AMERICAN SIGN LANGUAGE RECOGNITION USING HAND GESTURES

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Abstract

Consistently we see many impaired individuals like hard of hearing, stupid and visually impaired, and so forth They face trouble cooperating with others. Around 4 million individuals in India are hard of hearing and around 10 million individuals in India are moronic. Also, they utilize communication via gestures to speak with one another and ordinary individuals. Be that as it may, Normal individuals think that it's hard to comprehend the communication through signing and motions made by not too sharp individuals. So there are numerous methods that can be utilized to change the communication through signing made by the impaired into a form(such as text, voice, and so on) that can be perceived by ordinary individuals. Recently created strategies are for the most part sensors based and they didn't give the overall arrangement. As of late various vision-based methods are accessible to achieve this. We will take a stab at carrying out such an application that identifies pre-characterized American marked language (ASL) through hand motions. For the recognition of the development of motion, we would utilize the cv2 library and an outside camera as an equipment prerequisite is required. In this way, our application will have a primary module that basically identifies the motion and shows the fitting letters in order.

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Introduction

One of the serious issues looked at by an individual who can't talk is they can't communicate their feelings as uninhibitedly in this world. They can't use (Artificial Intelligence/individual Butler) like google help, or Apple's SIRI, and so forth since each one of those applications depends on voice control. There is a requirement for such stages for such sorts of individuals. American Sign Language (ASL) is a finished, complex language that utilizes signs made by moving the hands joined with looks and stances of the body. It is the go-to language of numerous North Americans who can't talk and is one of the different correspondence choices utilized by individuals who are hard of hearing or nearly deaf. While gesture-based communication is fundamental for hard of hearing quiet individuals, to impart both with typical individuals and with themselves, is as yet standing out enough to be noticed by ordinary individuals. Significant communication through signing has been tending to be disregarded except if there are spaces of worry with people who are hard of hearing quiet. One of the answers for a talk with hard-of-hearing quiet individuals is by utilizing the instruments of communication through signing. Hand motion is one of the techniques utilized in communication through signing for non-verbal correspondence. It is most usually utilized by hard of hearing and idiotic individuals who have hearing or talking issues to convey among themselves or with typical individuals. Different gesture-based communication frameworks have been created by numerous producers around the world, yet they are neither adaptable nor financially savvy for the end clients.

Domain

One of the answers for speak with hard-of-hearing quiet individuals is by utilizing the administrations of a communication via gestures translator. Yet, the use of gesture-based communication mediators could be costly. A financially savvy arrangement is required so the hard of hearing quiet and typical individuals can convey ordinarily and without any problem. Our system includes executing such an application that recognizes pre-characterized American gesture-based communication (ASL) through hand signals. For the recognition of the development of signal, we would utilize an essential degree of equipment parts like camera and interfacing is required. Rather than utilizing innovations like gloves or Kinect, we are attempting to take care of this issue by utilizing cutting-edge PC vision and AI calculations. This application will contain two center modules one is that just recognizes the motion and shows the proper letters in order.

Problem Statement

Communication through signing is the method for correspondence among the hard of hearing and the quiet local area. Communication via gestures arises and develops normally inside the conference and impedes the local area. Communication through signing correspondence includes manual and non-manual signs where manual signs include fingers, hands, arms, and non-manual signs include the face, head, eyes, and body. Communication through signing is a very much organized language with phonology, morphology, sentence structure, and syntax. Communication through signing is a finished characteristic language that utilizations various methods of articulation for correspondence in regular daily existence. Communication through The signing acknowledgment framework moves the correspondence from human to human-PC cooperation. Given a hand motion, carrying out such an application which identifies pre-characterized American communication through signing (ASL) progressively through hand signals so the issues looked by people who can't talk vocally can be obliged with mechanical help and the boundary of communicating can be eclipsed.

