trained on large picture datasets, such as ImageNet, makes it possible for them to learn a broad range of attributes that are of great importance for use by many applications. We have used that pre-trained model in order to let the model itself extract most of the relevant attributes from our Kurdish Sign Language dataset. Now, with this feature extraction process in place, the models would be able to make sense of the raw picture data in a manner which would allow prediction.

Model Architecture: MobileNetV2: given its very low space complexity compared to other algorithms (Sandler et al., 2018). We added dropout (0.5) to the architecture for model improvement and to avoid the problem of overfitting. It also helps in reducing the size of the model concerning memory, as it drops randomly some of the nodes.

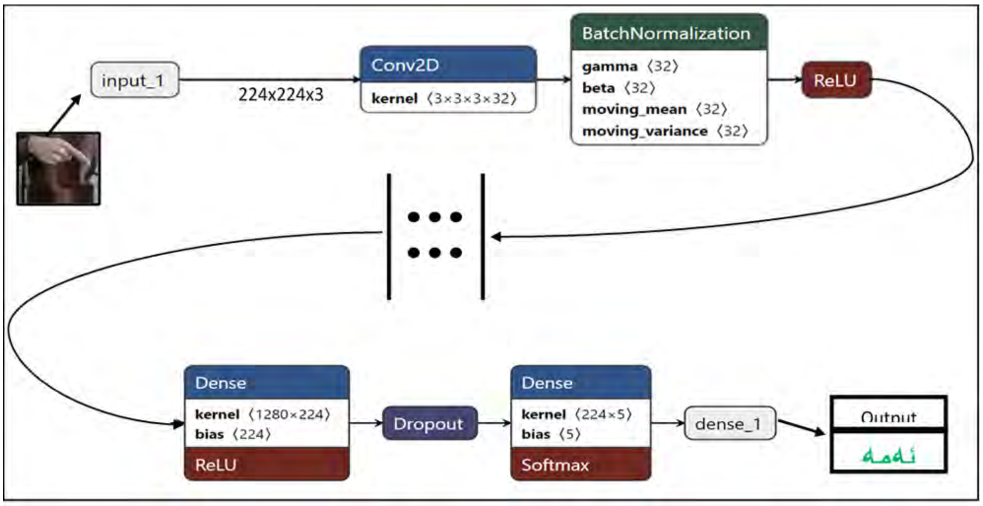


Figure (4) Architecture used for MobileNet V2

IV. Result and analysis

The relationship with respect to time between accuracy and loss is another strong ally of the machine learning practitioner in making the visualization of how the model's learning process evolves. Our study uses three different types of deep learning models, namely Inception V3, MobileNet V2, ResNet50 (He et al., 2016), to determine the same relation. The authors refer to Figure (5) and (6) in looking at Inception V3. From the plot of accuracy, there is a steady inclining trend indicated, representing the growing competence of the model with the dataset for the Kurdish sign language. Similarly, the plot loss showed a decreasing trend. The same pattern was exhibited when comparing MobileNet V2 with Figure (7) and (8). The diagram explains almost a steady line rising, meaning that the model worked successfully in its learning through its processes. At the same time, over time, the loss plot becomes less so much, so much to emphasize how well the model is doing its predictions. The final result of our experiment is ResNet50, as presented in Figures (9) and (10). The trend of the accuracy plot is rising, and the trend of the loss plot is falling in this case, which does show the model's ability to learn in both cases. It shows how well the model has learned and hence transformed in every epoch. Importantly, these inclinations did not change even after exposure to the new data was proffered to the models and were, therefore, indicative of thorough learning processes, instead of rote memory. This finding suggests that these models may be able to detect Kurdish Sign Language accurately in practical, real-world applications (Szegedy et al., 2016). Tables 2, 3, and 4 showcase the performance of InceptionV3, MobileNetV2, and ResNet50, respectively, in detecting Kurdish sign language. The assessment includes metrics such as loss, accuracy, validation loss, and validation accuracy across eight training epochs. The classification performance is described in various figures and tables to represent the finding of three deep learning models. Against this backdrop, this test gets set for the classification reports and confusion matrices of three models: MobileNetV2, InceptionV3, and ResNet50. Quite outstanding across all precisions and recalls of gesture classes is InceptionV3, almost scoring 1.00 in most metrics. InceptionV3 attains a perfect score of 1.0 for "HowAreYou." Little variances are depicted from the scores of 1.0 in "Myself," "Sorry," "Soso," and "This," with a precision and recall score of around 0.99. This means InceptionV3 impressively manages an accuracy of 0.99 over MobileNetV2 mod el, on the other hand, performed very well, having an overall precision, recall, and F1-score of 1.00 for each class of gesture. Its confusion matrix, however, points to an exact distinction of all classes except for the "Myself" gesture, which gets confused with "This" gesture.

