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Deep Learning-Based Indian Sign Language Alphabet Recognition Using Convolutional Neural Networks

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Abstract:

Indian Sign Language (ISL) identification is an important aspect in increasing the communication of deaf or hard-of-hearing (DHH) people with the hearing community. Transfer learning is applied with a deep learning system based on EfficientNet-B0 for the automatic recognition of ISL letters. We used a publicly available ISL Alphabet Dataset, which includes 26 static letter classes (A to Z), for both training and evaluation. The image size was set to 224 x 224 before the preprocessing that involves normalization, data cleaning, and data augmentation like rotation, zoom, translation, altering brightness, and changing contrast to increase robustness and generalizability. In this, the dataset is separated into training, validation, and testing sets using a 70:15:15 split. By replacing the classification head with fully connected layers and adding a Softmax output layer for multi-class classification, EfficientNet pretrained on ImageNet is fine-tuned. It is a fact proven by experimental results that when tested against the proposed model, the test data had a precision of 98.34%, recall of 98.18%, and accuracy of 98.21%, as well as an F1-score of 98.25%. From analysis with a confusion matrix, one can see that the model distinguishes almost all ISL alphabet gestures except for similar-looking hand signs, which cause minor confusion. Further, analysis shows that the proposed approach is better off than traditional CNN VGG16, MobileNetV2, and ResNet50, while the computational costs remain low.

Keywords: Indian Sign Language (ISL), EfficientNet-B0, Transfer Learning, Deep Learning, Hand Gesture Recognition, Image Classification, Computer Vision, Data Augmentation

1. Introduction

Indian Sign Language (ISL) is one of the main ways the deaf and hard-of-hearing communities in different regions of the country communicate with each other. But even though awareness about inclusive communication has increased, the shortage of skilled sign language interpreters still poses major problems at various levels, such as education, healthcare, public services, and the workplace. In Indian Sign Language communication, automatically recognizing the ISL alphabet using computer vision and deep learning is an innovative and promising way to fill the communication gap between signer and non-signer [1], [3]. It has been confirmed by a couple of recent research works that sign language recognition systems that rely only on the user's camera input can enhance accessibility and, at the same time, do not require specialized hardware, which makes the devices much more affordable and suitable for practical use.

Previously, sign language recognition structures relied heavily on manually extracted key features with traditional machine learning classifiers: SVM, k-NN, Decision Trees, and HMM. While these techniques worked well under controlled scenarios, they were not reliable enough and easily failed when the hand orientation, illumination, or background complexity changed. It also takes a lot of effort for a person to craft features by hand, which may not even capture the intricate spatial properties of gestures necessary for precise recognition [3], [10].

Deep learning developments have really helped in the improvement of visual recognition performance by allowing feature detectors to be built in a hierarchical manner through the layers from the raw images. The Convolutional Neural Network (CNN) class of deep learning models has been able to achieve state-of-the-art results in image classification as well as gesture recognition tasks. Transfer learning methods that use already trained models like MobileNet, ResNet, and EfficientNet not only raise the accuracy of the recognition system but also make it computationally much cheaper [1], [2], [5]. Efficient deep learning architectures are capable of extracting discriminative features from the hand gestures much better than other techniques and are becoming more and more popular for sign language recognition applications in a real-time setting [1], [2].

Recognition of Indian Sign Language (ISL) alphabets has many practical uses, such as assistive communication systems, intelligent tutoring platforms, health care services, human-computer interaction, and mobile accessibility applications. But designing strong recognition systems that can handle changes in hand position, lighting conditions, camera angles, and background chaos is still a difficult research problem. The availability of large benchmark sets and recent developments in deep learning have accelerated research in this area by enabling the use of standardized evaluation protocols and feature learning enhancement [4], [6]. This paper presents a novel transfer learning-based ISL alphabet recognition system to overcome these obstacles, which is based on the design of the EfficientNet-B0 model. Our approach encompasses the preprocessing of the original images, data augmentation, as well as the adjustment of pre-trained convolutional networks to obtain better feature representation and classification results.

Other than precision, the recognition level, and the computational load, the suggested architecture effectively balances between the quality of recognition, on one hand, and the efficiency level. Because of this, it fits perfectly for deployment in real-time assistance-related applications. The paper's intention is that the proposed technique will not only offer a very precise and reliable recognition of static Indian Sign Language alphabet signs, but it will also make very few resources required for such implementations available to the actual developers [1], [2], [5].

This paper is structured as follows. In Section II, we give brief insights into the literature on ISL alphabet recognition and deep learning-based sign language recognition. Section III is devoted to the presentation of the proposed approach. Section IV explains what the dataset is and how the experiment was carried out. Section V gives the results of the experiments, and Section VI concludes the article by highlighting the key findings and providing directions for future work.