Background Study

Hearing issues are one of the most significant medical issues in the world. In spite of the degree of hearing weaknesses and their financial effect, there is a scarcity of exact populace putting together information with respect to these[1]. Hearing misfortune is the fourth most elevated reason for handicap all around the world, with an expected yearly expense of more than 750 billion dollars. These realities are notable and have added to developing worldwide cognizance on the requirement for available hearing consideration in all districts of the world. The rising quantities of individuals with hearing misfortune represents a reason for concern. In any case, by recognizing the main sources of hearing misfortune and executing precautionary activity, the pattern of raising hearing misfortune could be controlled. With premonition, arranging and execution of good arrangements, we can restrict the unfriendly effect of hearing misfortune around the world[2].

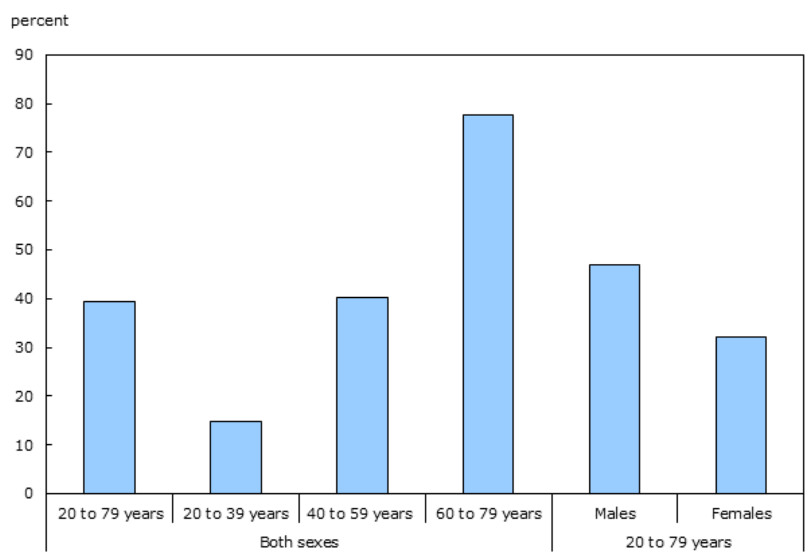


Figure 1. Statistics of hearing loss[3]

Many technologies have already been developed for people with hearing disorders. Studies have intended to make correspondence for elderly individuals simple and thus proposing a sign translator, which consequently changes over communication via gestures into sound yield. It is hard for average citizens to comprehend that communication through signing along these lines of correspondence gets troublesome. Instrumented gloves with sound out are the answer for this issue. The gloves appended with different sensors are worn for sign understanding[4].As speech impaired people are also disconnected from standard society because of the lack of appropriate correspondence help. Communication through signing or sign languages is the essential method for correspondence for them which ordinary individuals don't comprehend. To work with the discussion transformation of communication from signing to sound is exceptionally important. Some innovations have focused on the change of communication through signing to discourse so that incapacitated individuals have their own voice to speak with the overall individuals. Hand Gesture acknowledgment is performed utilizing HOG (Histogram of Oriented Gradients) for extraction of highlights from the signal picture and SVM (Support Vector Machine) as a classifier. At last, anticipate the signal picture with yield text. This yield text is changed over into discernible sound utilizing TTS (Text to Speech) converter[5]. One more way the creators introduced a plan utilizing a data set driven hand signal acknowledgment dependent on skin shading model methodology and thresholding approach alongside a successful format coordinating which can be viably utilized for human mechanical technology applications and comparable different applications. At first, the hand locale is fragmented by applying the skin shading model in the YCbCr shading space. In the following stage, thresholding was applied to isolate the forefront and foundation. At last, a format based on coordinating the method is created utilizing Principal Component Analysis (PCA) for acknowledgment[6]. A vision based translator device was developed for programmed interpretation of Indian gesture-based communication into discourse in English to help the conference and additionally, discourse weakened individuals to speak with hearing individuals. It very well may be utilized as an interpreter for individuals that don't comprehend gesture based communication, staying away from by this way the intercession of a halfway individual and permit correspondence utilizing their regular method of talking. The proposed framework is an intuitive application program created utilizing labview[8] programming and consolidated into a cell phone. The communication through signing motion pictures are gained utilizing the inbuilt camera of the cell phone; vision examination capacities are acted in the working framework and give discourse yield through the inbuilt sound gadget in this manner limiting equipment necessities and cost. The accomplished slack time between the gesture-based communication and the interpretation is little a result of equal preparation. This takes into consideration practically quick acknowledgment from finger and hand developments to interpretation. This can remember one-gave sign portrayals of letter sets (A-Z) and numbers (0-9). The outcomes are discovered to be exceptionally reliable, reproducible, with genuinely high exactness and precision.[7].

