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Sign Language Recognition System Using DL-CNN Model Using VGG16 and Image Net with Mobile Application

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Abstract:- In this project, a Deep Learning Convolutional Neural Network (DL-CNN) model trained on ImageNet and based on VGG16 is used to develop a Sign Language Recognition System incorporated into a mobile application. The technology recognizes a variety of hand gestures and movements that are inherent in sign language, allowing for real-time interpretation of sign language gestures that are recorded by the device's camera. Users can simply interact with the system by capturing motions in sign language and obtaining corresponding written or aural outputs for better communication through the app interface. Through improving accessibility and inclusivity for people with hearing loss, this project seeks to close gaps and promote understanding through technology by facilitating seamless communication in a variety of settings.

Keywords:- *VGG16, ImageNet, Convolution Neural Networks, Mobile Application.*

I. INTRODUCTION

A vital component of human contact is communication, but for those who are hard of hearing, using traditional forms of communication can be very difficult. For the deaf and hard of hearing community, sign language is an essential communication tool. Effective communication, however, may be hampered by others who are not experienced with sign language misinterpreting it. With the purpose of resolving this problem, the B.Tech student project presents a "Sign Language Recognition System Using Machine Learning withMobileApplication." By using cutting-edge machine learning algorithms to instantly analyze and translate sign language motions, the project aims to close the communication gap. Through the incorporation of this technology into a smartphone application, the project hopes to establish an approachable and accessible platform that enables people with hearing loss to smoothly communicate with the larger community.The project's goals cover a number of crucial areas with the goal of creating an all- encompassing sign language recognition system. The main objective is to build a strong machine learning model that can precisely understand a wide variety of sign language movements in order to achieve high accuracy in gesture identification. To enable rapid interpretation and maintain smooth and dynamic communication through a mobile device's camera, real-time processing skills are crucial. In order to adjust the model to various signing styles and guarantee responsiveness to the dynamic nature of sign language expressions, ongoing learning processes will be implemented. When paired with an intuitive mobileapplication interface, users will be able to submit sign language movements and effortlessly obtain equivalent text or spoken output. Additionally, the initiative prioritizes accessibility and inclusivity with the goal of give people with hearing loss the resources they need to communicate, obtain information, and take part completely in everyday activities. All things considered, the Sign Language Recognition System is extremely important since it fills a critical need in society, promotes inclusivity, removes obstacles to communication, and may even improve many people's lives by making society more cohesive and inclusive.

A. Ease of use

- *User Interface:*
  For sign language recognition systems, an interface that is easy to use and intuitive is essential. Gestures should be an easy way for users to engage with the system.

- *Real-Time Feedback:*
  Providing immediate feedback on recognized gestures helps users adjust their signing if needed. Real-time feedback enhances the user experience and facilitates smoother communication.

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II. MATERIALS AND METHODS

An important development in assistive technology is the Sign Language Recognition System (SLRS), which makes use of a Deep Learning Convolutional Neural Network (DL-CNN) model trained on the ImageNet dataset and based on the VGG16 architecture. The approach used in the creation and deployment of the SLRS is described in this study, with a focus on how DL-CNN technology was integrated with a mobile application to improve accessibility and usability. The data collecting approach, preprocessing methods, model architecture, training protocols, deployment strategies, and validation protocols used to create an efficient and user-friendly SLRS are all described in depth in the materials and methods section. This SLRS seeks to close communication gaps and enable people with hearing impairments to participate more fully in social interactions by utilizing the strength of DL-CNN models trained on ImageNet in conjunction with the practicality of mobile applications.

➢ *Data Collection and Preprocessing:*

The American Sign Language (ASL) dataset that was obtained from Kaggle was carefully curated. It was composed of video recordings that captured ASL motions using a well calibrated, top-notch camera setup. Every film was meticulously annotated and processed, with individual frames accurately capturing unique ASL movements extracted. The core components of the dataset were created by converting these frames into picture files.