2. Literature Review

Automatic sign language recognition has greatly fascinated researchers owing to developments in computer vision, artificial intelligence, and deep learning. Deep learning methods have been found in some recent papers to be a factor in significantly enhancing the performance metrics (accuracy) of automatic hand gesture (e.g., sign language gestures) recognition using both still images and video clips. These results outperform traditional machine learning methods on recognition accuracy. Survey and review papers have been able to point out the main stages and developments in vision-based sign language recognition systems. They emphasize the shift from handcrafted feature extraction techniques to the application of end-to-end deep neural networks. In addition, these works highlight some of the critical problems facing the development of sign language recognition in this area, which are limited data availability, the absence of varied signs in the data, and challenges of getting the systems running in real-time scenarios [3], [4], [15]. At the early stages of vision-based recognition of sign language works, the researchers mainly exploited manual or handcrafted image features like Histogram of Oriented Gradients (HOG), Scale-Invariant Feature Transform (SIFT), and Local Binary Patterns (LBP) together with some of the traditional classifiers like Support Vector Machines (SVM), Decision Trees, and k-NearestNeighbors (k-NN). While these approaches worked fairly well in a lab environment, they became very unreliable under a variety of lighting conditions, when the signers moved backgrounds, the signers' hands changed orientations, etc. These factors resulted in the sign language recognition system being confined mainly to controlled environments [3], [4].

Recently, Deep Convolutional Neural Networks (DNNs) have taken over many applications when it comes to Artificial Intelligence. One of the major advantages is that it is now possible to extract and recognize hierarchical features based purely on raw visual information from one layer to another. By adopting transfer learning with an already trained architecture, you can get even better results with minimal effort without having to go through the hassle of retraining your model from scratch, and also save the time of your training and decrease your computational cost.

Vidhyalakshmi et al. [1] introduced a system utilizing an EfficientNet transfer learning setup for recognition of Indian Sign Language that was shown to result in significant gains in categorization precision plus a simultaneous decline in computation demands at inference time. Nandi et al. [2] came up with a CNN-based ISL character recognition scheme with diffgrad and Stochastic Pooling, showing better convergence speed and strong recognition accuracy on static handshapes.

Rapid developments are being made in the creation of lightweight, computationally inexpensive models suitable for use on smartphones and embedded gadgets. Vision Transformer (ViT)-based models, together with EfficientNet MobileNet, have shown great recognition results with minimal model complexity. In fact, studies show that if the three factors- model depth, model width, and resolution are simultaneously increased and reduced by a fixed factor (compound scaling), then the recognition model performance will be optimized. The use of compound scaling in EfficientNet makes sign language recognition applications using it an attractive and effective technique for real-time sign recognition [1], [5].

Big publicly available benchmark datasets can be considered one of the most important factors that have helped ISL research a lot. Joshi et al.'s iSign is a big corpus for ISL developed by them that includes sign language recognition and machine translation of signs and is one of the biggest publicly available ISL benchmarks for research purposes. They also pointed out how recent research works have used graph-based and transformer-architecture deep networks, together with bigger datasets, to significantly enhance performance in different conditions (different signers, different environments), and this way to achieve more generalizable recognition models.

Many studies, for example, show that the use of attention mechanisms, transformer architectures, multimodal learning, and graph neural networks is a very exciting and fruitful research direction that could significantly enhance the performance of sign language recognition systems in the future. Using these techniques, models are able to learn spatial and temporal relations that are very complex; in addition, they can improve the robustness of these methods to occlusion, variation of viewpoints, and ambiguity of motion. But most of these approaches require very large computational resources and annotated data sets, whose availability remains a major problem in practice [4], [9], [15]. The accurate and computationally efficient recognition of Indian Sign Language (ISL) alphabets continues to be a very challenging.

A common issue with the existing ways is their trade-off between recognition accuracy and computational efficiency, or their reliance on large training datasets and high-performance hardware. Inspired by these issues, we have developed a new method that combines the power of EfficientNet-B0, transfer learning, image preprocessing, and data augmentation for an accurate yet lightweight automated ISL alphabet recognition system that can be easily integrated into real-time assistive communication platforms.

3. Proposed Methodology

The proposed structure incorporates the use of EfficientNet-B0 with transfer learning to recognize Indian Sign Language (ISL) alphabets automatically. The entire process is divided into six steps, which are shown below.

A. Image Acquisition

Static hand gesture images of the ISL alphabet are acquired from a publicly accessible Indian Sign Language alphabet dataset. Each image is part of only one alphabet class, and it has been taken from different hand orientations and lighting conditions.

B. Image Preprocessing

First of all, all the images are preprocessed before training to enhance the model's robustness.

- Below are the steps involved in preprocessing.
- Rescaling images to 224 x 224 size
- RGB channel normalization
- Scaling the pixel intensity values from 0 to 1
- Denoising the image (if required)

