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Sign Language Prediction Using CNN

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Abstract— Sign Language are a form of nonverbal communication in which visible bodily actions are used to communicate important messages, either in place of speech or together and in parallel with spoken words. Sign Language include movement of the hands, face, or other parts of the body. Physical non-verbal communication such as purely expressive displays, proxemics, or displays of joint attention differ from gestures, which communicate specific messages. Gestures are culture-specific and may convey very different meanings in different social or cultural settings. This project is to train a Deep Learning algorithm capable of classifying images of different sign language, such as a alphabet letter, and numeric A comparison of the proposed and current algorithms reveals that the accuracy hand gesture types classification based on CNNs is higher than other algorithms. It is predicted that the success of the obtained results will increase if the CNN method is supported by adding extra feature extraction methods and classify successfully fruits types on image.

Keywords: ***Sign Language, Deep Learning, CNN, NLP.***

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I. INTRODUCTION

Data science is an interdisciplinary field that uses scientific methods, processes, algorithms and systems to extract knowledge and insights from structured and unstructured data, and apply knowledge and actionable insights from data across a broad range of application domains. Data science is the field of study that combines domain expertise, programming skills, and knowledge of mathematics and statistics to extract meaningful insights from data. Data science can be defined as a blend of mathematics, business acumen, tools, algorithms and machine learning techniques, all of which help us in finding out the hidden insights or patterns from raw data which can be of major use in the formation of big business decisions. Artificial intelligence (AI) refers to the simulation of human intelligence in machines that are programmed to think like humans and mimic their actions. The term may also be applied to any machine that exhibits traits associated with a human mind such as learning and problem-solving.

Artificial intelligence (AI) is intelligence demonstrated by machines, as opposed to the natural intelligence displayed by humans or animals. Leading AI textbooks define the field as the study of "intelligent agents" any system that perceives its environment and takes actions that maximize its chance of achieving its goals. Artificial intelligence is the simulation of human intelligence processes by machines, especially computer systems. Specific applications of AI include expert systems, natural language processing, and speech recognition and machine vision. Artificial intelligence was founded as an academic discipline in 1956, and in the years since has experienced several waves of optimism, followed by disappointment and the loss of funding (known as an "AI winter"), followed by new approaches, success and renewed funding.AI research has tried and discarded many different approaches during its lifetime, including simulating the brain, modeling human problem solving, formal logic, large databases of knowledge and imitating animal behavior. In the first decades of the 21st century, highly mathematical statistical machine learning has dominated the field, and this technique has proved highly successful, helping to solve many challenging problems throughout industry and academia. To solve these problems, AI researchers use versions of search and mathematical optimization, formal logic, artificial neural networks, and methods based on statistics, probability and economics. AI also draws upon computer science, psychology, linguistics, philosophy, and many other fields. The field was founded on the assumption that human intelligence "can be so precisely described that a machine can be made to simulate it". This raises philosophical arguments about the mind and the ethics of creating artificial beings endowed with human-like intelligence.

AI requires a foundation of specialized hardware and software for writing and training machine learning algorithms. No one programming language is synonymous with AI, but a few, including Python, R and Java, are popular. Natural language processing (NLP) allows machines to read and understand human language. A sufficiently powerful natural language processing system would enable natural-language user interfaces and the acquisition of knowledge directly from human-written sources, such as newswire texts. Some straightforward applications of natural language processing include information retrieval, text mining, question answering and machine translation. Many current approaches use word co-occurrence frequencies to construct syntactic representations of text. “Keyword spotting” strategies for search are popular and scalable but dumb; a search query for “dog” might only match documents with the literal word “dog” and miss a document with the word “poodle”. “Lexical affinity” strategies use the occurrence of words such as “accident” to assess the sentiment of a document. Modern statistical NLP approaches can combine all these strategies as well as others, and often achieve acceptable accuracy at the page or paragraph level. Beyond semantic NLP, the ultimate goal of “narrative” NLP is to embody a full understanding of commonsense reasoning. By 2019, transformer-based deep learning architectures could generate coherent text.

Machine learning is to predict the future from past data. Machine learning (ML) is a type of artificial intelligence (AI) that provides computers with the ability to learn without being explicitly programmed. Machine learning focuses on the development of Computer Programs that can change when exposed to new data and the basics of Machine Learning, implementation of a simple machine learning algorithm using python.