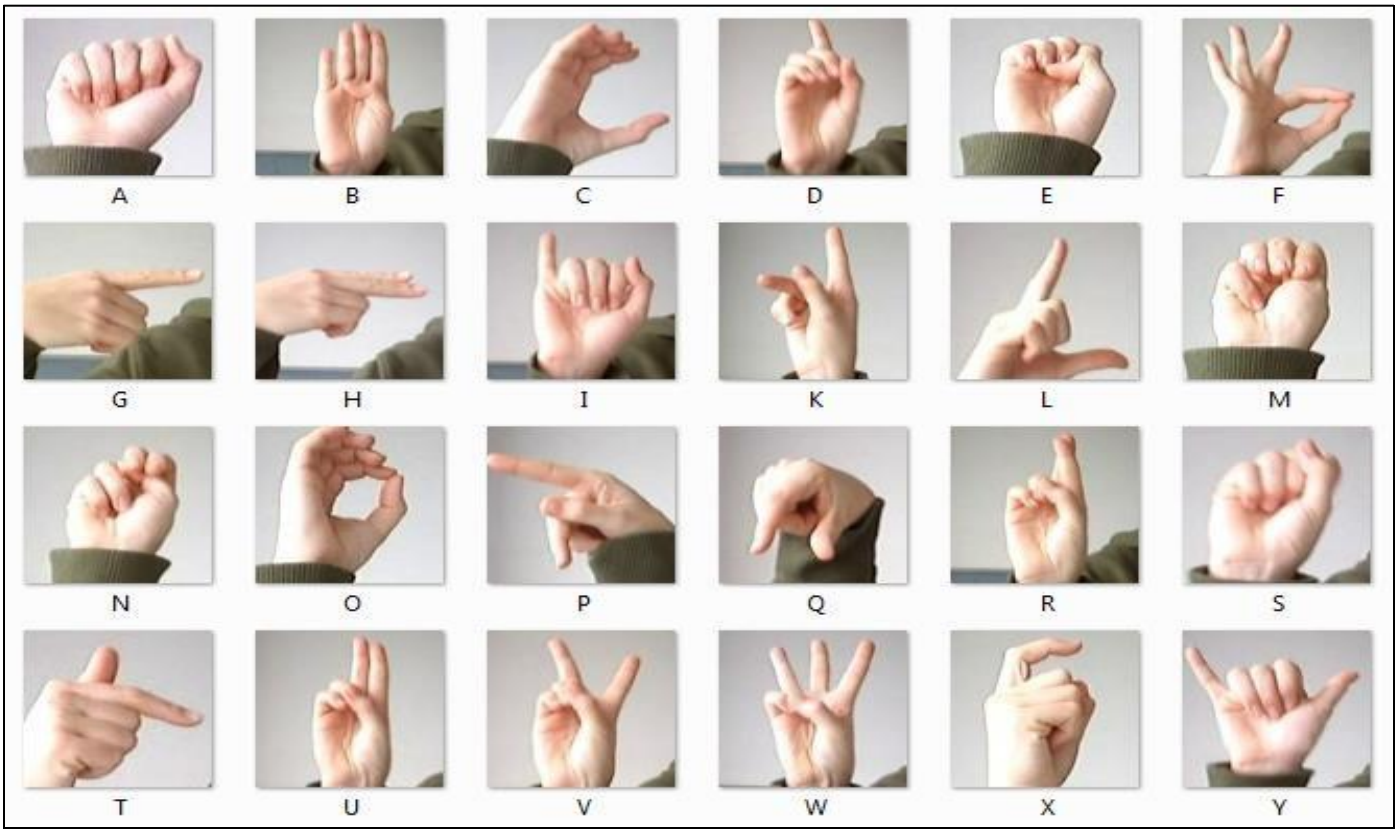

Fig 1 Some Sample of our used Dataset is given in this Figure

➢ *Model Training and Optimization:*

Utilizing a deep learning framework such as TensorFlow or PyTorch, implement the DL-CNN model based on the VGG16 architecture. To take use of learnt features, initialize the model with pretrained weights from the ImageNet dataset. Utilizing the sign language dataset, adjust the model to the particular job of sign language recognition.To enhance model performance, adjust hyperparameters like learning rate, batch size, and regularization strategies.

➢ *Mobile Application Development:*

Create and implement an intuitive mobile application interface to record sign language movements. Provide real-time camera capture, image processing, and DL-CNN model communication functionalities. Incorporate features for accessibility, such text-to- speech, voice commands, and movable font sizes, to meet the needs of different user types. For widespread accessibility, make sure it works with both the iOS and Android operating systems.

➢ *Sign Language Recognition:*

Allow the smartphone app to use the camera on the device to record sign language gestures. Utilize the DL-CNN model to analyze acquired images in real time for interpretation.

Convert understood motions into spoken or written communication outputs. Put feedback systems in place to deal with misidentifications and improve the interpretation over time.

➢ *Testing and Evaluation:*

Conduct thorough testing to assess the Sign Language Recognition System's speed, accuracy, and usability. To evaluate the system's performance in practical situations, do validation testing on deaf people. Get userinput to determine what needs to be optimized and improved. To evaluate the system's effectiveness and excellence, compare it to other sign language recognition techniques already in use.