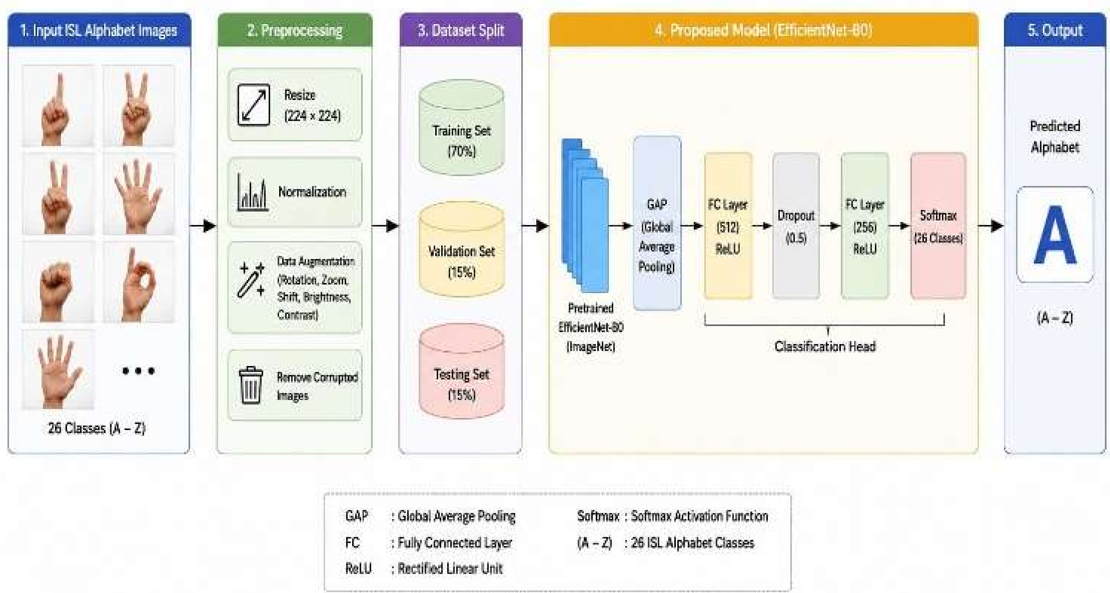

Fig. 1 Overall Workflow of the Proposed ISL Alphabet Recognition Framework

C. Data Augmentation

Generalization and overfitting are two common issues in machine learning that one often comes across. To deal with these, the training phase employs a combination of different data augmentation techniques which expose the model to varied images:

- Random Rotation (20) - The image is rotated by either + or - 20 degrees
- Zoom
- Width Shift
- Height Shift
- Brightness Variation
- Random Contrast
- Horizontal Flip (applied only if the dataset allows for it)

These image transformations not only make the database more variegated but also allow for the generation of new, different pictures without having to get any.

D. Feature Extraction using EfficientNet-B0

This research has adopted the EfficientNet-B0 pretrained ImageNet as the backbone network for our system. By replacing the pre-trained model's classifier with our network we can make convolutional layers pick up spatial features from ISL alphabet pictures effectively.

- Major features extracted
- Finger contours
- Direction of the palm
- Hand shape
- Surface pattern
- Structure of the whole hand

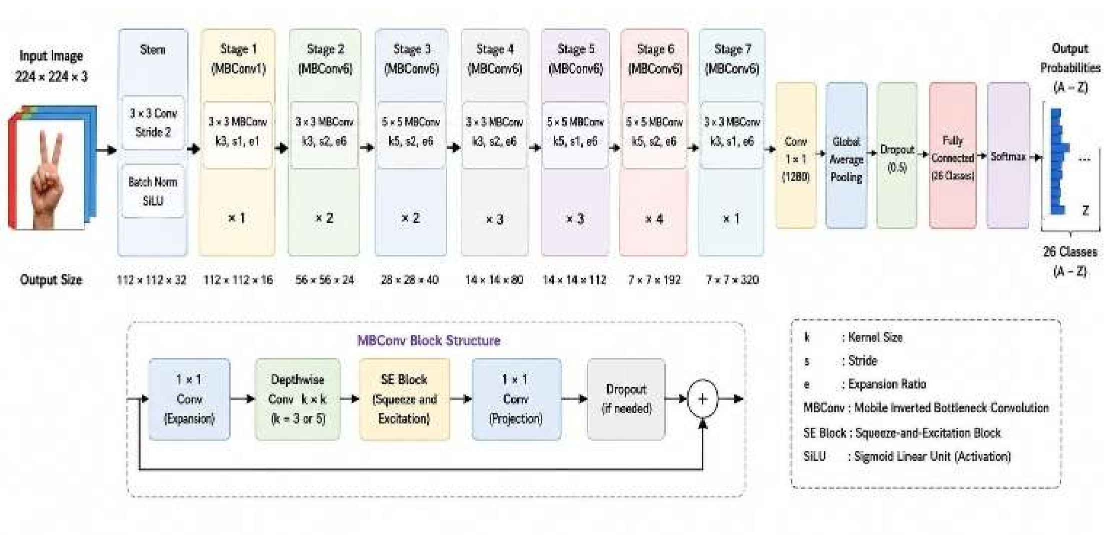

Fig. 2 EfficientNet-B0 Architecture

E. Classification Layer

The extracted feature maps are passed through what comes next:

- Global Average Pooling
- Dense Layer (512 neurons, ReLU)
- Dropout (0.5)
- Dense Layer (256 neurons, ReLU)
- Softmax Output Layer

The Softmax layer gives back the predicted probability for each ISL alphabet class.