Process of training and prediction involves use of specialized algorithms. It feed the training data to an algorithm, and the algorithm uses this training data to give predictions on a new test data. Machine learning can be roughly separated in to three categories. There are supervised learning, unsupervised learning and reinforcement learning. Supervised learning program is both given the input data and the corresponding labeling to learn data has to be labeled by a human being beforehand.

Unsupervised learning is no labels. It provided to the learning algorithm. This algorithm has to figure out the clustering of the input data. Finally, Reinforcement learning dynamically interacts with its environment and it receives positive or negative feedback to improve its performance.

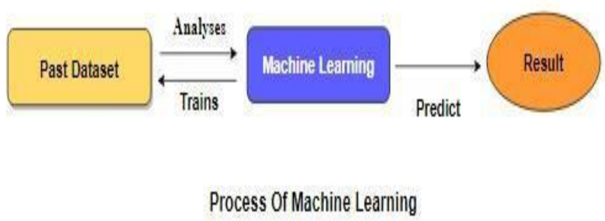

Fig 1. Machine Learning

Data scientists use many different kinds of machine learning algorithms to discover patterns in python that lead to actionable insights. At a high level, these different algorithms can be classified into two groups based on the way they “learn” about data to make predictions: supervised and unsupervised learning.

Classification is the process of predicting the class of given data points. Classes are sometimes called as targets/ labels or categories. Classification predictive modeling is the task of approximating a mapping function from input variables(X) to discrete output variables(y). In machine learning and statistics, classification is a supervised learning approach in which the computer program learns from the data input given to it and then uses this learning to classify new observation. Supervised Machine Learning is the majority of practical machine learning uses supervised learning. Supervised learning is where have input variables (X) and an output variable (y) and use an algorithm to learn the mapping function from the input to the output is y = f(X).The goal is to approximate the mapping function so well that when you have new input data (X) that you can predict the output variables (y) for that data. Techniques of Supervised Machine Learning algorithms include logistic regression, multi-class classification, Decision Trees and support vector machines etc.The difference between the two tasks is the fact that the dependent attribute is numerical for categorical for classification. A classification model attempts to draw some conclusion from observed values. Given one or more inputs a classification model will try to predict the value of one or more outcomes. A classification problem is when the output variable is a category, such as “red” or “blue”.

Deep learning is a branch of machine learning which is completely based on artificial neural networks, as neural network is going to mimic the human brain so deep learning is also a kind of mimic of human brain. It’s on hype nowadays because earlier we did not have that much processing power and a lot of data. A formal definition of deep learning is- neurons.

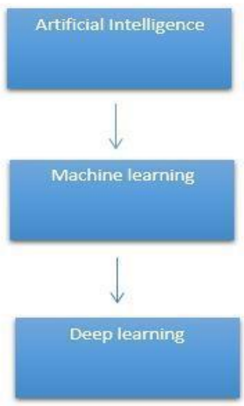

Fig 2. Deep Learning

Deep learning is a particular kind of machine learning that achieves great power and flexibility by learning to represent the world as a nested hierarchy of concepts, with each concept defined in relation to simpler concepts, and more abstract representations computed in terms of less abstract ones. It needs to identify the actual problem in order to get the right solution and it should be understood, the feasibility of the Deep Learning should also be checked (whether it should fit Deep Learning or not). It needs to identify the relevant data which should correspond to the actual problem and should be prepared accordingly. Choose the Deep Learning Algorithm appropriately. Algorithm should be used while training the dataset. Final testing should be done on the dataset

Deep neural networks are generally interpreted in terms of the universal approximation theorem or probabilistic inference. The universal approximation theorem for deep neural networks concerns the capacity of networks with bounded width but the depth is allowed to grow proved that if the width of a deep neural network with ReLU activation is strictly larger than the input dimension, then the network can approximate any Lebesgue integrable function; If the width is smaller or equal to the input dimension, then deep neural network is not a universal approximator. The probabilistic interpretation derives from the field of machine learning. It features inference, as well as the optimization concepts of training and testing, related to fitting and generalization, respectively

II. RELATED WORKS

Hand Gesture Recognition for Sign Language Using 3DCNN [1] Automatic hand gesture recognition has gained increasing importance for two principal reasons: the growth of the deaf and hearing-impaired population, and the development of vision-based applications and touchless control on ubiquitous devices. As hand gesture recognition is at the core of sign language analysis a robust hand gesture recognition system should consider both spatial and temporal features. In the pre- processing phase, linear sampling was used to normalize the temporal dimension of hand gesture samples. For spatial dimension normalization, they used the length of the detected face and human body part ratios. they proposed approach by performing a holistic search to optimize all the hyperparameters. They will test the proposed approach online while receiving a live video feed. In this aspect, we may utilize the edge-cloud computing to distribute the processing over edge devices and the core cloud.

