NATIONAL INSTITUTE OF TECHNOLOGY

KURUKSHETRA

Project Report

Topic: -

Sign Language to Text Conversion for Dumb and Deaf

Branch: - Computer Engineering

Section: - CS A- 04

Submitted to: -

Dr. Mohit Dua

Submitted by: -

Shubham (12112077)

Satyam (12112078)

Contents

DECLARATION

We, Shubham and Satyam, solemnly declare that this project report is solely my original work and has not been previously submitted to any other academic institution for any credential. All referenced sources are duly acknowledged through proper citations.

Moreover, We affirm that any aid received during the preparation of this report, whether from individuals or organizations, is duly acknowledged within the text or appended. Contributions from any external sources are duly recognized.

Mentor Signature

(Dr. Mohit Dua)

ACKNOWLEDGEMENTS

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I am equally thankful to my peers and colleagues whose explanations and insights enriched my understanding of complex topics during my studies.
Their collaboration and camaraderie have greatly contributed to my learning experience.

Furthermore, I am deeply indebted to my family members for their boundless love and unwavering support, which served as a constant source of motivation, even during the most challenging times. Their encouragement propelled me forward when I felt like giving up.
To all these exceptional individuals, I extend my deepest appreciation and affection. Without their collective encouragement and support, this endeavor would not have been possible.

Abstract

Sign language is one of the oldest and most natural form of language for communication, but since most people do not know sign language and interpreters are very difficult to come by we have come up with a real time method using neural networks for fingerspelling based american sign language. In our method, the hand is first passed through a filter and after the filter is applied the hand is passed through a classifier which predicts the class of the hand gestures. Our method provides 92.7 % accuracy for the 26 letters of the alphabet.

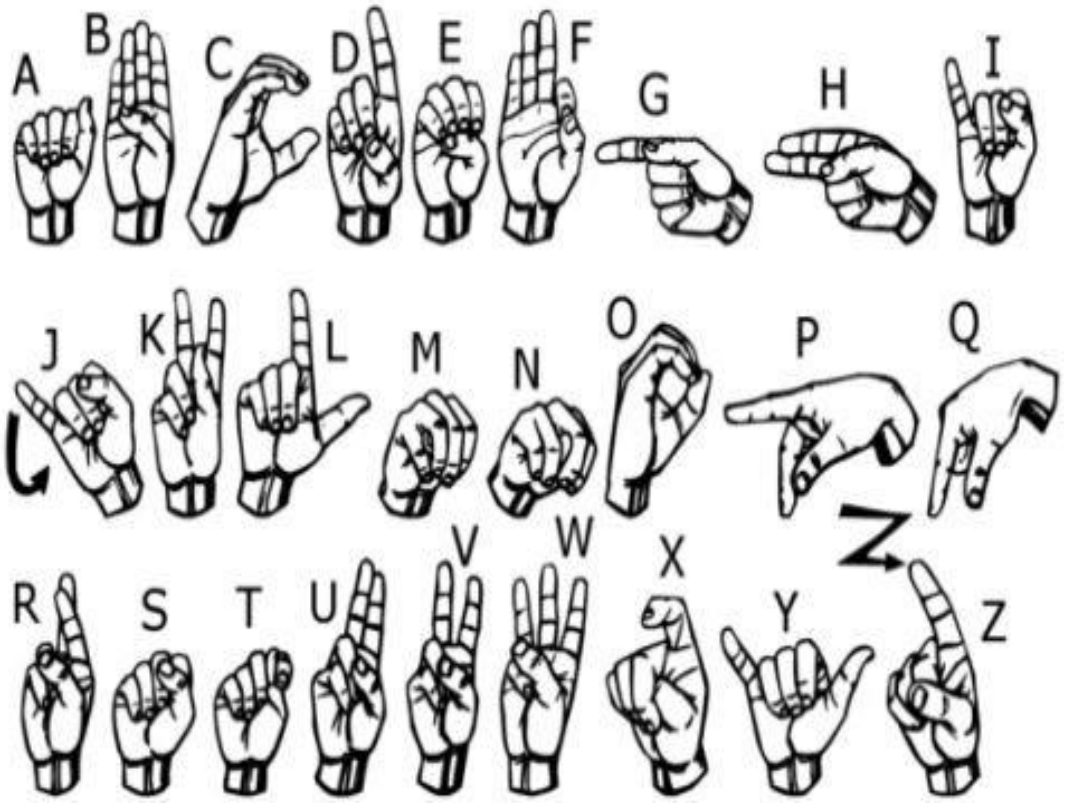
Introduction

American sign language is a predominant sign language Since the only disability D&M people have is communication related and they cannot use spoken languages hence the only way for them to communicate is through sign language. Communication is the process of exchange of thoughts and messages in various ways such as speech, signals, behavior and visuals. Deaf and dumb(D&M) people make use of their hands to express different gestures to express their ideas with other people. Gestures are the nonverbally exchanged messages and these gestures are understood with vision. This nonverbal communication of deaf and dumb people is called sign language.

