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International Journal on Advanced Computer Engineering and Communication Technology

ISSN: 2278-5140
Volume 14 Issue 01, 2025

Sign Language Recognition using Deep Learning

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Peer Review Information

Submission: 16 Jan 2025
Revision: 13 Feb 2025
Acceptance: 12 March 2025

Keywords

CNN
Dense201
Deep learning
Hand Gestures
Indian Sign Language

Abstract

Sign language is a vital way for people with hearing impairments to communicate, but unfortunately, many of us don't know how to use it. That's where technology comes in! Sign language recognition systems use artificial intelligence and computer vision to translate sign gestures into text or speech. Sign language recognition (SLR) systems help by using artificial intelligence (AI) and computer vision to convert sign gestures into text or speech. This study proposes a convolutional neural network (CNN)-based SLR model for recognizing numeric gestures in sign language. The proposed model is trained on a digit and alphabet-based dataset to ensure accurate classification of hand gestures. In this study, we developed a model which based on deep learning and recognize the hand gestures perfectly. Our experimental results show that the proposed Sequential model and Dense201 model on pre-trained dataset. The sequential model achieved accuracy 95.43 while dense model performed better and show accuracy 99.41, to perfectly recognize the gestures. These results show that our approach is highly effective in correctly identifying sign language gestures.

INTRODUCTION

Communication is the foundation of human connection. But for people who are deaf or hard of hearing, communicating with others can be a challenge. Sign language is their main way of communicating, but many people don't know how to sign. That's why we need to find ways to break down this communication barrier. One solution is to develop tools that can translate sign language into spoken language or text. This technology has the potential to make a big difference in people's lives. Imagine being able to converse with someone who uses sign language, without needing an interpreter. Imagine being able to order food, ask for directions, or have a conversation with a friend who uses sign language, without any barriers.

This technology can help people communicate more easily, connect with others in new ways, and feel more included in their communities. It can also help bridge the gap between the deaf and hearing worlds. Our goal is to make communication more accessible and inclusive for everyone. By developing this technology, we can help create a world where everyone can communicate freely and easily, regardless of their abilities. A world where everyone can connect, share, and thrive together. Ultimately, this research aims to contribute to the development of assistive technologies that enhance accessibility and communication for individuals with hearing impairments.

Fig.1. Sign language Hand Gestures

Literature Review

Many studies have been carried out on sign language recognition, using different sensor technologies and machine learning techniques. Below is a brief summary of some recent research focused on sign language detection and recognition.

Two feature extraction methods. Among these the thresholding feature extraction technique is used for getting an accurate output with 98.69%accuracy. Whereas RGB converted data sets did not get the accurate results for the given input gesture by [1].

The study proposed, utilizing background subtraction to isolate the hand region. The palm and fingers are then segmented, and the fingers are identified and recognized based on this segmentation, this show that the method works well and suitable for real time applications [2]. Paper proposes a real-time, efficient technique using image processing and artificial neural networks to translate sign language into voice/text. A webcam captures hand shapes, sending images to Raspberry Pi 3 for processing [3]. Vaidhya proposed various strategies of gesture recognition for communication. Accurate skin segmentation is crucial for recognition, while feature extraction enables efficient classification. Effective segmentation and feature extraction are key to reliable gesture recognition [4]. They proposed normalizing and rescaling images to 64 pixels for feature extraction, and used CNN to classify 10 American sign gestures, achieving 98% accuracy, outperforming existing research [5].

Authors proposed hand gesture recognition system uses a shape-based approach, incorporating steps such as smudges removal, orientation detection, thumb identification, and finger counting to achieve accurate recognition. This system gives 94%accuracy [6].

Trained 3 CNN architectures LeNet-5, MobileNetV2 and, their own architecture and made one final model that performs ensemble of these 3 models instead of taking one of them. By using this ensemble technique, they have been achieved high accuracy [7]. Our study modified four popular deep learning architectures and identified the optimized VGG16 model as the most effective solution for recognizing 11 essential Bengali Sign Words [8]. The system accurately recognizes signs as input and converts them into their corresponding letters or numbers. To optimize both accuracy and efficiency, they used CNN for gesture analysis and interpretation. Their approach yielded impressive results [9].

The LSTM network adjusts the weights and biases of its gates and memory cells through backpropagation during training. After training, the models are evaluated using a confusion matrix and accuracy scores. Model with the highest accuracy is selected as the final model [10]. A sign language recognition system for American Sign Language (ASL) was developed using machine learning algorithms, achieving accuracy rates of 97% with Random Forest, 96% with KNN, and 95% with SVM, improving inclusivity for the deaf and hard-of-hearing [11].