Proposed Methodology

We wanted to build a system to assist the people with hearing or vocal disabilities. As we saw in the literature review above, most of the aids were physical and not virtual. It is not possible for a person to carry and use physical aids everywhere and for elderly people who majorly face the problem of hearing loss it is difficult for them to remember to carry the physical aid everywhere. So hence we came up with the idea of a software implementation so the people using the hearing and vocal aids. As we all now know that we need to make our peace with the Covid-19 pandemic and most of the meetings and gatherings are online. So we made a python program trained using machine learning algorithms to find a feasible solution. Our solution was to use OpenCV so that if a person shows a sign language to the camera our program will automatically convert it into english alphabets so that both people will be able to communicate. We trained our model using Convolution Neural Network(CNN) as we found it to be highly accurate in terms of training machine learning models with images. We experimented with several activation functions, image pre-processing and as well as epochs to reach the highest accuracy possible to achieve, which in our case was 0.996352 as training accuracy and 0.988769 as validation accuracy. After training the model we implemented OpenCV which has been described in detail in the section below. Our proposed solution is different from the ones pre existing in the market as we provide a medium to connect the people with disabilities who know sign language and the rest of the world.

Implementation

1. Choosing the dataset

We chose a predefined dataset from kaggle which satisfied all our need of the sign language.

2. Choosing the model

We chose Convolutional Neural Networks (CNN or ConvNet) as they are unpredictable feed forwarding neural networks. CNNs are utilized for picture characterization and acknowledgment due to its high precision. The CNN follows a progressive model which chips away at building an organization, similar to a channel, lastly gives out a completely associated layer where every one of the neurons are associated with one another and the yield is prepared.

3) Image Pre-processing

The aim of pre-processing is to improve the quality of the image so that we can analyse it in a better way. By pre-processing we can suppress undesired distortions and enhance some features which are necessary for the particular application we are working for. Those features might vary for different applications.

The main benefit of using the Keras ImageDataGenerator class is that it is designed to provide real-time data augmentation. ImageDataGenerator class ensures that the model receives new variations of the images at each epoch. But it only returns the transformed images and does not add it to the original corpus of images. If it was, in fact, the case, then the model would be seeing the original images multiple times which would definitely overfit our model.

4) Fine tuning

i)Rescale:

For a colourful image, it contains three maps: Red, Green and Blue, and all the pixels are still in the range 0~255. (note:, pixel value ranges according to the storage size, the pixel range is 0~2^bits)

Since 255 is the maximum pixel value. Rescale 1./255 is to transform every pixel value from range [0,255] -> [0,1].

Advantage of rescale:

Treat all images in the same manner: some images are high pixel range; some are low pixel range. The images are all sharing the same model, weights and learning rate. The high range image tends to create stronger loss while low range image creates weak loss, the sum of them will all contribute to the back propagation update. Scaling every image to the same range [0,1] will make images contribute more evenly to the total loss.

ii) Shear transformation slants the shape of the image. This is different from rotation in the sense that in shear transformation, we fix one axis and stretch the image at a certain angle known as the shear angle. This creates a sort of 'stretch' in the image, which is not seen in rotation. shear_range specifies the angle of the slant in degrees.

iii) The zoom augmentation either randomly zooms in on the image or zooms out of the image.ImageDataGenerator class takes in a float value for zooming in the **zoom_range** argument.

iv) Flipping images is also a great augmentation technique and it makes sense to use it with a lot of different objects.

v)Train test split:

Separating data into training and testing sets is an important part of evaluating accuracy of models. Typically, when we separate a data set into a training set and testing set, most of the data is used for training, and a smaller portion of the data is used for testing.