Sign language is a visual language and consists of 3 major components[6]:

Fingerspelling	Word level sign vocabulary	Non-manual features
Used to spell words letter by letter .	Used for the majority of communication.	Facial expressions and tongue, mouth and body position.

In our project we basically focus on producing a model which can recognise Fingerspelling based hand gestures in order to form a complete word by combining each gesture. The gestures we aim to train are as given in the image below.



Progress of Project

Jan 2024: Project Initiation and Technology Exploration

- ***Objective***: Lay the foundation for the project by exploring relevant technologies and setting up the initial environment.
- ***Activities***:
  - Explored and familiarized with OpenCV for image and video processing.
  - Investigated MediaPipe for hand tracking and landmark extraction.
  - Conducted initial research on Scikit-Learn for machine learning model training.
  - Set up the development environment and installed necessary libraries.
  - ***Challenges***:
    - Understanding the integration of different libraries.
    - Deciding on the most suitable approach for hand gesture recognition.
- ***Outcome***: Established a solid understanding of the tools and techniques required for the project.

Feb 2024: Data Collection and Preprocessing

- ***Objective***: Collect a comprehensive dataset of hand gestures and preprocess the images for model training.
- ***Activities***:
  - Created a custom dataset by capturing images of hand gestures (A-X) using OpenCV.
  - Developed a script to automate the image capture process, ensuring consistency.
  - Preprocessed the captured images using MediaPipe to extract hand landmarks.
  - Normalized and organized the data for use in model training.

- ***Challenges***:
  - Ensuring consistent image quality and lighting during data capture
  - Handling variations in hand size and positioning.
- ***Outcome***: Successfully created and preprocessed a dataset of hand gestures, ready for model training.

March 2024: **Model Training and Evaluation**

- ***Objective***: Train a machine learning model to recognize hand gestures and evaluate its performance.
- ***Activities***:
  - Split the dataset into training and test sets using Scikit-Learn.
  - Trained a Random Forest Classifier on the extracted hand landmarks.
  - Tuned hyperparameters to optimize model performance.
  - Evaluated the model's accuracy using the test set, achieving a satisfactory classification accuracy.
  - ***Challenges***:
    - Balancing the dataset to prevent bias towards certain gestures.
    - Tuning the model to achieve the best possible accuracy.
- ***Outcome***: Developed a working model with good accuracy, capable of recognizing hand gestures.

April 2024: **Real-Time Gesture Recognition and System Integration**

- ***Objective***: Integrate the trained model into a real-time gesture recognition system with text-to-speech functionality.
- ***Activities***:
  - Integrated the trained model with a live video feed using OpenCV and MediaPipe.
  - Implemented real-time hand gesture recognition, displaying

predictions on the screen.
    - Added GTTS to convert recognized gestures to speech, enhancing the user interface.
    - Optimized the code for real-time performance, ensuring smooth operation.
    - ***Challenges***:
        - Achieving low-latency real-time performance while maintaining accuracy.
        - Handling false positives and noisy predictions.
- ***Outcome***: Successfully implemented a real-time hand gesture recognition system with text-to-speech output.

May 2024: **Showcase and Demonstration**

- ***Objective***: Present our project to a broader audience by creating and launching a dedicated webpage that highlights our work, objectives, and achievements.
- ***Activities***:
    - Developed and launched a comprehensive webpage to showcase the project.
    - Demonstrated the application's real-time gesture recognition capabilities to users.
    - Collected feedback from the showcase to identify potential areas for further improvement
    - ***Challenges***:
        - Ensuring the webpage effectively communicates the technical details and significance of the project.
        - Integrating real-time demonstrations seamlessly into the webpage.
- ***Outcome***: Successfully launched a functional and informative webpage that effectively showcased the project's capabilities and achievements, receiving positive feedback and laying the groundwork for future enhancements.

Motivation

For interaction between normal people and D&M people a language barrier is created as sign language structure which is different from normal text. So they depend on vision based communication for interaction.

If there is a common interface that converts the sign language to text the gestures can be easily understood by the other people. So research has been made for a vision based interface system where D&M people can enjoy communication without really knowing each other's language.

The aim is to develop a user friendly human computer interfaces (HCI) where the computer understands the human sign language. There are various sign languages all over the world, namely American Sign Language (ASL), French Sign Language, British Sign Language (BSL), Indian Sign language, Japanese Sign Language and work has been done on other languages all around the world.

Literature survey

In the recent years there has been tremendous research done on the hand gesture recognition.
With the help of literature survey done we realized the basic steps in hand gesture recognition are :-

- Data acquisition
- Data preprocessing
- Feature extraction
- Gesture classification

Data acquisition:

The different approaches to acquire data about the hand gesture can be done in the following ways:

1. Use of sensory devices

It uses electromechanical devices to provide exact hand configuration, and position. Different glove based approaches can be used to extract information .But it is expensive and not user friendly.

2. Vision based approach

In vision based methods computer camera is the input device for observing the information of hands or fingers. The Vision Based methods require only a camera, thus realizing a natural interaction between humans and computers without the use of any extra devices. These systems tend to complement biological vision by describing

artificial vision systems that are implemented in software and/or hardware.