Methodology

1. Dataset:

Dataset is downloaded from Kaggle [14] of images of Indian Sign language, which includes 21600 images in 50x50 pixels. There are 36 classes which include 10 numbers (0-9) and 26 alphabets(A-Z) in the dataset.

2. Data preprocessing:

The images were pre-processed using a series of steps to ensure consistency and efficiency. Each image was first read in grayscale format, converting the original RGB images to a single-channel grayscale representation. The grayscale images were then converted to RGB format, ensuring consistency in colour representation across the dataset. Subsequently, the images were resized to a uniform size, reducing computational requirements while preserving essential features. Finally, the pixel values were normalized to the range [0, 1] by dividing by 255.0, improving the stability and efficiency of subsequent processing steps.

The dataset consist the 21600 images are in 240 x 240 pixels after normalization, each sign language class have a 600 images per class.

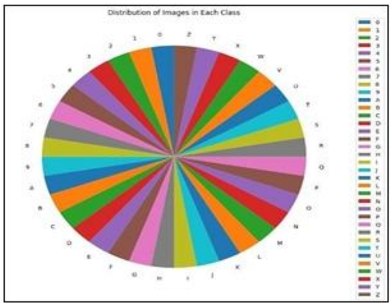


Fig 2. Number of images in each class

3. Dataset Split

The dataset, was divided into training, validation, and testing sets for both the Sequential and Dense models. For the Sequential model, the dataset was split into 15,120 images (70%) for training, 4,320 images (10%) for validation, and the remaining images (20%) for testing. In contrast, the Dense model utilized 12,096 images (56%) for training, 432 images (2%) for validation, and the remaining images (42%) for testing. Internally it is done by Random Sampling Algorithm

Algorithm Selection:

The experiment has 2 pre-trained & well-known deep learning algorithms were recognizing Sign language gestures.

1. Sequential

The proposed sign language recognition application utilizes a deep learning approach, leveraging a pre-trained convolutional neural network (CNN) as the base model. The pre-trained model is fine-tuned for sign language classification by adding additional layers on top of the base model. Specifically, a GlobalAveragePooling2D layer is added to reduce spatial dimensions, followed by a Dense layer with OUTPUT_SIZE units and softmax activation, enabling multi-class classification. The resulting model combines the feature extraction capabilities of the pre-trained base model with the customized classification layers, allowing for effective sign language recognition.

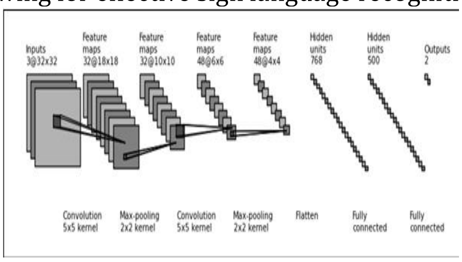
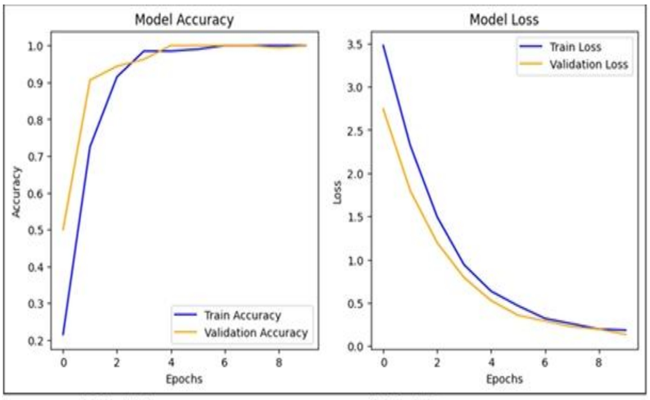


Fig 3. Architecture of sequential Model [15]

The final training and validation accuracy for Sequential model is

Sequential Model	
Training Accuracy	0.9543
Validation Accuracy	1.0000



(a)Model Accuracy *(b)Model Loss*

Fig 4. Model accuracy and Model Loss of Sequential Model

For a frontend we used Django farmwork to predict the output. The Sample JSON response from Django is as