The study deployed three algorithms with models exceeding a 98% accuracy rate in analyzing data across five categories, albeit with slight differences. The choice of the MobileNetV2 model was influenced by its lower space complexity, making it more suitable for mobile applications than for desktop use, thereby enhancing its deployability on mobile platforms. The classification of Kurdish Sign Language gestures using MobileNetV2 resulted in superior performance with reduced training loss, as documented by Sandler et al. (2018).

Table (2) Epochs of InceptionV3

Inception V3	Time (s)	Cum. Time	loss	accuracy	val_loss	val_accuracy
Epoch 1	188	188	0.1556	0.9494	0.0324	0.9917
Epoch 2	59	247	0.0239	0.9926	0.024	0.9928
Epoch 3	59	306	0.0104	0.9976	0.0135	0.995
Epoch 4	60	366	0.0054	0.999	0.01	0.9955
Epoch 5	59	425	0.0057	0.999	0.014	0.9961
Epoch 6	59	484	0.0033	0.9994	0.0114	0.9947
Epoch 7	59	543	0.0024	0.9997	0.0086	0.9967
Epoch 8	59	602	0.0015	0.9999	0.0071	0.9978

Table (3) Epochs of MobileNet V2

MobileNet V2	Time (s)	Cum. Time	loss	accuracy	val_loss	val_accuracy
Epoch 1	102	102	0.2021	0.9338	0.039	0.9892
Epoch 2	58	160	0.042	0.9871	0.0263	0.9914
Epoch 3	58	218	0.0273	0.992	0.0339	0.9869
Epoch 4	59	277	0.015	0.9961	0.0164	0.9933
Epoch 5	58	335	0.0123	0.9962	0.0168	0.9944
Epoch 6	59	394	0.0117	0.9964	0.0154	0.995
Epoch 7	58	452	0.0114	0.9969	0.0122	0.9961
Epoch 8	58	510	0.0143	0.9948	0.0126	0.9953

Table(4) Epochs of ResNet50

ResNet50	Time (s)	Cum. Time	loss	accuracy	val_loss	val_accuracy
Epoch 1	201	110	0.158	0.9474	0.015	0.9972
Epoch 2	69	179	0.0265	0.9917	0.0087	0.9972
Epoch 3	70	249	0.0156	0.9945	0.0049	0.9997
Epoch 4	69	318	0.0143	0.9957	0.0048	0.9992
Epoch 5	69	387	0.016	0.9951	0.0035	0.9997
Epoch 6	69	456	0.013	0.9964	0.0027	0.9989
Epoch 7	68	524	0.0072	0.9977	0.0021	0.9992
Epoch 8	76	600	0.0131	0.9956	0.0025	0.9989