A Novel Detection and Recognition Method for Continuous Hand Gesture Using FMCW Radar [2] A novel method for continuous hand gesture detection and recognition is proposed based on a frequency modulated continuous wave (FMCW) radar. Firstly, we adopt the 2-Dimensional Fast Fourier Transform (2D-FFT) to estimate the range and Doppler parameters of the hand gesture raw data, and construct the range-time map (RTM) and Doppler-time map (DTM). Meanwhile, we apply the Multiple Signal Classification (MUSIC) algorithm to calculate the angle and construct the Angle Time Map (ATM). Secondly, a hand gesture detection method is proposed to segment the continuous hand gestures using a decision threshold. Thirdly, the central time-frequency trajectory of each hand gesture spectrogram is clustered using the k-means algorithm, and then the Fusion Dynamic Time Warping (FDTW) algorithm is presented to recognize the hand gestures. Hand gesture detection and recognition method was proposed. Firstly, we collected the raw data of the radar to obtain the IF signal, and used the IF signal to estimate the RTM, DTM and ATM of hand gestures. Then, we proposed an amplitude-based detection method, which applied the amplitude of the normalized hand gesture spectrogram in conjunction with a threshold. Finally, the k-means algorithm was adopted to cluster the centre time-frequency trajectories of RTM, DTM and ATM, and FDTW algorithm was proposed to recognize the hand gestures. Experimental results showed that the segmentation accuracy of the proposed hand gesture detection method could reach 96.17%, and the average recognition accuracy of the proposed FDTW algorithm for six types of hand gestures was improved by more than 5% while saving half of the running time.

Hand Gesture Recognition Based on Active Ultrasonic Sensing of Smartphone: A Survey [3] Hand gesture recognition has drawn wide attention in the field of ubiquitous computing because it provides us with simple and natural human-computer interaction mode. Among these various implementations, hand gesture recognition using ultrasonic signals of smartphone has become a hot research topic due to its various advantages. In this paper, we consider the smartphone as an active sonar sensing system to identify hand movements. Specifically, the speakers emit ultrasonic signal and the microphone on the same phone receives the changed echo affected by hand movements. This paper investigates the state-of-the-art hand gesture applications and presents a comprehensive survey on the characteristics of studies using the active sonar sensing system. Rapid development of hardware and software technology, smartphone is becoming a strong communication and entertainment tool and has become an indispensable electric device in daily lives because it provides us with various functions to facilitate our work, lives, entertainment, and mutual communications. A detailed discussion about these systems from signal acquisition, signal processing, and performance evaluation. Finally, based on current study trends, we discuss the limitations and open issues involved in human hand gesture recognition based on the ultrasonic signal of smartphone and present some potential solution to these issues.

Electromyography-Based Hand Gesture Recognition System for Upper Limb Amputees [4] Electromyography (EMG) signals are emerging as one of the indispensable biological parameters, which have extensive variety of utilizations in human– machine interaction, prosthetic device development, and rehabilitation devices. EMG measures muscle potential and can provide useful investigatory or diagnostic information regarding neuromuscular activity and rich motor control information for prosthetic devices. EMG signals can be decoded in order to control smart prosthetic devices using pattern recognition (PR) methods. This can be achieved by applying EMG electrodes on the residual limb, and a classification technique is utilized in the embedded platform to determine the user intention. a real-time arm gesture recognition system is presented for the amputees. This system can be utilized for myoelectric prosthetic control in the real-time environment, with above 91% of accuracy. Four-time domain features and LDA classifier are incorporated within the DSP processor. With this system, grasping motion can decode easily in 75ms completion time after training model generation. This system has light weight and battery power support up to 40 Hrs. This system presents admirable results for low-power applications in rehabilitation and myoelectric prosthetics. Power optimization will further enhance the life time of the proposed system.