The main challenge of vision-based hand detection is to cope with the large variability of human hand's appearance due to a huge number of hand movements, to different skin-colour possibilities as well as to the variations in view points, scales, and speed of the camera capturing the scene.

Data preprocessing and Feature extraction for vision based approach:

- In [1] the approach for hand detection combines threshold-based color detection with background subtraction.We can use Adaboost face detector to differentiate between faces and hands as both involve similar skin-color.

- We can also extract necessary image which is to be trained by applying a filter called Gaussian blur. The filter can be easily applied using open computer vision also known as OpenCV and is described in [3].

- For extracting necessary image which is to be trained we can use instrumented gloves as mentioned in [4]. This helps reduce computation time for preprocessing and can give us more concise and accurate data compared to applying filters on data received from video extraction.

- We tried doing the hand segmentation of an image using color segmentation techniques but as mentioned in the research paper skin color and tone is highly dependent on the lighting conditions due to which output we got for the segmentation we tried to do were no so great. Moreover we have a huge number of symbols to be trained for our project many of which look similar to each other like the gesture for symbol 'V' and digit '2', hence we decided that in order to produce better accuracies for our large number of symbols, rather than

segmenting the hand out of a random background we keep background of hand a stable single color so that we don't need to segment it on the basis of skin color . This would help us to get better results.

Gesture classification :

- In [1] Hidden Markov Models (HMM) is used for the classification of the gestures .This model deals with dynamic aspects of gestures.Gestures are extracted from a sequence of video images by tracking the skin-colour blobs corresponding to the hand into a body– face space centered on the face of the user. The goal is to recognize two classes of gestures: deictic and symbolic.The image is filtered using a fast look–up indexing table. After filtering, skin colour pixels are gathered into blobs. Blobs are statistical objects based on the location (x,y) and the colourimetry (Y,U,V) of the skin colour pixels in order to determine homogeneous areas.

- In [2] Naïve Bayes Classifier is used which is an effective and fast method for static hand gesture recognition. It is based on classifying the different gestures according to geometric based invariants which are obtained from image data after segmentation.Thus,unlike many other recognition methods, this method is not dependent on skin colour. The gestures are extracted from each frame of the video,with a static background. The first step is to segment and label the objects of interest and to extract geometric invariants from them. Next step is the classification of gestures by using a K nearest neighbor algorithm aided with distance weighting algorithm (KNNDW) to provide suitable data for a locally weighted Naïve Bayes‟classifier.

- According to paper on "Human Hand Gesture Recognition Using a Convolution Neural Network" by Hsien-I Lin , Ming-Hsiang Hsu, and Wei-Kai Chen graduates of Institute of Automation Technology National Taipei University of Technology Taipei,

Taiwan, they construct a skin model to extract the hand out of an image and then apply binary threshold to the whole image. After obtaining the threshold image they calibrate it about the principal axis in order to center the image about it. They input this image to a convolutional neural network model in order to train and predict the outputs. They have trained their model over 7 hand gestures and using their model they produce an accuracy of around 92% for those 7 gestures.

Key Words and Definitions

.

Feature Extraction and Representation :

The representation of an image as a 3D matrix having dimension as of height and width of the image and the value of each pixel as depth (1 in case of Grayscale and 3 in case of RGB). Further, these pixel values are used for extracting useful features using CNN.

Artificial Neural Networks :

Artificial Neural Network is a connections of neurons, replicating the structure of human brain. Each connection of neuron transfers information to another neuron. Inputs are fed into first layer of neurons which processes it and transfers to another layer of neurons called as hidden layers. After processing of information through multiple layers of hidden layers, information is passed to final output layer.

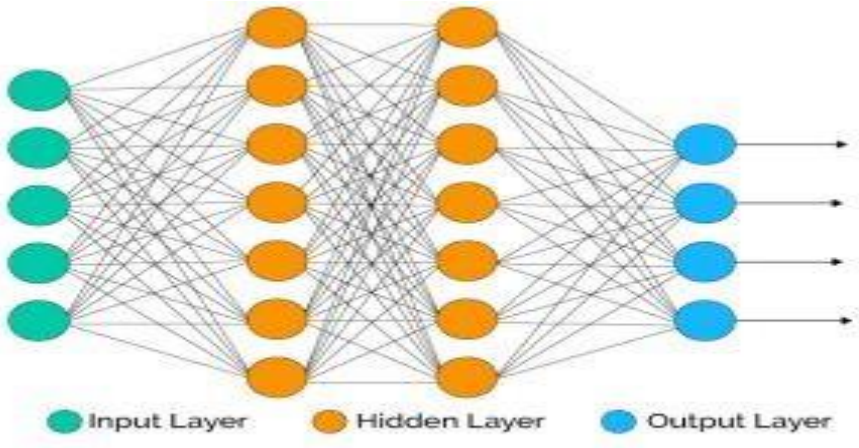


Figure 5.1: Artificial neural networks

There are capable of learning and they have to be trained. There are different learning strategies :

1. Unsupervised Learning
2. Supervised Learning
3. Reinforcement Learning

Convolution Neural Network :

Unlike regular Neural Networks, in the layers of CNN, the neurons are arranged in 3 dimensions: width, height, depth. The neurons in a layer will only be connected to a small region of the layer (window size) before it, instead of all of the neurons in a fully-connected manner. Moreover, the final output layer would have dimensions (number of classes), because by the end of the CNN architecture we will reduce the full image into a single vector of class scores.