The train-test split procedure is used to estimate the performance of trained model when they are used to make predictions on data not used to train the model. It is also necessary that the trained model shouldn't overfit.

5) **Activation function**

Activation functions are a critical part of the design of a neural network.

The choice of activation function in the hidden layer will control how well the network model learns the training dataset. The choice of activation function in the output layer will define the type of predictions the model can make.

A network may have three types of layers: input layers that take raw input from the domain, **hidden layers** that take input from another layer and pass output to another layer, and **output layers** that make a prediction.

All hidden layers typically use the same activation function. The output layer will typically use a different activation function from the hidden layers and is dependent upon the type of prediction required by the model.

Typically, a differentiable nonlinear activation function is used in the hidden layers of a neural network. This allows the model to learn more complex functions than a network trained using a linear activation function.

Relu

> The rectified linear activation function, or ReLU activation function, is perhaps the most common function used for hidden layers.It is common because it is both simple to implement and effective at overcoming the limitations of other previously popular activation functions, such as Sigmoid and Tanh. Specifically, it is less susceptible to vanishing gradients that prevent deep models from being trained

Sigmoid

> The sigmoid activation function is also called the logistic function. It is the same function used in the logistic regression classification algorithm. The function takes any real value as input and outputs values in the range 0 to 1. The larger the input (more positive), the closer the output value will be to 1.0, whereas the smaller the input (more negative), the closer the output will be to 0.0.

Tanh

The hyperbolic tangent activation function is also referred to simply as the Tanh (also "*tanh*" and "*TanH*") function. It is very similar to the sigmoid activation function and even has the same S-shape. The function takes any real value as input and outputs values in the range -1 to 1. The larger the input (more positive), the closer the output value will be to 1.0, whereas the smaller the input (more negative), the closer the output will be to -1.0.

Swish

Swish is a lesser-known activation function which was discovered by researchers at Google. Swish is as computationally efficient as ReLU and shows better performance than ReLU on deeper models. The values for swish ranges from negative infinity to infinity.

SoftMax

SoftMax function is often described as a combination of multiple sigmoids. We know that sigmoid returns values between 0 and 1, which can be treated as probabilities of a data point belonging to a particular class. Thus, sigmoid is widely used for binary classification problems. The SoftMax function can be used for multiclass classification problems. This function returns the probability for a datapoint belonging to each individual class.

<u>6) Number of layers</u>

0 Hidden layer - Only capable of representing linear separable functions or decisions.

1 Hidden layer - Can approximate any function that contains a continuous mapping from one finite space to another.

2 Hidden layer - Can represent an arbitrary decision boundary to arbitrary accuracy with rational activation functions and can approximate any smooth

mapping to any accuracy.

There are many rule-of-thumb methods for determining the correct number of neurons to use in the hidden layers, such as the following:

- The number of hidden neurons should be between the size of the input layer and the size of the output layer.
- The number of hidden neurons should be 2/3 the size of the input layer, plus the size of the output layer.
- The number of hidden neurons should be less than twice the size of the input layer.

7) **Number of epochs and early stopping**

The number of epochs is not that significant. More important is the validation and training error. As long as it keeps dropping, training should continue. For instance, if the validation error starts increasing that might be an indication of overfitting. We should set the number of epochs as high as possible and terminate training based on the error rates. An epoch is one learning cycle where the learner sees the whole training data set. If you have two batches, the learner needs to go through two iterations for one epoch.

Early stopping is a method that allows you to specify an arbitrary large number of training epochs and **stop** training once the model performance stops improving on a holdout validation dataset. Early stopping also avoids the model from overfitting.