High-Dimensional Signature Compression for Large-Scale Image Classification [5] We address image classification on a large-scale, i.e. when a large number of images and classes are involved. First, we study classification accuracy as a function of the image signature dimensionality and the training set size. We show experimentally that the larger the training set, the higher the impact of the dimensionality on the accuracy. In other words, high-dimensional signatures are important to obtain state-of-the-art results on large datasets. Second, we tackle the problem of data compression on very large signatures (on the order of 105 dimensions) using two lossy compression strategies: a dimensionality reduction technique known as the hash kernel and an encoding technique based on product quantizers. We explain how the gain in storage can be traded against a loss in accuracy and / or an increase in CPU cost. We report results on two large databases – ImageNet and a dataset of 1M Flickr images – showing that we can reduce the storage of our signatures by a factor 64 to 128 with little loss in accuracy. Integrating the decompression in the classifier learning yields an efficient and scalable training algorithm. On ILSVRC2010 we report a 74.3% accuracy at top-5, which corresponds to a 2.5% absolute improvement with respect to the state-of-the-art. On a subset of 10K classes of ImageNet we report a top-1 accuracy of 16.7%, a relative improvement of 160% with respect to the state-of-the-art.

Deep Residual Learning for Image Recognition [6]Deeper neural networks are more difficult to train. We present a residual learning framework to ease the training of networks that are substantially deeperthan those used previously. We explicitly reformulate the layers as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions. We provide comprehensive empirical evidence showing that these residual networks are easier to optimize, and can gain accuracy from considerably increased depth. On the ImageNet dataset we evaluate residual nets with a depth of up to 152 layers—8× deeper than VGG nets [40] but still having lower complexity. An ensemble of these residual nets achieves 3.57% error on the ImageNet test set. This result won the 1st place on the ILSVRC 2015 classification task. We also present analysis on CIFAR-10 with 100 and 1000 layers. The depth of representations is of central importance for many visual recognition tasks. Solely due to our extremely deep representations, we obtain a 28% relative improvement on the COCO object detection dataset. Deep residual nets are foundations of our submissions to ILSVRC & COCO 2015 competitions1, where we also won the 1st places on the tasks of ImageNet detection, ImageNet localization, COCO detection, and COCO segmentation.

ImageNet Classification with Deep Convolutional Neural Networks [7]We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way soft max. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

Recurrent Convolutional Neural Networks for Continuous Sign Language Recognition by Staged Optimization [8]This work presents a weakly supervised framework with deep neural networks for vision-based continuous sign language recognition, where the ordered gloss labels but no exact temporal locations are available with the video of sign sentence, and the count of labeled sentences for training is limited. Our approach addresses the mapping of video segments to glosses by introducing recurrent convolutional neural network for spatiotemporal feature extraction and sequence learning. We design a three-stage optimization process for our architecture. First, we develop an end-to-end sequence learning scheme and employ connectionist temporal classification (CTC) as the objective function for alignment proposal. Second, we take the alignment proposal as stronger supervision to tune our feature extractor. Finally, we optimize the sequence learning model with the improved feature representations, and design a weakly supervised detection network for regularization. We apply the proposed approach to a real-world continuous sign language recognition benchmark, and our method, with no extra supervision, achieves results comparable to the state of-the-art.

Continuous Gesture Recognition with Hand-oriented Spatiotemporal Feature [9]In this paper, an efficient spotting-recognition framework is proposed to tackle the large-scale continuous gesture recognition problem with the RGB-D data input. Concretely, continuous gestures are firstly segmented into isolated gestures based on the accurate hand positions obtained by two streams Faster R-CNN hand detector. In the subsequent recognition stage, firstly, towards the gesture representation, a specific hand-oriented spatiotemporal (ST) feature is extracted for each isolated gesture video by 3D convolutional network (C3D).

In this feature, only the hand regions and face location are considered, which can effectively block the negative influence of the distractors, such as the background, cloth and the body and so on. Next, the extracted features from calibrated RGB and depth channels are fused to boost the representative power and the final classification is achieved by using the simple linear SVM. Extensive experiments are conducted on the validation and testing sets of the Continuous Gesture Datasets (Con-GD) to validate the effectiveness of the proposed recognition framework. Our method achieves the promising performance with the mean Jaccard Index of 0.6103 and outperforms other results in the Cha-Learn LAP Large-scale Continuous Gesture Recognition Challenge.