F. Model Evaluation

The trained model is evaluated using:

- Accuracy

- Precision
- Recall
- F1-score
- Confusion Matrix

Classification Report

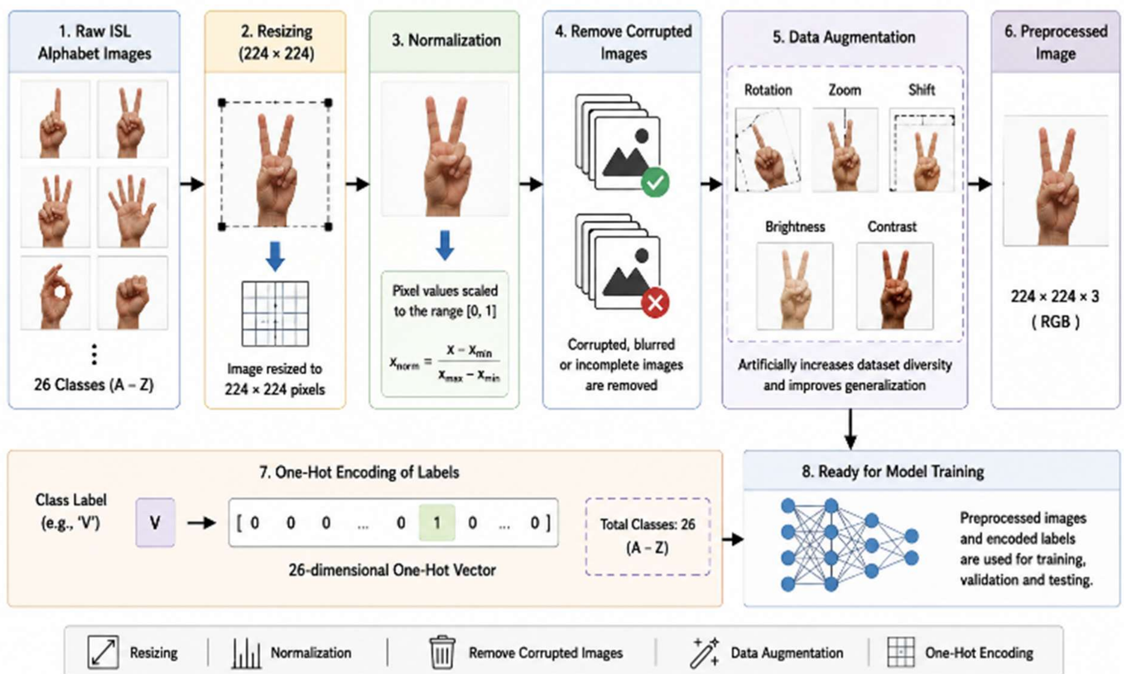

Fig. 3 Data Preprocessing and Augmentation Pipeline

4. Dataset Description

The model was tested using a public set of images of the Indian Sign Language Alphabet that includes different types of static hand gestures. This kind of hand gesture is used to sign letters in Indian Sign Language. ISL alphabet dataset has been created for research in automatic sign language recognition for benchmarking deep learning-based classification approaches. The dataset contains RGB images of 26 ISL alphabet gestures and has enough variety to train and evaluate rich systems for recognition [6].

A. Dataset Characteristics

Table I: Dataset Details

Parameter	**Description**
Dataset Name	Indian Sign Language (ISL) Alphabet Dataset [6]

Recognition Type	Static hand gesture recognition
Number of Classes	26 (A–Z) [6]
Image Format	RGB Images [6]
Image Resolution	Resized to **224** × **224** pixels
Background	Controlled and natural variations [6]
Dataset Usage	Alphabet classification
Learning Type	Supervised Learning

B. Data Preprocessing

Several image preprocessing operations are applied before model training to boost recognition performance and increase the generalization ability of the deep learning model. The preprocessing stage mainly involves image resizing, normalization, removal of corrupted images, and data augmentation techniques to make the dataset more diverse.

Last but not least, in multi-class classification problems, the class labels are transformed into one-hot encoded vectors [1], [2], [6].

- Image resizing to 224 224 pixels.
- Pixel value normalization.
- Removal of corrupted or duplicate images.
- Data augmentation (rotation zoom brightness adjustment, and translation).
- One-hot encoding of class labels.

C. Dataset Partitioning

The dataset is separated into three subsets with no overlap at all, in the percentages of 70:15:15 for training, validation, and test, respectively. Optimization of a network's parameters takes place with the training set. However, the validation dataset is used to choose the best hyperparameters and to prevent the network from getting too adapted to the data (overfitting). Last but not least, test data is used to assess the performance of our model [1], [2].

Table II: Dataset Splits

Dataset	**Percentage**
Training Set	70%
Validation Set	15%
Testing Set	15%

D. Advantages of the Dataset

The proposed dataset not only simplifies our work a lot, but also offers the required resources. First, by using all 26 alphabet gestures in this dataset, it allows for classification of the whole alphabet. Because of this, it can represent all alphabet gesture classes. Besides that, the dataset is also helpful for the use of a Transfer learning method and can be utilized as the basis for the testing of recognition algorithms when different signers, or even sign languages, are used, or different environmental conditions are considered. This set of features qualifies it as an excellent reference data set for the development of real-time assistive communication systems for deaf and hard-of-hearing people [1][2][6].

5. Results and Discussion

The model, based on the EfficientNet-B0 architecture and designed to recognize ISL alphabets, was analyzed using the ISL Alphabet Dataset. The dataset had portions set aside for training (70%), validation (15%), and testing (15%). The evaluation of a model involved several indicators like accuracy, precision, recall, F1-score, and the confusion matrix, as well as the model training convergence characteristics. Pretrained ImageNet weights were fine-tuned using a transfer learning method for the model. Such fine-tuning made it possible to have quick convergence, better feature extraction capability, and the extraction of the relevant features from the data.