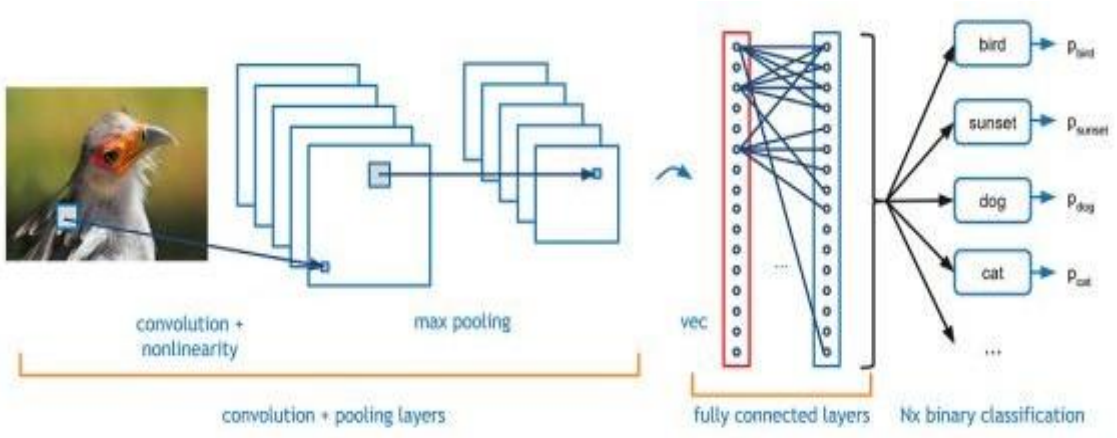


Figure 5.2: Convolution neural networks

1. Convolution Layer : In convolution layer we take a small window size [typically of length 5*5] that extends to the depth of the input matrix. The layer consist of learnable filters of window size. During every iteration we slid the window by stride size [typically 1], and compute the dot product of filter entries and input values at a given position. As we continue this process well create a 2-Dimensional activation matrix that gives the response of that matrix at every spatial position. That is, the network will learn filters that activate when they see some type of visual feature such as an edge of some orientation or a blotch of some color

2. Pooling Layer : We use pooling layer to decrease the size of activation matrix and ultimately reduce the learnable parameters. There are two type of pooling :

a) Max Pooling : In max pooling we take a window size [for example window of size 2*2], and only take the maximum of 4 values. Well lid this window and continue this process, so well finally get a activation matrix half of its original Size.

b) Average Pooling : In average pooling we take average of all

Values in a window.

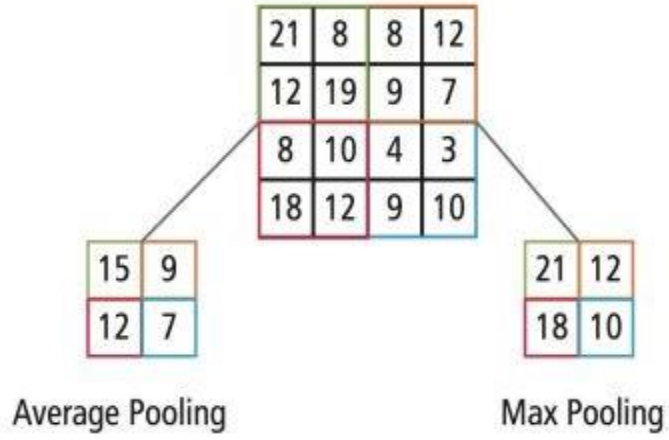


Figure 5.3: Types of pooling

3. Fully Connected Layer : In convolution layer neurons are connected only to a local region, while in a fully connected region, well connect the all the inputs to neurons.

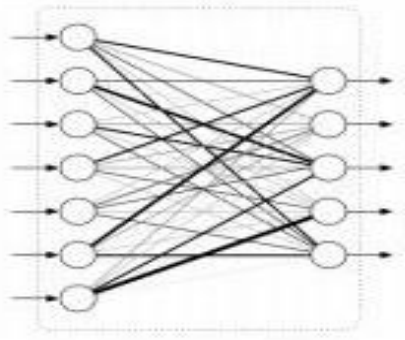


Figure 5.4: Fully Connected Layer

4. Final Output Layer : After getting values from fully connected layer, well connect them to final layer of neurons[having count equal to total number of classes], that will predict the probability of each image to be in different classes.

TensorFlow :

Tensorflow is an open source software library for numerical computation. First we define the nodes of the computation graph, then inside a session, the

actual computation takes place. TensorFlow is widely used in Machine Learning.