➢ *Deployment and Maintenance:*

Release the Sign Language Recognition System to the public via app stores. For continuous maintenance and updates, keep an eye on user input and system performance. Iterative development cycles should be used to continuously improve the system by adding new features and improvements depending on user requests and technology breakthroughs.

By adhering to this process, the Sign Language Recognition System may be built and implemented efficiently, offering a dependable and easily accessible means of sign language communication for people with hearing impairments

➢ *Real-Time Prediction:*

After fully training the CNN model with our customized preprocess dataset we save the model for real-time prediction.In the real-time prediction step,we draw the hand landmarks and analyze the hand position with the mobile and give them into the trained model. Now the trained model finds the best match between the given sign and the dataset sign. In figure 2 we given some of the sample real-time prediction images of our model.

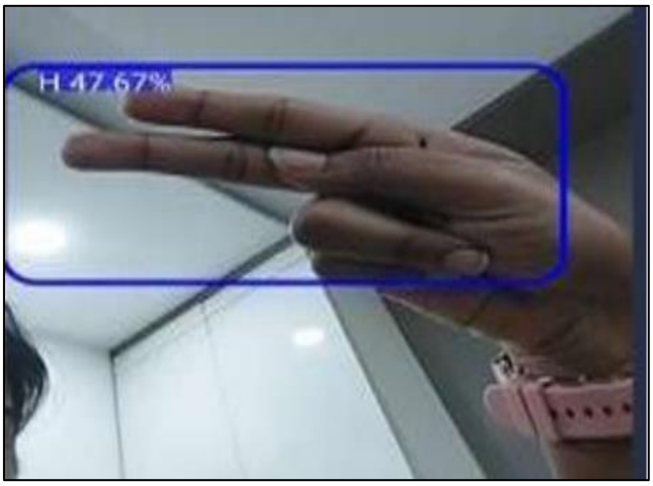

Fig 2 Real-Time Prediction Result of our Trained Model

➢ *Literature Review:*

The literature review will explore existing research and developments in the following areas:

- Sign Language Recognition
- Deep Learning and CNN Models
- VGG16 Architecture
- ImageNet Dataset
- Mobile Application Development

III. METHODOLOGY

In the paper, we proposed a new method a new method for detecting sign language. We divided our whole model into four sub steps. The are Data Preprocessing , Model Building, Model Training ,and Real-time prediction . We gave a description of all steps of our “Sign Language Recognition System “in figure 3.