8) **Model save**

Training a model takes a lot of time and it is necessary to save it so that the trained model can be used in future for some purpose. If we don’t save the model then for the next time, we want to use the model we trained. We can't use it and therefore we need to train the model from the beginning which takes a lot of time.

9) **<u>OpenCV implementation</u>**

Once the model is trained with better accuracy on train and test dataset, we can create a GUI using OpenCV library. On showing the sign language posture with our hand, our webcam should capture the image hand every moment. The captured image should be given to the model to predict the output. Once prediction is done, the output (Sign language alphabet) should be displaced on the screen.

Results and Discussion

After saving the model, we should analyze testing and training metrics :

- ❑ **Model performance analysis**

We can analyze model performance by plotting a graph of accuracy and validation accuracy against the number of epochs. From the graph we can figure out at which epoch accuracy was highest as well as validation accuracy. We can also plot a graph of loss and validation loss against the number of epochs from which we can figure out at which epoch loss was minimum. The above graphs help us to know whether there was overfitting in the model as well as how well the model was trained at each epoch.

- ❑ **Testing on dataset**

It is important to run a test on model on testing dataset to know how well the model Is predicting the unseen dataset or new dataset from which we can conclude how well the model is trained and then changes can be made in the model (Learning rate, activation function, layers) based on the accuracy on testing dataset.

- ❑ **Testing Metrics**

Testing metrics tells how well our model performed on a dataset which can be both seen or unseen dataset.

The most commonly used Performance metrics for classification problem are as follows,

· Accuracy.

· Confusion Matrix.

· Precision, Recall, and F1 score.

Accuracy

Accuracy will help us to know how better the model is when it is scaled in terms of accuracy which ranges between 0 to 1. The model which has accuracy closer to 1 is much better than the one which is far from 1.

Confusion matrix

A Confusion matrix is an N x N matrix used for evaluating the performance of a classification model, where N is the number of target classes. The matrix compares the actual target values with those predicted by the model. This gives us a holistic view of how well our classification model is performing and what kinds of errors it is making.

Precision, Recall, and F1 score

Precision quantifies the number of positive class predictions that actually belong to the positive class.

Recall quantifies the number of positive class predictions made out of all positive examples in the dataset.

F-Measure provides a single **score** that balances both the concerns of **precision** and **recall** in one number.

```
Confusion Matrix  [[1 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]
 [0 1 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 0 1 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 0 1 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 0 1 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 0 1 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 0 1 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 0 1 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 0 1 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 0 1 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 0 1 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 0 1 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 0 1 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 0 1 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 0 1 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 0 1 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 0 1 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 0 1 0 0 0 0 0 0 0 0]
 [0 0 0 0 1 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 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 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 0 1 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 0 1 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 0 1 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 0 1 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 0 1 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 0 1]]
```

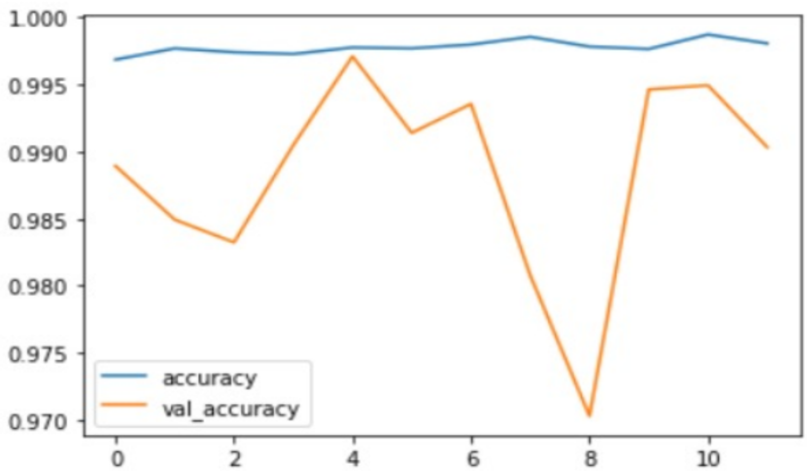
```python
import pandas as pd
metrics = pd.DataFrame(model.history.history)
print("The model metrics are")
metrics
```

```
The model metrics are
```