Keras :

Keras is a high-level neural networks library written in python that works as a wrapper to TensorFlow. It is used in cases where we want to quickly build and test the neural network with minimal lines of code. It contains implementations of commonly used neural network elements like layers, objective, activation functions, optimizers, and tools to make working with images and text data easier.

OpenCV :

OpenCV(Open Source Computer Vision) is an open source library of programming functions used for real-time computer-vision. It is mainly used for image processing, video capture and analysis for features like face and object recognition. It is written in C++ which is its primary interface, however bindings are available for Python, Java, MATLAB/OCTAVE.

MediaPipe:

MediaPipe is an open-source framework developed by Google for building multimodal perceptual pipelines. It enables developers to create complex pipelines for processing media such as video and audio. MediaPipe supports a variety of tasks like object detection, facial recognition, and hand tracking through modular components. It's designed to be flexible, efficient, and portable across different platforms.

Scikit-Learn(Sklearn):

scikit-learn (sklearn) is a popular machine learning library in Python, offering a wide range of tools for data analysis and modeling. It provides easy-to-use implementations of algorithms for classification, regression, clustering, and more. Sklearn is built on NumPy, SciPy, and matplotlib, making it powerful for both research and production

environments.

Pickle :

Pickle is a Python module used for serializing and deserializing Python objects into a byte stream, allowing objects to be saved and reconstructed later. It's often used for saving machine learning models, among other purposes.

NumPy :

NumPy is a powerful Python library for numerical computations, featuring a multidimensional array object and a variety of tools for working with these arrays. It provides efficient operations on arrays of data, enabling tasks such as mathematical, logical, shape manipulation, sorting, selecting, I/O, discrete Fourier transforms, basic linear algebra, basic statistical operations, random simulation and more

Methodology

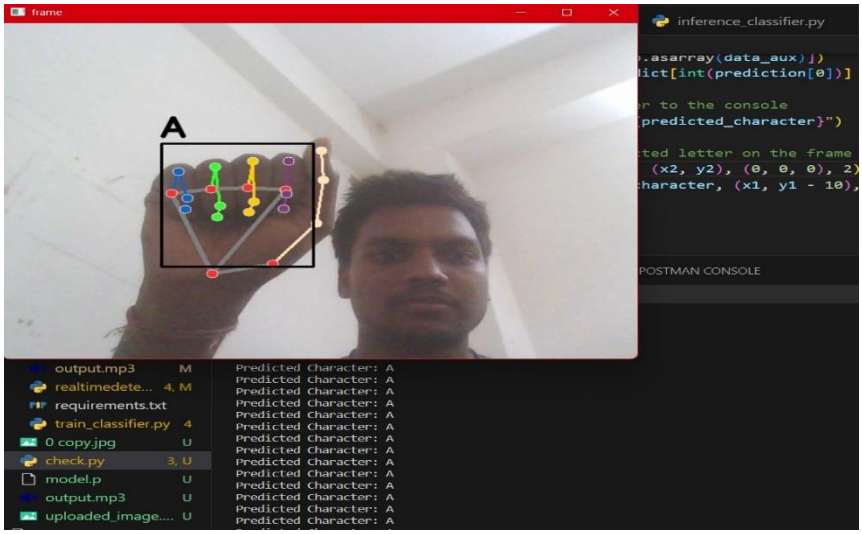
The system is a vision based approach. All the signs are represented with bare hands and so it eliminates the problem of using any artificial devices for interaction.

Data Set Generation

For the project we tried to find already made datasets but we couldn't find dataset in the form of raw images that matched our requirements. All we could find were the datasets in the form of RGB values. Hence we decided to create our own data set. Steps we followed to create our data set are as follows.

We used Open computer vision(OpenCV) library in order to produce our dataset.Firstly we captured around 800 images of each of the symbol in ASL for training purposes and around 200 images per symbol for testing purpose.

First we capture each frame shown by the webcam of our machine. In the each frame we define a region of interest (ROI) which is denoted by a blue bounded square as shown in the image below.



From this whole image we extract our ROI which is RGB and convert it into gray scale Image as shown below.

Finally we apply our gaussian blur filter to our image which helps us extracting various features of our image. The image after applying gaussian blur looks like below.

GESTURE CLASSIFICATION

The approach which we used for this project is :

Our approach uses two layers of algorithm to predict the final symbol of the user.

Algorithm Layer 1:

1. Apply gaussian blur filter and threshold to the frame taken with opencv to get the processed image after feature extraction.
2. This processed image is passed to the CNN model for prediction and if a letter is detected for more than 50 frames then the letter is printed and taken into consideration for forming the word.
3. Space between the words are considered using the blank symbol.

Algorithm Layer 2:

1. We detect various sets of symbols which show similar results on getting detected.
2. We then classify between those sets using classifiers made for those sets only.

Layer 1:

CNN Model:

1. **1st Convolution Layer :**

   The input picture has resolution of 128x128 pixels. It is first processed in the first convolutional layer using 32 filter weights (3x3 pixels each). This will result in a 126X126 pixel image, one for each Filter-weights.