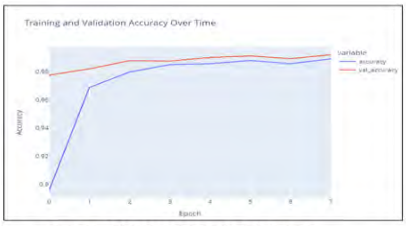


Figure (5) Training and Validation accuracy of InceptionV3

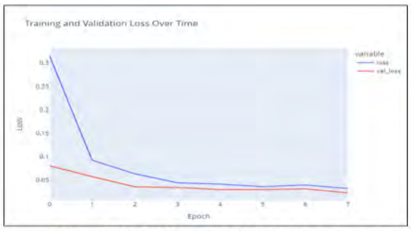


Figure (6) Training and Validation accuracy of InceptionV3

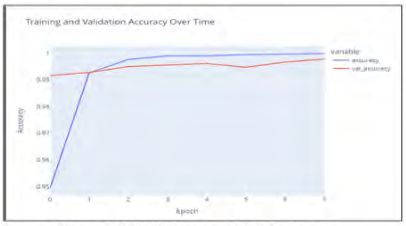


Figure (7) Training and Validation accuracy of MobileNetV2

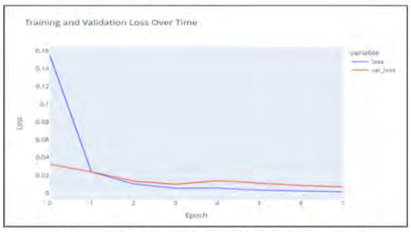


Figure (8) Training and Validation accuracy of MobileNetV2

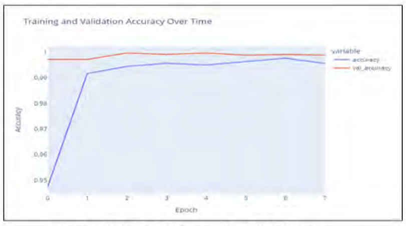


Figure (9) Training and Validation accuracy of ResNet50

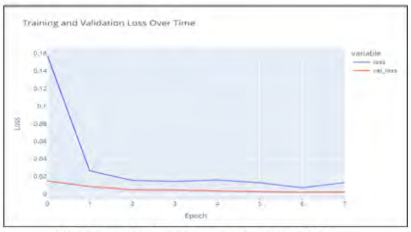


Figure (10) Training and Validation accuracy of ResNet50

Table(5) Classification report of MobileNet V2

MobileNet	precision	recall	f1-score	support
HowAreYou	1.00	1.00	1.00	270
Myself	1.00	1.00	1.00	270
Sorry	1.00	1.00	1.00	270
Soso	1.00	1.00	1.00	270
This	1.00	1.00	1.00	270
accuracy			1.00	1350
macro avg	1.00	1.00	1.00	1350
weighted avg	1.00	1.00	1.00	1350

Table(6) Classification report of InceptionV3

InceptionV3	precision	recall	f1-score	support
HowAreYou	1.00	1.00	1.00	270
Myself	0.99	1.00	1.00	270
Sorry	1.00	0.99	0.99	270
Soso	0.99	0.99	0.99	270
This	0.99	0.99	0.99	270
accuracy			0.99	1350
macro avg	0.99	0.99	0.99	1350
weighted avg	0.99	0.99	0.99	1350

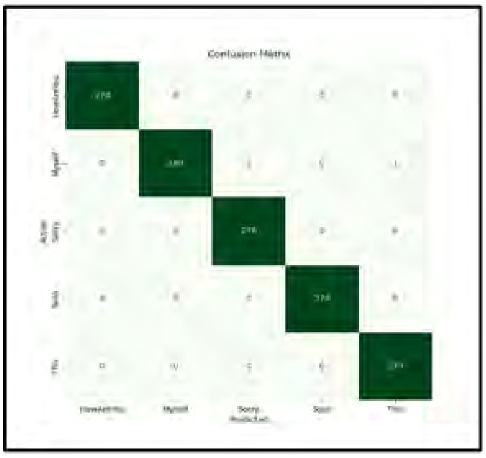
Table(7) Classification report of ResNet50

ResNet50	precision	recall	f1-score	support
How Are You	1.00	1.00	1.00	270
Myself	1.00	1.00	1.00	270
Sorry	1.00	1.00	1.00	270
Soso	1.00	1.00	1.00	270
This	1.00	1.00	1.00	270
accuracy			1.00	1350
macro avg	1.00	1.00	1.00	1350
weighted avg	1.00	1.00	1.00	1350

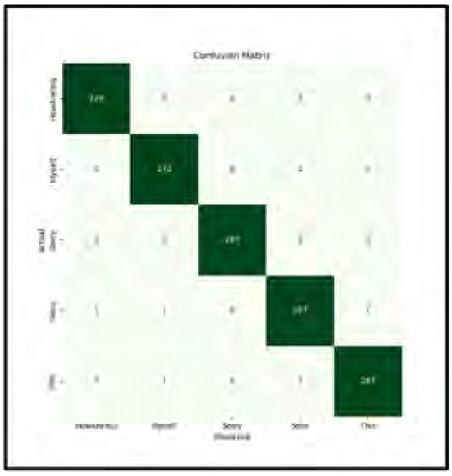
Table(8) Comparison between accuracy, space complexity and time complexity of the 3 algorithms

Algorithm	Test accuracy	Space complexity	Time complexity
MbileNetvV2	99.926%	12,980 kb	209.4ms/step
InceptionV3	99.333%	93,616 kb	207.8ms/step
ResNet50	99.852%	100,407 kb	250.4ms/step

To further enhance the model's robustness, data augmentation techniques such as rotation, rescaling, and flipping of the inputs were applied, alongside the integration of dropout layers in the architecture. These improvements have significantly bolstered MobileNetV2's ability to generalize, reaffirming its reliability and flexibility for gesture recognition tasks. When compared to InceptionV3, MobileNetV2's mean time complexity is nearly identical, at 209.4 ms/step versus InceptionV3's 207.8 ms/step. This contrasts sharply with ResNet50's higher mean time complexity of 250.4 ms/step, highlighting the efficiency of MobileNetV2 and InceptionV3 and pointing to the higher time demands of ResNet50.