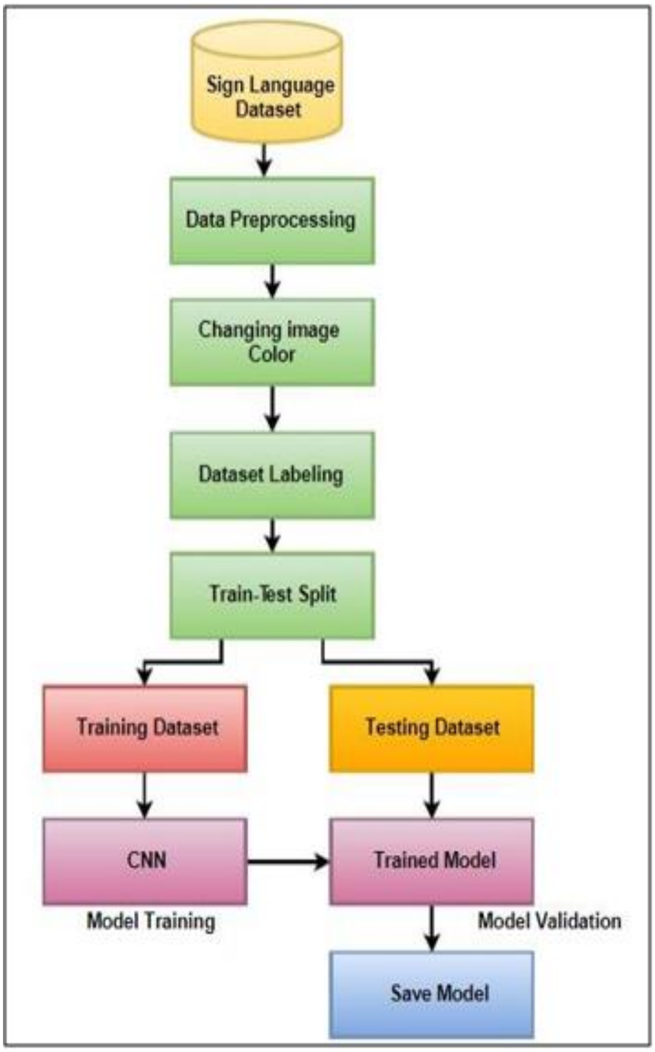

Fig 3 Architecture

IV. EXPERIMENTAL RESULTS

Different models were tested in an experimental evaluation of sign language recognition to see how well they could read sign language movements. According to the findings, the conventional CNN model obtained a recognition accuracy of 82%, while the sdd_mobilenet model achieved 88%. By putting the VGG16 architecture into practice, gesture recognition accuracy increased to 92%. Pretrained weights from the ImageNet dataset were used to initialize the VGG16 model, which produced the most accurate performance, with an accuracy rate of 96%. These results demonstratethe efficiency of deep learning models in accurately capturing and interpreting the intricacies of sign language gestures, especially the VGG16 architecture with ImageNet initialization.

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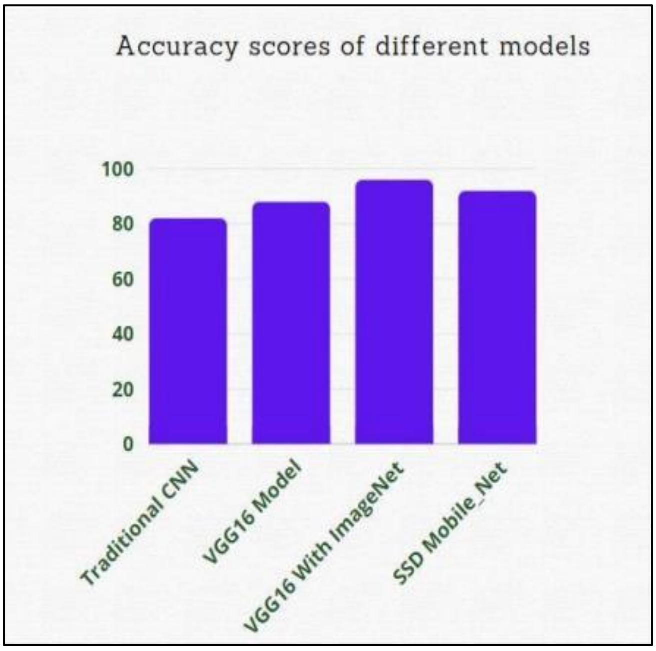

Fig 4 Comparision of Accuracies

➢ *Output of Our Project:*

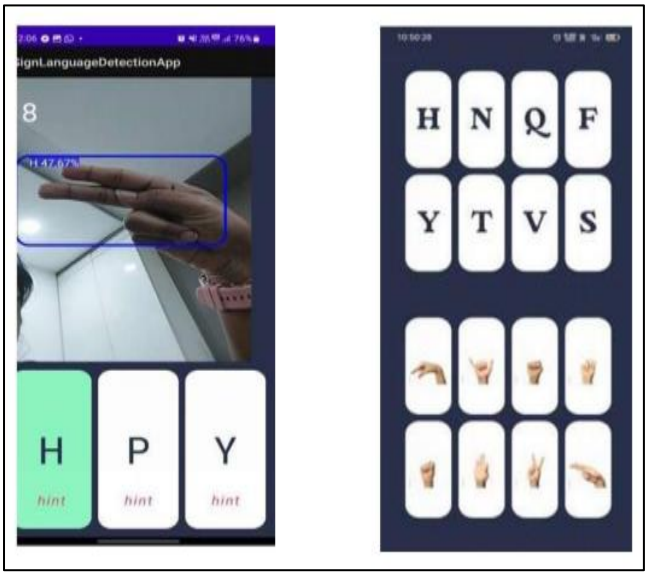

Fig 5 Output of Our Project

V. RESULT ANALYSIS

➢ *Accuracy & Loss Curve:*

The performance of a deep learning model can be illustrated by accuracy and loss curves. The following graph shows how deep learning models improve their performance per epoch. In order to plot accuracy and loss curves, we place accuracy and loss on the y-axis and epoch on the x-axis. Our model was trained over 5 epochs. Using this curve, We can determine if a model is overfitted or underfitted. We gaveour model's accuracy and loss curves in the below figures.