2. **1st Pooling Layer :**

   The pictures are downsampled using max pooling of 2x2 i.e we keep the highest value in the 2x2 square of array. Therefore, our picture is downsampled to 63x63 pixels.

3. **2nd Convolution Layer :**

   Now, these 63 x 63 from the output of the first pooling layer is served as an input to the second convolutional layer.It is processed in the second convolutional layer using 32 filter weights (3x3 pixels each).This will result in a 60 x 60 pixel image.

4. **2nd Pooling Layer :**

   The resulting images are downsampled again using max pool of 2x2 and is reduced to 30 x 30 resolution of images.

5. **1st Densely Connected Layer :**

   Now these images are used as an input to a fully connected layer with 128 neurons and the output from the second convolutional layer is reshaped to an array of 30x30x32 =28800 values. The input to this layer is an array of 28800 values. The output of these layer is fed to the 2nd Densely Connected Layer.We are using a dropout layer of value 0.5 to avoid overfitting.

6. **2nd Densely Connected Layer :**

   Now the output from the 1st Densely Connected Layer are used as an input to a fully connected layer with 96 neurons.

7. **Final Output layer:**

   The output of the 2nd Densely Connected Layer serves as an input for the final layer which will have the number of neurons as the number of classes we are classifying (alphabets + blank symbol).

Activation Function :

We have used ReLu (Rectified Linear Unit) in each of the layers(convolutional as well as fully connected neurons). ReLu calculates max(x,0) for each input pixel. This adds nonlinearity to the formula and helps to learn more complicated features.It helps in removing the vanishing gradient problem and speeding up the training by reducing the computation time.

Pooling Layer :

We apply **Max** pooling to the input image with a pool size of (2, 2) with relu activation function.This reduces the amount of parameters thus lessening the computation cost and reduces overfitting.

Dropout Layers:

The problem of overfitting, where after training, the weights of the network are so tuned to the training examples they are given that the network doesn't perform well when given new examples.This layer "drops out" a random set of activations in that layer by setting them to zero.The network should be able to provide the right classification or output for a specific example even if some of the activations are dropped out[5].

Optimizer :

We have used Adam optimizer for updating the model in response to the output of the loss function. Adam combines the advantages of two extensions of two stochastic gradient descent algorithms namely adaptive gradient algorithm(ADA GRAD) and root mean square propagation(RMSProp)

Layer 2:

We are using two layers of algorithms to verify and predict symbols which are more similar to each other so that we can get us close as we can get to detect the symbol shown. In our testing we found that following symbols were not showing properly and were giving other symbols also :

a) For D : R and U
b) For U : D and R
c) For I : T, D, K and I
d) For S : M and N

So to handle above cases we made three different classifiers for classifying these sets:

1. {D,R,U}
2. {T,K,D,I}
3. {S,M,N}

Finger spelling sentence formation

Implementation :

1. Whenever the count of a letter detected exceeds a specific value and no other letter is close to it by a threshold we print the letter and add it to the current string(In our code we kept the value as 50 and difference threshold as 20).

2. Otherwise we clear the current dictionary which has the count of detections of present symbol to avoid the probability of a wrong letter getting predicted.

3. Whenever the count of a blank(plain background) detected exceeds a specific value and if the current buffer is empty no spaces are detected.

4. In other case it predicts the end of word by printing a space and the current gets appended to the sentence below.

5. ### Autocorrect Feature :

   A python library **Hunspell_suggest** is used to suggest correct alternatives for each (incorrect) input word and we display a set of words matching the current word in which the user can select a word to append it to the current sentence.This helps in reducing mistakes committed in spellings and assists in predicting complex words.

Training and Testing :

We convert our input images(RGB) into grayscale and apply gaussian blur to remove unnecessary noise.We apply adaptive threshold to extract our hand from the background and resize our images to 128x 128.

We feed the input images after preprocessing to our model for training and testing after applying all the operations mentioned above.

The prediction layer estimates how likely the image will fall under one of the classes. So the output is normalized between 0 and 1 and such that the sum of each values in each class sums to 1. We have achieved this using softmax function.

At first the output of the prediction layer will be somewhat far from the actual value. To make it better we have trained the networks using labeled data. The cross-entropy is a performance measurement used in the classification. It is a continuous function which is positive at values which is not same as labeled value and is zero exactly when it is equal to the labeled value. Therefore we optimized the cross-entropy by minimizing it as close to zero. To do this in our network layer we adjust the weights of our neural networks. TensorFlow has an inbuilt function to calculate the cross entropy.

As we have found out the cross entropy function, we have optimized it using Gradient Descent in fact with the best gradient descent optimizer is called Adam Optimizer.

Challenges Faced :

There were many challenges faced by us during the project. The very first issue we faced was of dataset. We wanted to deal with raw images and that too square images as CNN in Keras as it was a lot more convenient working with only square images. We couldn't find any existing dataset for that hence we decided to make our own dataset. Second issue was to select a filter which we could apply on our images so that proper features of the images could be obtained and hence then we could provided that image as input for CNN model. We tried various filter including binary threshold, canny edge detection, gaussian blur etc. but finally we settled with gaussian blur filter. More issues were faced relating to the accuracy of the model we trained in earlier phases which we eventually improved by increasing the input image size and also by improving the dataset.