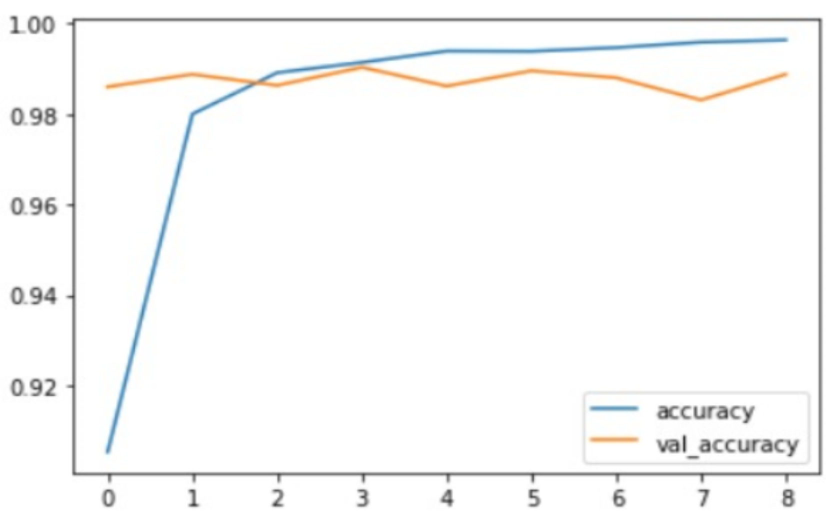
	loss	accuracy	val_loss	val_accuracy
0	0.294833	0.905275	0.081018	0.986000
1	0.058904	0.979978	0.043004	0.988769
2	0.033455	0.989121	0.097007	0.986308
3	0.027653	0.991385	0.076855	0.990308
4	0.019626	0.993912	0.091546	0.986154
5	0.019564	0.993846	0.057897	0.989538
6	0.018313	0.994659	0.056353	0.988000
7	0.012689	0.995868	0.081022	0.983077
8	0.011344	0.996352	0.044330	0.988769