Deep Hand: How to Train a CNN on 1-Million Hand Images When Your Data Is Continuous and Weakly Labelled [10]This work presents a new approach to learning a frame-based classifier on weakly labelled sequence data by embedding a CNN within an iterative EM algorithm. This allows the CNN to be trained on a vast number of example images when only loose sequence level information is available for the source videos. Although we demonstrate this in the context of hand shape recognition, the approach has wider application to any video recognition task where frame level labelling is not available. The iterative EM algorithm leverages the discriminative ability of the CNN to iteratively refine the frame level annotation and subsequent training of the CNN. By embedding the classifier within an EM-framework the CNN can easily be trained on 1 million hand images. We demonstrate that the final classifier generalizes over both individuals and data sets. The algorithm is evaluated on over 3000 manually labelled hand shape images of 60 different classes which will be released to the community. Furthermore, we demonstrate its use in continuous sign language recognition on two publicly available large sign language data sets, where it outperforms the current state-of-the-art by a large margin. To our knowledge no previous work has explored expectation maximization without Gaussian mixture models to exploit weak sequence labels for sign language recognition.

III. OUR PROPOSED METHODS

A. Existing System

They proposed for a novel framework based on word existence verification, sentence generation and cross modal re-ranking for SLT. The framework first checks the existence of words in the vocabulary by a series of binary classification to learn a cross modal similarity measurement model to re-rank the candidate sentences by learning their similarity with sign videos which contain gesture transition information, they introduce a spoken language generation model pretrained on a large-corpus sentence dataset to filter such noises and obtain multiple spoken language sentences with linguistic rule constraint. Further, to identify the target sentence, they first check the existence of words in the vocabulary by a series of binary classification in parallel. After that, the appearing words are assembled and guided by a pretrained spoken language generator to produce multiple candidate sentences in spoken language manner. Last but not least, we select the sentence most semantically similar to the input sign video as the translation result with a cross modal re-ranking model. The disadvantage of existing system are they are not using proper technique for accurate sign language and they are not using CNN model.

B. Proposed System

The proposes the sign language presented are reasonably distinct, the images are clear and without background. Also, there is a reasonable quantity of images, which makes our model more robust. The drawback is that for different problems, we would probably need more data to stir the parameters of our model into a better direction.

The proposed this project is to train a Deep Learning algorithm capable of classifying images of different sign language, such as a alphabet and numeric. This particular classification problem can be useful for Gesture Navigation, for example. The method I'll be using is Deep Learning with the help of Convolutional Neural Networks based on TensorFlow and Keras.

We proposed a deep learning (DL) based sign language classification method to prevent gestures. the deep learning method used in the study is the LeNet convolutional neural network (CNN). it is predicted that the success of the obtained results will increase if the CNN method is supported by adding extra feature extraction methods and classify successfully sign language. The advantages of proposed system are To identify the sign language used on artificial neural network and It is best model for deep learning technique to easily identify the sign language types of alphabets and numeric.

In this section, we have discussed our proposed method that how the deep learning algorithms are handled and predict the output.

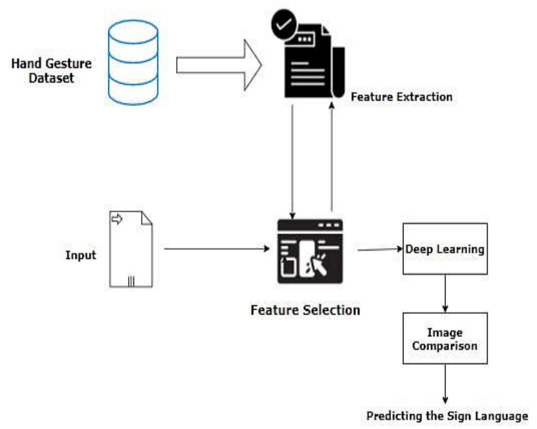

Fig 3. A Block Diagram of Our Proposed Method

A block diagram on our proposed method is presented in Fig. 3 that shows our workflow of the proposed method from beginning to end. This block diagram also shows the seven basic steps of our proposed method.