Results :

We have achieved an accuracy of 95.8% in our model using only layer 1 of our algorithm , and using the combination of layer 1 and layer 2 we achieve an accuracy of 98.0%, which is a better accuracy then most of the current research papers on american sign language. Most of the research papers focus on using devices like kinect for hand detection. In [7] they build a recognition system for flemish sign language using convolutional neural networks and kinect and achieve an error rate of 2.5%. In [8] a recognition model is built using hidden markov model classifier and a vocabulary of 30 words and they achieve an error rate of 10.90%. In [9] they achieve an average accuracy of 86% for 41 static gestures in japanese sign language. Using depth sensors map [10] achieved an accuracy of 99.99% for observed signers and 83.58% and 85.49% for new signers. They also used CNN for their recognition system. One thing should be noted

that our model doesn't uses any background subtraction algorithm whiles some of the models present above do that.

So once we try to implement background subtraction in our project the accuracies may vary. On the other hand most of the above projects use kinect devices but our main aim was to create a project which can be used with readily available resources. A sensor like kinect not only isn't readily available but also is expensive for most of audience to buy and our model uses a normal webcam of the laptop hence it is great plus point.. Below are the confusion matrices for our results.

		Predicted Values																								
		A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y
	A	147	0	0	0	0	0	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	2	0	0
	B	0	139	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0
	C	0	0	152	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	D	0	0	0	145	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	E	0	0	0	0	152	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	F	0	0	0	0	0	135	0	0	0	0	0	4	0	0	0	0	0	1	0	0	2	10	0	0	0
C	G	0	0	0	0	0	0	150	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
o	H	1	0	0	0	0	0	7	143	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	1
r	I	0	0	0	33	0	0	0	0	108	0	2	0	0	0	0	0	0	0	0	7	1	0	0	0	0
r	J	0	0	0	0	0	0	0	0	0	153	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
e	K	0	0	0	0	0	0	0	0	0	0	153	0	0	0	0	0	0	0	0	0	0	0	0	0	0
c	L	0	0	0	0	0	0	0	0	0	0	0	153	0	0	0	0	0	0	0	0	0	0	0	0	0
t	M	0	0	0	0	0	0	0	0	0	0	2	0	152	0	0	0	0	0	0	0	0	0	0	0	0
	N	0	0	0	0	0	0	0	0	0	0	0	0	0	152	0	0	0	0	0	0	0	0	0	0	0
V	O	0	0	0	0	0	0	0	0	0	0	0	0	0	0	154	0	0	0	0	0	0	0	0	0	0
a	P	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	153	0	0	0	0	0	0	0	0	0
l	Q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	147	1	0	0	0	0	0	0	0
u	R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	150	0	0	0	0	0	0	0
e	S	0	0	0	0	1	0	0	0	0	0	0	0	0	1	10	0	0	0	132	0	0	0	0	8	0
s	T	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	151	0	0	0	0	0
	U	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	35	0	0	115	0	0	0	0
	V	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	151	1	0	0
	W	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	149	0	0
	X	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	148	0
	Y	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	151
	Z	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Algo 1

						Predicted Values																				
		A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y
	A	147	0	0	0	0	0	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	2	0	0
	B	0	139	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0
	C	0	0	152	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	D	0	0	0	153	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	E	0	0	0	0	152	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	F	0	0	0	0	0	135	0	0	0	0	0	4	0	0	0	0	0	0	0	0	3	10	0	0	0
Correct Values	G	0	0	0	0	0	0	150	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
	H	1	0	0	0	0	0	7	143	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	1
	I	0	0	0	0	0	0	0	0	150	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
	J	0	0	0	0	0	0	0	0	0	153	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	K	0	0	0	0	0	0	0	0	0	0	153	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	L	0	0	0	0	0	0	0	0	0	0	0	153	0	0	0	0	0	0	0	0	0	0	0	0	0
	M	0	0	0	0	0	0	0	0	0	0	2	0	152	0	0	0	0	0	0	0	0	0	0	0	0
	N	0	0	0	0	0	0	0	0	0	0	0	0	0	152	0	0	0	0	0	0	0	0	0	0	0
	O	0	0	0	0	0	0	0	0	0	0	0	0	0	0	154	0	0	0	0	0	0	0	0	0	0
	P	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	153	0	0	0	0	0	0	0	0	0
	Q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	147	1	0	0	0	0	0	0	0
	R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	150	0	0	0	0	0	0	0
	S	0	0	0	0	1	0	0	0	0	0	0	0	0	0	10	0	0	0	133	0	0	0	0	8	0
	T	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	151	0	0	0	0	0
	U	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	150	0	0	0	0
	V	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	151	1	0	0
	W	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	149	0	0
	X	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	148	0
	Y	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	151
	Z	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Algo 1 + Algo 2

Conclusion :

In this report, a functional real time vision based american sign language recognition for D&M people have been developed for ASL alphabets.We achieved final accuracy of 94.0% on our dataset. We are able to improve our prediction after implementing two layers of algorithms in which we verify and predict symbols which are more similar to each other.