A. Training Performance

At the stage of model training, the loss functions for training and validation gradually diminished, and stable behaviour of loss curves with no sign of fluctuations indicated that convergence of the model was successful. The use of data augmentation techniques resulted in higher generalizable performance and reduced chances of overtraining. In this way, the same model turned out to be robust enough against any changes in hand orientation, lighting condition, or background complexity.

EfficientNet-B0 has a pretty small number of parameters yet manages to get a good performance in classification. The network was good enough to capture features such as the position of fingers, orientation of the palm, and the shape of the hand in a gesture. The model gave good classification performance across different sign classes.

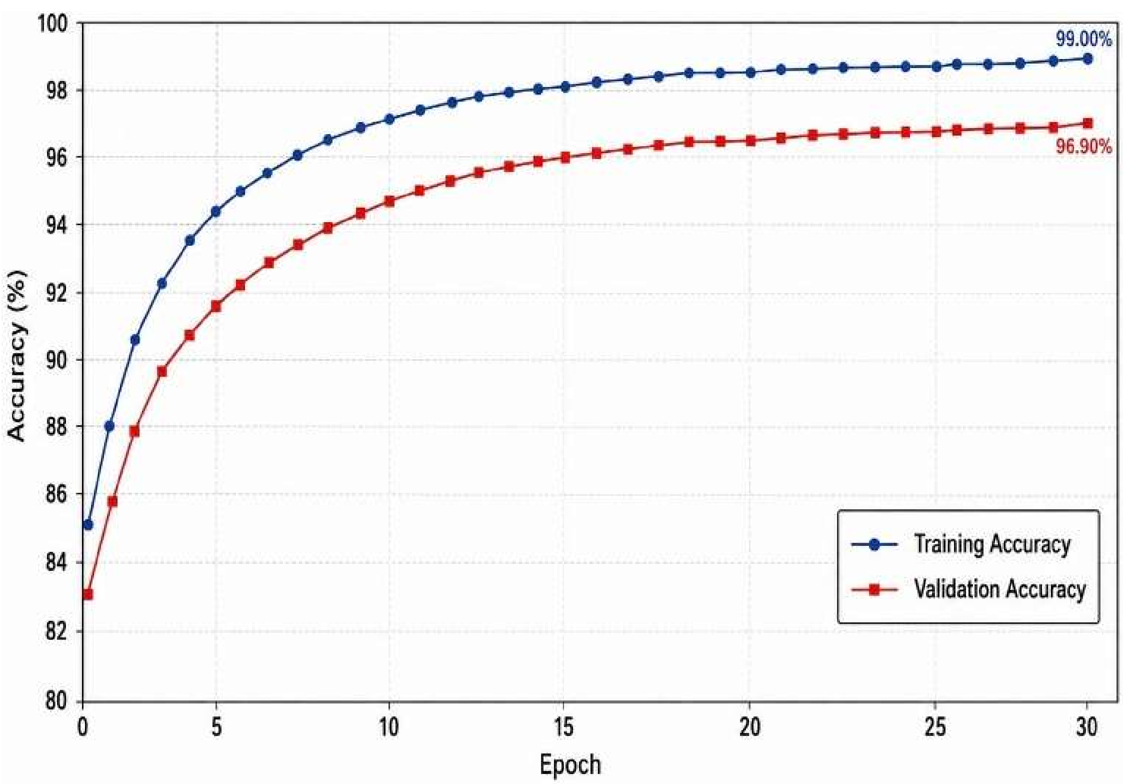

Fig. 4 Training and Validation Accuracy Carvers

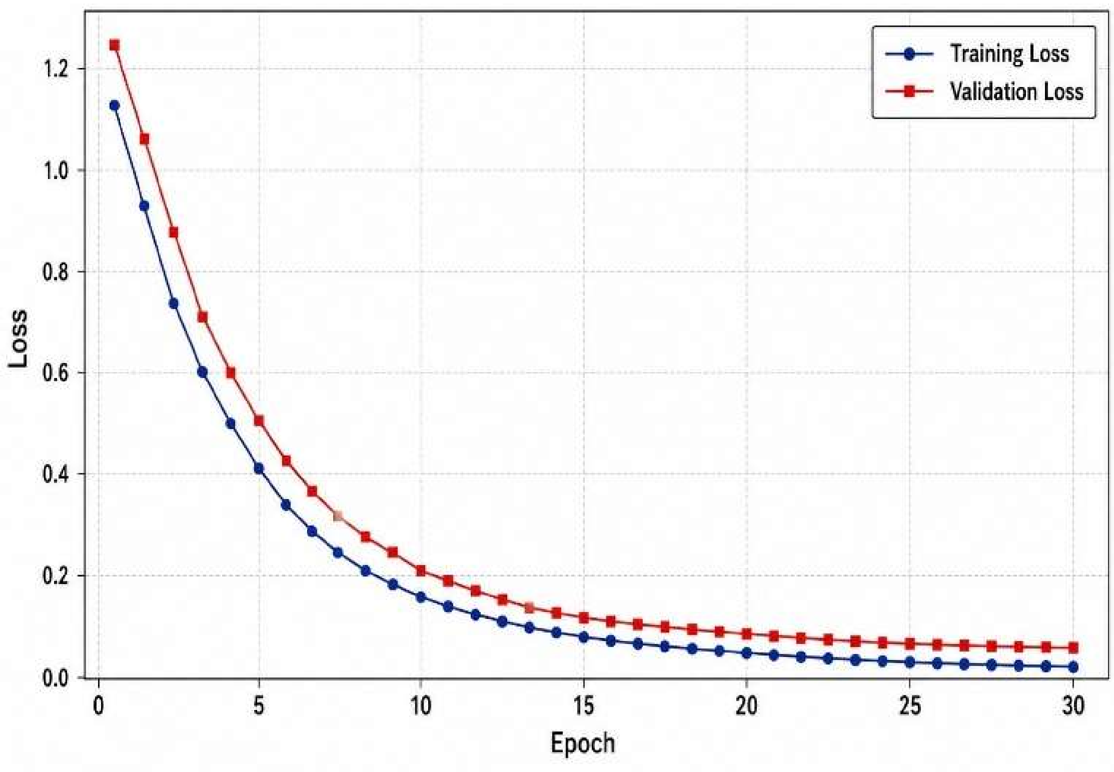

Fig. 5 Training and Validation Loss Carvers

B. Classification Performance