Uploaded image

Fig 5. JSON response from Django

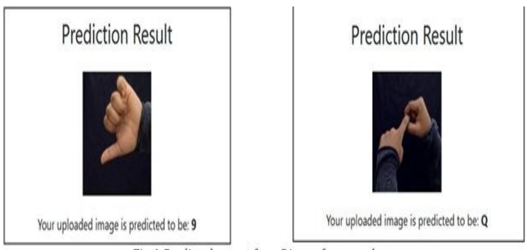


Fig 6. Predicted output from Django framework

2. Dense201:

The proposed sign language recognition application utilizes a deep learning approach, leveraging a pre-trained DenseNet121 convolutional neural network (CNN) as the base model. The pre-trained model is fine-tuned for sign language classification by adding custom classification layers on top of the base model. Specifically, a GlobalAveragePooling2D layer is added to reduce spatial dimensions, followed by two Dense layers with 256 and OUTPUT_SIZE units, respectively. The first Dense layer uses ReLU activation and L2 regularization with a strength of 0.05, while the second Dense layer uses SoftMax activation and L2 regularization with a strength of 0.01. Additionally, a Dropout layer with a dropout rate of 0.6 is added to prevent overfitting. The resulting model combines the feature extraction capabilities of the pre-trained DenseNet121 base model with the customized classification layers, enabling effective sign language recognition.

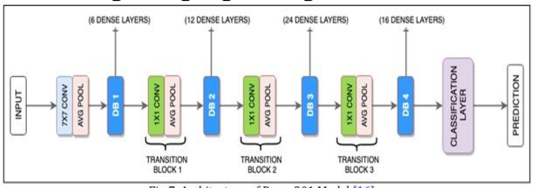


Fig 7. Architecture of Dense201 Model [16]

The final training and validation accuracy for Dense model is

Dense Model	
Training Accuracy	0.9941
Validation Accuracy	1.0000

a) Model accuracy b) Model Loss

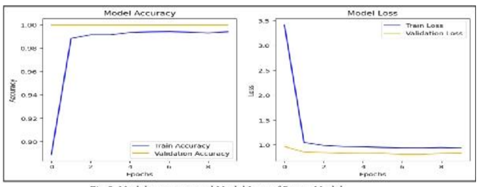


Fig 8. Model accuracy and Model Loss of Dense Model

For a frontend we used Django farmwork to predict the output. The Sample JSON response from Django is as:

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Fig 9. JSON response from Django

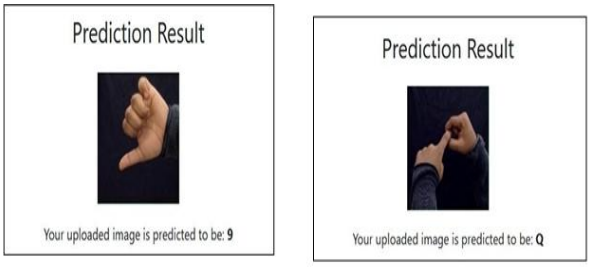

Fig 10. Predicted output from Django framework

COMPARISON

"We trained the model using 10 epochs and 32 batch size, to make an efficient application and it predict the output".

Model	Accuracy
Sequential	0.9543
Dense201	0.9941

(a) Confusion matrix for Sequential model (b) Confusion matrix for Dense Model

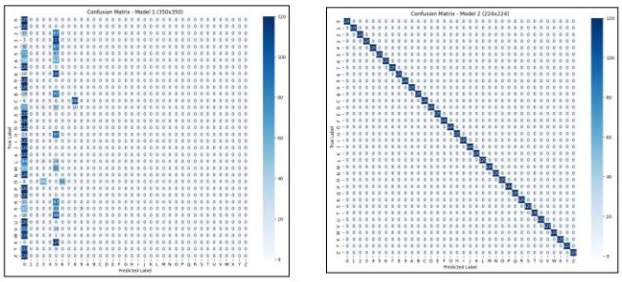

Fig 11. Confusion Matrix

We compared the performance of two deep learning models, a sequential model and a Dense201 model, on a sign language recognition. Our results show that both models achieved good performance, but the Dense201 model outperformed the sequential model in terms of accuracy.

The confusion matrices for both models revealed that the sequential model struggled to correctly classify certain numbers and alphabets, whereas the Dense201 model achieved near-perfect classification for all classes.

Based on the results, we conclude that the Dense201 model is a more suitable architecture for sign language recognition.

Conclusion

This research paper presents a CNN-based sign language recognition application for Indian Sign Language (ISL), achieving high accuracy in classifying hand gestures for numbers (0-9) and alphabets (A-Z). The system utilizes deep learning techniques, specifically Sequential and Dense201 models, and is implemented using Django. The model outputs predictions via a JSON response, contributing to the field of assistive technology by improving communication for the deaf and hard-of-hearing community.

However, one of the significant challenges faced by our model is its limited generalizability to recognize other signs, words, or special characters outside the 36-class dataset. This limitation highlights the need for future research to focus on expanding the dataset, improving model generalization, and implementing real-time recognition for broader applications.

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