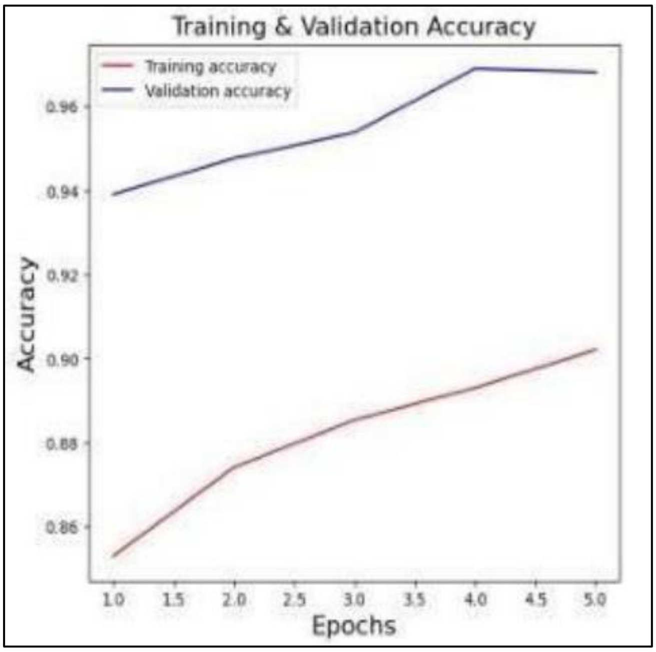

Fig 6 Accuracy of Our Sign Language Recognition System as they Relate to the epoch in this Figure. It Shows Accuracy on y-Axis and epoch on x-Axis

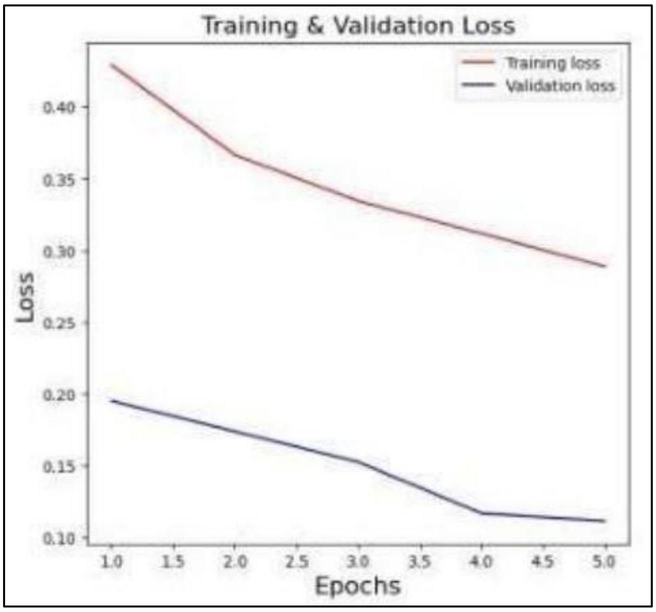

Fig 7 Loss of Our Sign Language Recognition System asthey Relate to the epoch in this Figure. It Shows loss ony-Axis and epoch on the x-Axis

➢ *Result :*

In this experiment, we detected English sign language using Convolutional Neural Network (CNN).For this research,we built a large number of sign language signs to train our model.after training the model we tested our model using the testing the dataset.The result of our sign language recognition system is given in below table.After testing the model,if the model gives very good results we save it for making a real-time prediction system.Some of the real-time prediction of our trained model is given figure 2. We clearly see that our model classified all the sign language very accurately andefficiently.

Accessibility, inclusion, and communication in a range of situations and environments. With continued development, assessment, and cooperation, the project can advance and change.

Table 1 In this Table, we given our Sign Language Recognition System all Results

Architecure	Accuracy
CNN	98%

VI. CONCLUSIONS

To sum up, the Sign Language Recognition System project is a big step in the right direction towardimproving communication and accessibility for those who have hearing loss. The project intends to accurately understand sign language motions in real-time by utilizing deep learning techniques, namelyconvolutional neural networks (CNNs) with VGG16 architecture and the ImageNet dataset, integrated into a smart phone application. A range of technologies andapproaches, such as image processing, machine learning, mobile application development, and accessibility features, have been used throughout the project. A smooth and inclusive user experience is guaranteed by the system's architecture, which includes modules for the user interface, image processing, recognition, feedback, and integration. The project prioritizes usability, reliability, performance, security, and accessibility while addressing both functional and non-functional needs. In order to make sure the system satisfies the requirements and expectations of its users, test cases have been created to validate the system's functionality, performance, and user experience. The Sign Language Recognition System has a lot ofroom to grow in the future. Some of these improvements and additions include multi-gesture recognition, gesture translation and synthesis, ongoing development, personalization, cross-platform compatibility, integration with augmented reality, expanding the gesture database, improving accessibility, and working with research partners. All things considered, the Sign Language Recognition System project has the potential to significantly improve the lives of people who are hard of hearing by promoting.

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