C. Dataset Collection

The dataset contains 2600 records of features, which were classified into 10 classes, which 2000 training images and 600 testing images as in figure 3and 4. We have to import our data set using keras preprocessing image data generator function also we create size, rescale, range, zoom range, horizontal flip. Here we set train, test, and validation also we set target size, batch size and class-mode from this function we have to train using our own created network by adding layers of CNN.

Fig 4. Sample Image of Dataset- D

Fig5.Sample Image of Dataset-

Fig 6. Sample Image of Dataset- H

D. Data Preprocessing

The dataset is preprocessed such as Image reshaping, resizing and conversion to an array form. Similar processing is also done on the test image. A dataset consisting of about 4 different Sign languages is obtained, out of which any image can be used as a test image for the software. The train dataset is used to train the model (CNN) so that it can identify the test image and the disease it has CNN has different layers that are Dense, Dropout, Activation, Flatten, Convolution2D, and MaxPooling2D. After the model is trained successfully, the software can identify the Sign language Classification image contained in the dataset. After successful training and preprocessing, comparison of the test image and trained model takes place to predict the Sign language.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 75, 75, 32)        896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 37, 37, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 12, 12, 128)       36992
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 6, 6, 128)         0
_________________________________________________________________
flatten (Flatten)            (None, 4608)              0
_________________________________________________________________
dense (Dense)                (None, 256)               1179904
_________________________________________________________________
dense_1 (Dense)              (None, 4)                 1028
=================================================================
Total params: 1,218,820
Trainable params: 1,218,820
Non-trainable params: 0
```

Fig 7. Models Summary

IV. EXPERIMENTAL RESULTS AND DISCUSSION

We give input image using keras preprocessing package. That input Image converted into array value using pillow and image to array function package. We have already classified sign language image dataset. It classifies what are the sign languages. Then we have to predict our sign language using predict function. The sign language recognition method is based on a two-channel architecture that is able to recognize classification of sign languages. The sign language images are used as the input into the inception layer of the CNN. The Training phase involves the feature extraction and classification using convolution neural network.

We compare the performance of our proposed model with four metrics were accuracy and loss using CNN algorithm.

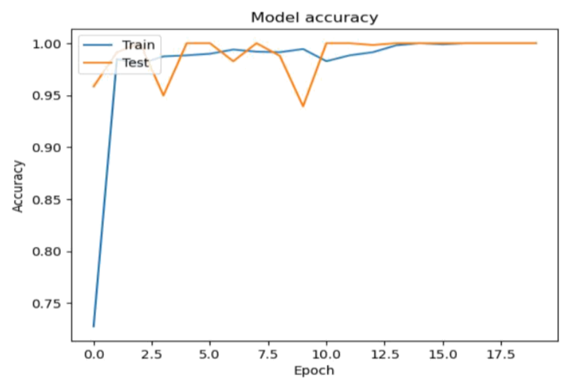

Fig 8. Models Accuracy

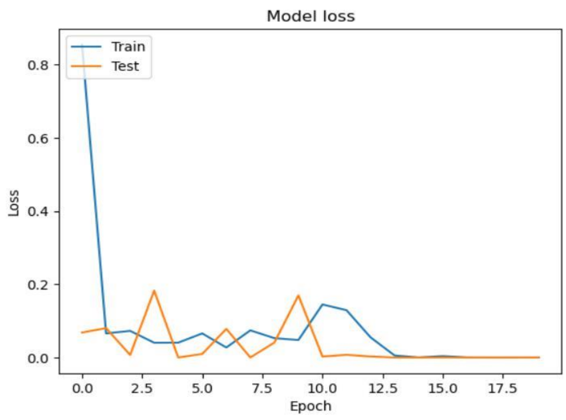

Fig 9. Models Loss

V. CONCLUSIONS

.It focused how image from given dataset (trained dataset) in field and past data set used predict the pattern of different hand gestures using CNN model. This brings some of the following different gestures prediction. We had applied different type of CNN compared the accuracy and saw that LeNet makes better classification and the .h5 file is taken from there and that is deployed in Django framework for better user interface.

VI. FUTURE ENHANCEMENT

Sign Language prediction to connect with AI model. To automate this process by show the prediction result in web application or desktop application. To optimize the work to implement in Artificial Intelligence environment

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