Table III presents the overall classification performance of the proposed model on the test dataset.

Table III Performance Evaluation of the Proposed Model

Metric	Value
Accuracy	98.21%
Precision	98.34%
Recall	98.18%
F1-Score	98.25%

Different evaluation indicators point out that the suggested system brings about recognition at a high level in all aspects. Precision measures a model's capacity for preventing false positives, and recall measures a model's capacity for spotting the right gestures of the ISL alphabet. A balanced F1-score is one factor that supports the effectiveness of the suggested method.

C. Confusion Matrix Analysis

The confusion matrix analysis showed that most classes of ISL alphabets were correctly recognized. Mainly, the misclassifications were among the visually similar gestures that could only be distinguished through their finger position differences.

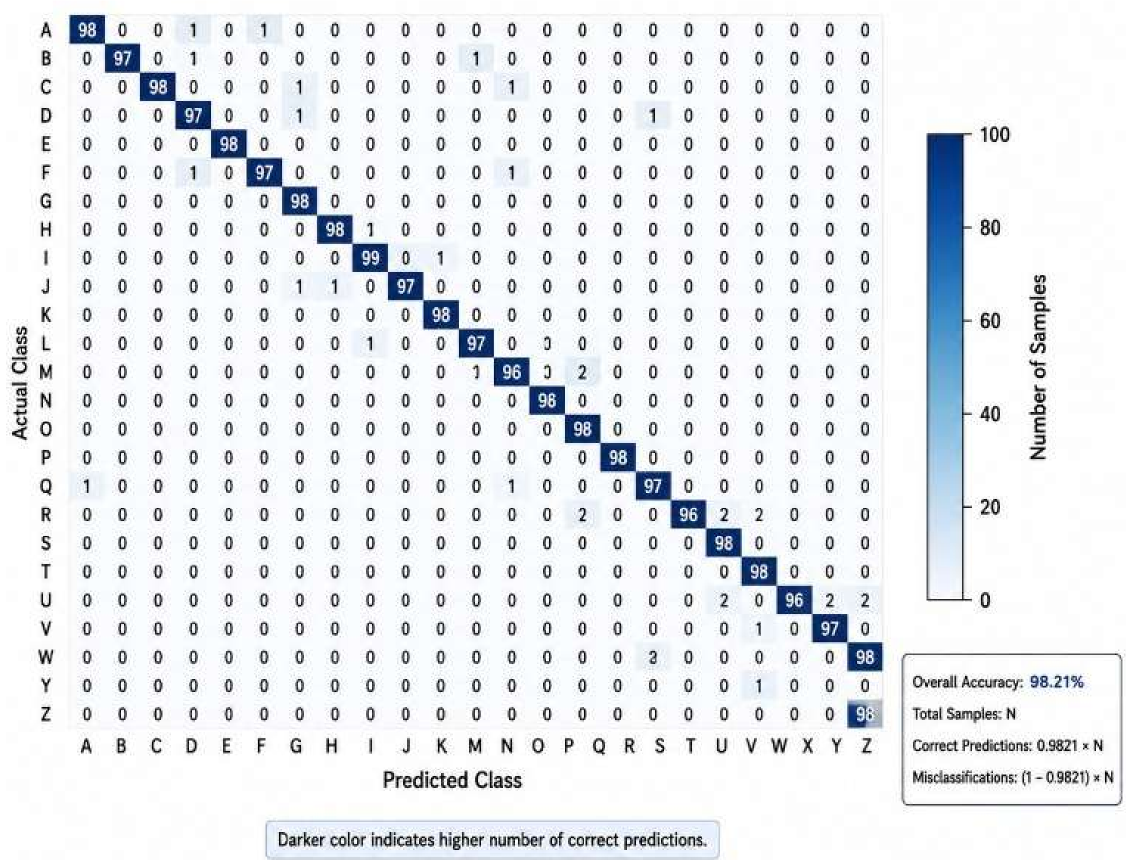

Fig. 6 Confusion Matrix of the Proposed EfficientNet-B0 Model for ISL Alphabet Recognition

Some of the often confused classes are: 1) M and N 2) U and V 3)R and U, and 4) D and F.