This way we are able to detect almost all the symbols provided that they are shown properly, there is no noise in the background and lighting is adequate.

Future Scope :

We are planning to achieve higher accuracy even in case of complex backgrounds by trying out various background subtraction algorithms. We are also thinking of improving the preprocessing to predict gestures in low light conditions with a higher accuracy.

References :

[1]T. Yang, Y. Xu, and “A. , Hidden Markov Model for Gesture Recognition”, CMU-RI-TR-94 10, Robotics Institute, Carnegie Mellon Univ.,Pittsburgh,PA, May 1994.

[2]Pujan Ziaie, Thomas M ¨uller , Mary Ellen Foster , and Alois Knoll“A Na ¨ıve Bayes Munich,Dept. of Informatics VI, Robotics and Embedded Systems,Boltzmannstr. 3, DE-85748 Garching, Germany.

[3]https://docs.opencv.org/2.4/doc/tutorials/imgproc/gausian_median_blur_b ilateral_filter/gausian_median_blur_bilateral_filter.html

[4]Mohammed Waleed Kalous, Machine recognition of Auslan signs using PowerGloves: Towards large-lexicon recognition of sign language.

[5]aeshpande3.github.io/A-Beginner%27s-Guide-To-Understanding-Convol utional-Neural-Networks-Part-2/

[6]http://www-i6.informatik.rwth-aachen.de/~dreuw/database.php

[7] Pigou L., Dieleman S., Kindermans PJ., Schrauwen B. (2015) Sign Language Recognition Using Convolutional Neural Networks. In: Agapito L., Bronstein M., Rother C. (eds) Computer Vision - ECCV 2014 Workshops. ECCV 2014. Lecture Notes in Computer Science, vol 8925.
Springer, Cham

[8]Zaki, M.M., Shaheen, S.I.: Sign language recognition using a combination of new vision based features. Pattern Recognition Letters 32(4), 572–577 (2011)

[9] N. Mukai, N. Harada and Y. Chang, "Japanese Fingerspelling Recognition Based on Classification Tree and Machine Learning," *2017 Nicograph International (NicoInt)*, Kyoto, Japan, 2017, pp. 19-24. doi:10.1109/NICOInt.2017.9

[10] Byeongkeun Kang , Subarna Tripathi , Truong Q. Nguyen ”Real-time sign language fingerspelling recognition using convolutional neural networks from depth map” 2015 3rd IAPR Asian Conference on Pattern Recognition (ACPR)

[11] https://opencv.org/

[12] https://en.wikipedia.org/wiki/TensorFlow

[13] https://en.wikipedia.org/wiki/Convolutional_neural_network

APPENDIX

OpenCV

OpenCV (Open Source Computer Vision Library) is released under a BSD license and hence it's free for both academic and commercial use. It has C++, Python and Java interfaces and supports Windows, Linux, Mac OS, iOS and Android. OpenCV was designed for computational efficiency and with a strong focus on real-time applications. Written in optimized C/C++, the library can take advantage of multi-core processing. Enabled with OpenCL, it can take advantage of the hardware acceleration of the underlying heterogeneous compute platform.

Adopted all around the world, OpenCV has more than 47 thousand people of user community and estimated number of downloads exceeding 14 million. Usage ranges from interactive art, to mines inspection, stitching maps on the web or through advanced robotics.

Convolution Neural network

CNNs use a variation of multilayer perceptrons designed to require minimal preprocessing. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on their shared-weights architecture and translation invariance characteristics.

Convolutional networks were inspired by biological processes in that the connectivity pattern between neurons resembles the organization of the animal visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field.

The receptive fields of different neurons partially overlap such that they cover the entire visual field.

CNNs use relatively little pre-processing compared to other image classification algorithms. This means that the network learns the filters that in traditional algorithms were hand-engineered. This independence from prior knowledge and human effort in feature design is a major advantage.

They have applications in image and video recognition, recommender systems, image classification, medical image analysis, and natural language processing.

Tensorflow

TensorFlow is an open-source software library for dataflow programming across a range of tasks. It is a symbolic math library, and is also used for machine learning applications such as neural networks. It is used for both research and production at Google.

TensorFlow was developed by the Google brain team for internal Google use. It was released under the Apache 2.0 open source library on November 9, 2015.

TensorFlow is Google Brain's second-generation system. Version 1.0.0 was released on February 11, 2017. While the reference implementation runs on single devices, TensorFlow can run on multiple CPUs and GPUs (with optional CUDA and SYCL extensions for general-purpose computing on graphics processing units). TensorFlow is available on 64-bit Linux, macOS, Windows, and mobile computing platforms including Android and iOS.

Its flexible architecture allows for the easy deployment of computation across a variety of platforms (CPUs, GPUs, TPUs), and from desktops to clusters of servers to mobile and edge devices.