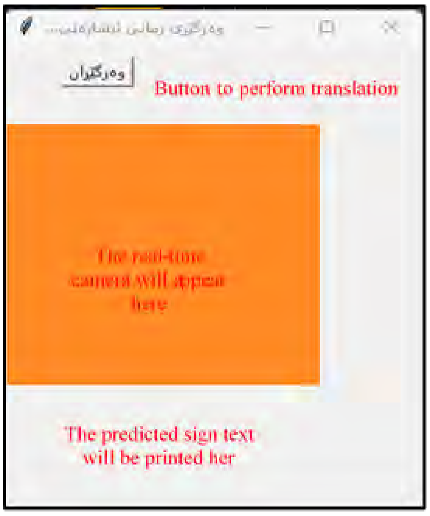


Figure(11) Confusion matrix for



Figure(12) Confusion matrix for

MobileNetV2 leads in accuracy among the models evaluated, achieving an impressive test accuracy of 99.926%, slightly surpassing ResNet50's accuracy of 99.852%. Despite InceptionV3's superior time complexity, it demonstrated slightly lower accuracy at 99.333%. The space complexity varied significantly across the models; MobileNetV2 required the least storage at only 12,980 KB, substantially less than InceptionV3's 93,616 KB and ResNet50's 100,407 KB. This difference underscores MobileNetV2's suitability and efficiency for gesture recognition applications, making it the preferred choice for tasks where space and time efficiency are paramount. Table 8 outlines the performance of the models in terms of accuracy, space complexity, and time complexity, illustrating the complex decision-making process involved in selecting a model for specific applications. While MobileNetV2 and InceptionV3 offer improved time complexity, selecting the most suitable model hinges on available computational resources, the required level of accuracy, and space constraints. Moreover, this study underlines the significance of the user interface (UI) as a crucial bridge between users and technology.



Figure(13) KSL translator UI

V. CONCLUSION

This study, whose aim was to explore the possibility of sign language recognition within deep learning models, with more detail given to Kurdish Sign Language, is yielding very promising results that might shed light on the potential of such technologies in overcoming communication barriers for the deaf and hard-of-hearing community. Out of all the models reviewed, MobileNetV2 turned out to be the most balanced in both its space and time complexities, besides being very accurate. It provides an ideal model for sign language applications in resource-constrained environments. This critical step with MobileNetV2 is a milestone not only in the practical deployment of sign language recognition systems but also marks what role efficiency and performance play in such technology development. The implication of this research goes far beyond technical success and heralds the onset of real-world applications with substantial benefits for the deaf and hard of hearing. The effectiveness and superior performance of MobileNetV2 become a pivot for the researchers, developers, etc., in their respective fields. Further emphasizing and giving a signal to them for the need to choose the models that give high accuracy and are feasible for deployment in real-time scenarios. The strategy that promises inclusion and understanding between the two cultures—one of the hearing and the other of the deaf community—to enhance the possibility for communication is vivid from this. It is thus quite explicit from this fact that potential areas for further research on sign language recognition remain very immense and varied in nature. Future works of this study include enhancing the model's robustness in different situations, making models more personalized with the person's signing style, and adding contextual information to gain more accuracy during the recognition process. Furthermore, their effectiveness when extrapolated to other sign languages and some ethical issues in the deployment of such approaches are further scope for studies. Findings from this study will be evidence that can be used to keep comparing effectiveness with different models, and an innovation base for further innovations in this area, aiming to make SLR more accurate, accessible, and inclusive. While the area develops, model performance will allow ethical considerations, including the delicate balance of all, and for resource efficiency, besides context-aware technologies. This work further augments the existing body of knowledge with the potential of different CNN models and lays a baseline for future developments aiming at making sign language recognition more precise, accessible, and inclusive.

Figure (14) KSL translator while recognizing “Sorry” sign

Figure (15) KSL translator while recognizing “How are you” sign

Figure (16) KSL translator while recognizing “So so” sign

Figure (17) KSL translator while recognizing “This” sign

Figure (18) KSL translator while recognizing “Myself” sign

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