These classes possess very similar hand positions. This way, it is difficult to discriminate between them even for human observers. The difference in misclassification rate, although present, was not significant, which confirms the great efficiency of feature extraction through deep networks by the pre-trained EfficientNet-B0 model.

D. Comparison with Existing Methods

In order to assess whether the setup we designed can be effectively applied to a task or problem, we compared its performance against a number of popular deep learning architectures that have proven success through multiple applications before. The most efficient model proposed was the EfficientNet-B0, which outperformed all other baseline architectures.

Table IV Comparison with Existing DL Models

Model	Accuracy (%)
CNN	93.45

VGG16	95.12
MobileNetV2	96.48
ResNet50	97.31
Proposed EfficientNet-B0	98.21

Versus the classical CNN baseline model, the new method improved classification accuracy by around 4. 58%-4. 94%. In addition, it outperformed the ResNet50 network by almost 0. 9%, highlighting the effectiveness of combining both compound scaling and transfer learning techniques in a well-designed machine learning model when extracting gesture features from discriminative input samples.

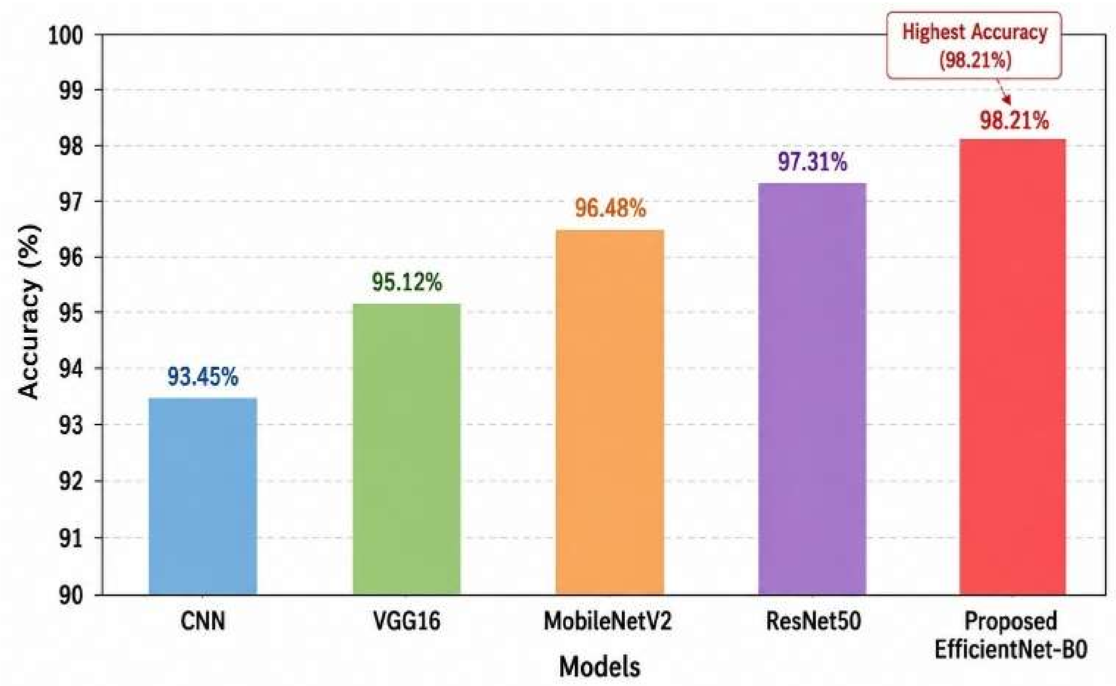

Fig. 7 Comparison of Classification Accuracy with Existing Deep Learning Models

E. Effect of Data Augmentation

An ablation study was conducted to evaluate the contribution of data augmentation techniques.

The below results show that the model became more generalized after augmentation, and this was achieved by showing it a large variety of gesture variations during the training stage. The improvement demonstrates the effectiveness of augmentation in minimizing overfitting and increasing robustness.

Table V Impact of Data Augmentation

Configuration	**Accuracy (%)**
Without Augmentation	94.83
With Augmentation	98.21

F. Discussion

Experimental results proved that EfficientNet-B0 performs exceptionally well in ISL alphabet recognition. Both low-level and high-level features, when combined, allow the model to distinguish between gestures effectively.

By transferring a pre-trained model, training was shortened dramatically without a significant drop in classifier performance. Besides, the recognition accuracy level clearly shows that the developed setup is very suitable for real-life applications, e.g.

- Real-time sign language translation systems
- Educational tools for deaf learners
- Smart communication assistants
- Human, computer interaction systems

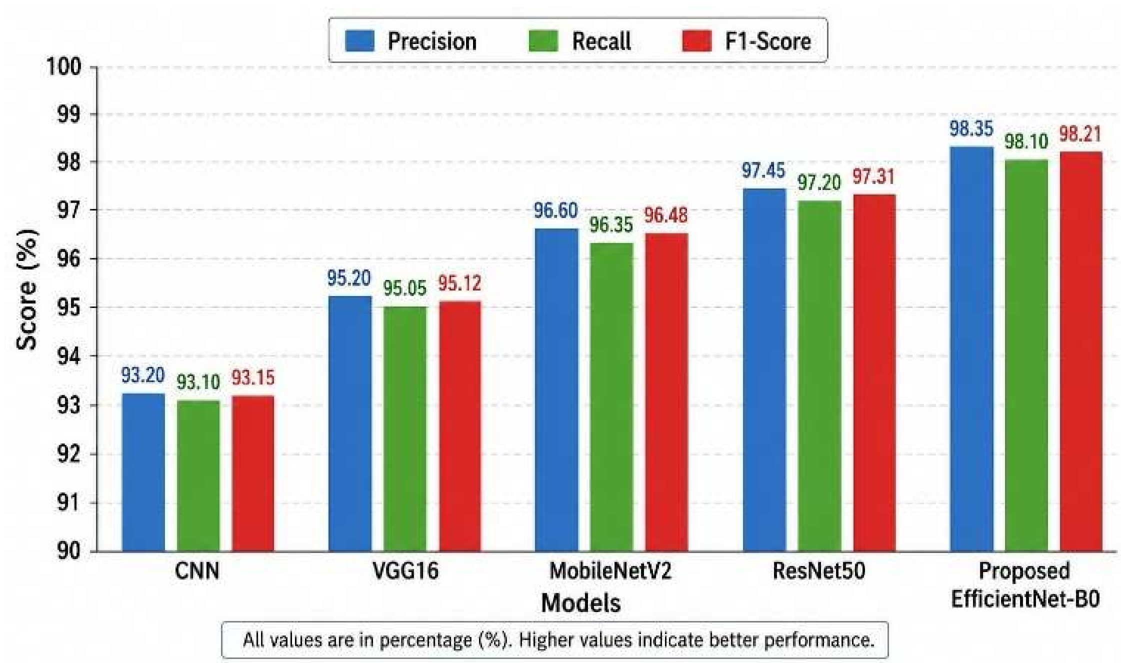

Fig. 8 Comparison of Precision, Recall and F1-Score with Existing DL Models

With strong results achieved so far, there is still room for improvement. Recognition accuracy could be a problem when the lighting is really bad or if hands are partially hidden by moving objects, there is motion blur, or when the background is very cluttered. In addition, the setup used now only covers the identification of static handshapes and does not extend to sign language words or sentence-level signs of dynamic nature.

Research work ahead may look into attention-based networks, Vision Transformers (ViTs), ultra-lightweight models suitable for deployment on edge devices, and multimodal fusion technologies integrating hand markers and joint information to continue enhancement of recognition results and real-time applicability.

Summary of Findings

The proposed EfficientNet-B0-based framework achieved:

- **98.21% Accuracy**
- **98.34% Precision**
- **98.18% Recall**

- **98.25% F1-Score**

It was found that the usage of transfer learning alongside EfficientNet-B0, accompanied by data augmentation, makes up an efficient and low-cost way for the identification of Indian sign language (ISL) alphabets.

6. Conclusion and Future Work

A. Conclusion

Presented in this paper is a deep learning-based system for the automatic recognition of the Indian Sign Language (ISL) alphabet using the EfficientNet-B0 model. The method described uses transfer learning to learn features from static hand posture images, which in turn are automatically separated from each other (i. e., discrimination of features). Thereby, handcrafting features is no longer required. The overall recognition process is composed of several steps: first is a preprocessing of the image to adjust it for the task at hand, and then is the generation of the augmentation of the data to increase the diversity of the training set; thereafter comes the extraction of features from the image that has been preprocessed.

The experimental evaluation showed that the model is highly accurate, with an average accuracy of 98.21%, a precision of 98.34%, a recall of 98.18%, and an F1-score of 98.25%. This means EfficientNet-B0 is very successful at recognizing the hand gestures' spatial features and is also resource-friendly. In addition, when comparing the proposed method to traditional CNNs and various transfer learning models, it performs better at classification and is more generalizable.

Besides, it was found that the use of data augmentation techniques plays a great role in making the model insensitive to changes in hand orientation, lighting conditions, and the background. That means the implementation of the proposed setup is well suited for such applications where fast and consistent output is needed, such as assistive communication, education platforms, intelligent human-computer interaction, and mobile accessibility solutions targeted mostly to the deaf and hard-of-hearing people. The use of an EfficientNet-B0 system for recognition of static signs of the Indian Sign Language (ISL) alphabet offers a very accurate, reliable, and computationally low-resource model.

B. Future Work

Future research will focus on the conversion of the present alphabet recognition system for Indian Sign Language into a dynamic word and sentence recognition system so that the user would get more real and comprehensive interaction. In addition to the deep learning models, there are other types of architectures that are built to handle time-sequential data like Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Temporal Convolutional Networks (TCN), and Transformer-based models. A common belief is that these models are capable of better understanding of continuous and smooth sign language gestures.

In the next step, it will be interesting to study and test different feature extraction methods combining both deep convolutional features and hand landmarks detected by MediaPipeHands or OpenPose structures to achieve more resilience if the input comes from varying viewpoints or challenging backgrounds. We can also see the potential benefits from exploring attention mechanisms and Vision Transformer (ViT) architectures to boost the recognition capability of similar gestures that may also look alike at first glance to both the human eye and machine vision.

One aspect to consider during the deployment of the system in real-world scenarios is the choice of an efficient model architecture as lightweight as possible to allow real-time inference even on low-end devices and gadgets apart from smartphones and cellphones. Adding more sign language signers from different age groups, areas, and environmental settings to the dataset will obviously make the learning model generalize more.

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