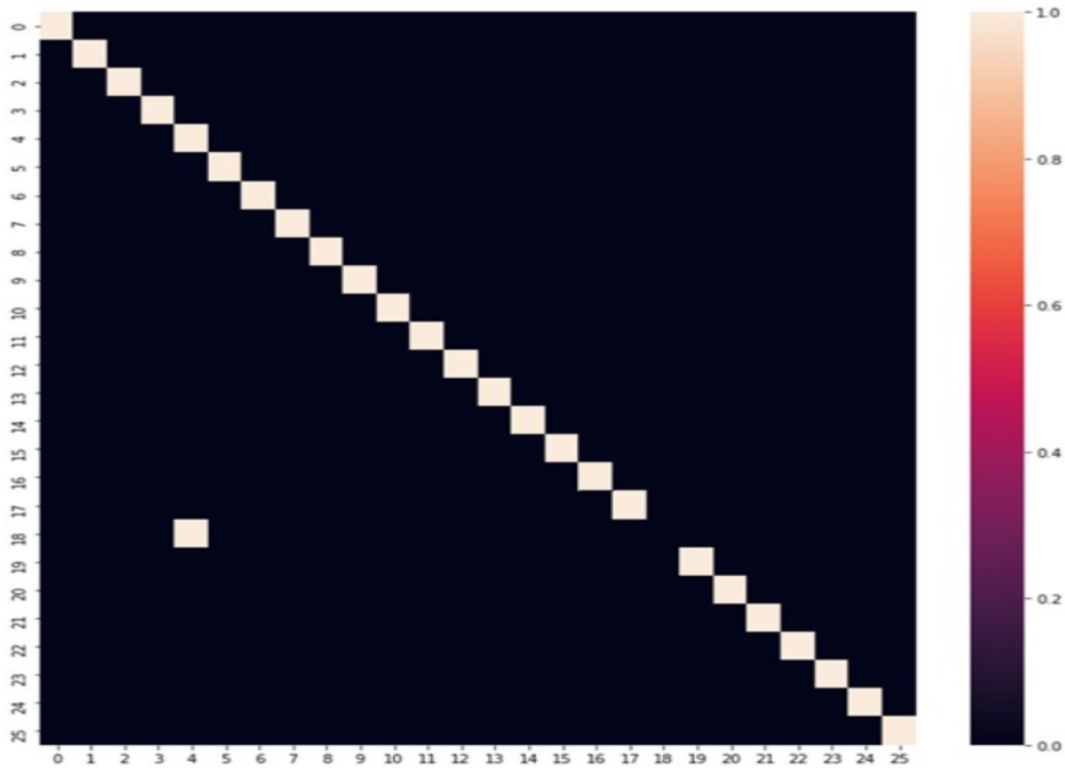
```
              precision    recall  f1-score   support

           A       1.00      1.00      1.00         1
           B       1.00      1.00      1.00         1
           C       1.00      1.00      1.00         1
           D       1.00      1.00      1.00         1
           E       0.50      1.00      0.67         1
           F       1.00      1.00      1.00         1
           G       1.00      1.00      1.00         1
           H       1.00      1.00      1.00         1
           I       1.00      1.00      1.00         1
           J       1.00      1.00      1.00         1
           K       1.00      1.00      1.00         1
           L       1.00      1.00      1.00         1
           M       1.00      1.00      1.00         1
           N       1.00      1.00      1.00         1
           O       1.00      1.00      1.00         1
           P       1.00      1.00      1.00         1
           Q       1.00      1.00      1.00         1
           R       1.00      1.00      1.00         1
           S       0.00      0.00      0.00         1
           T       1.00      1.00      1.00         1
           U       1.00      1.00      1.00         1
           V       1.00      1.00      1.00         1
           W       1.00      1.00      1.00         1
           X       1.00      1.00      1.00         1
           Y       1.00      1.00      1.00         1
           Z       1.00      1.00      1.00         1

    accuracy                           0.96        26
   macro avg       0.94      0.96      0.95        26
weighted avg       0.94      0.96      0.95        26
```

```
[23] metrics[['accuracy','val_accuracy']].plot()
     plt.show()
```

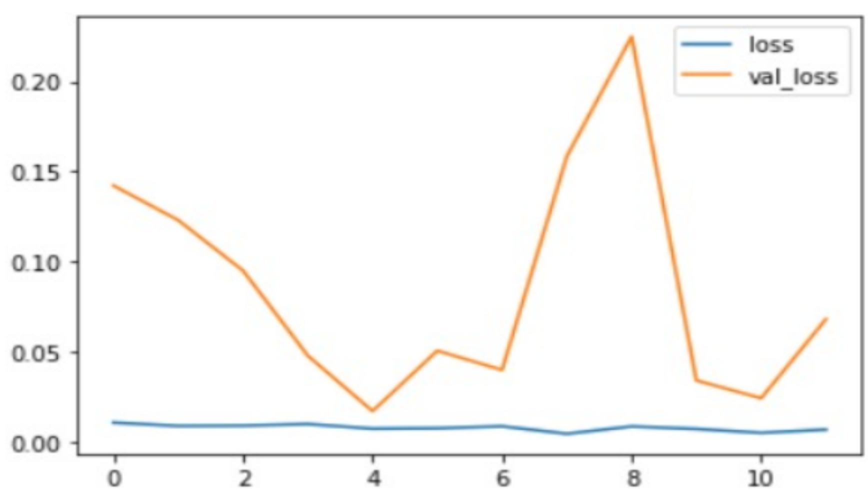



```
[19] metrics[['accuracy','val_accuracy']].plot()
     plt.show()
```

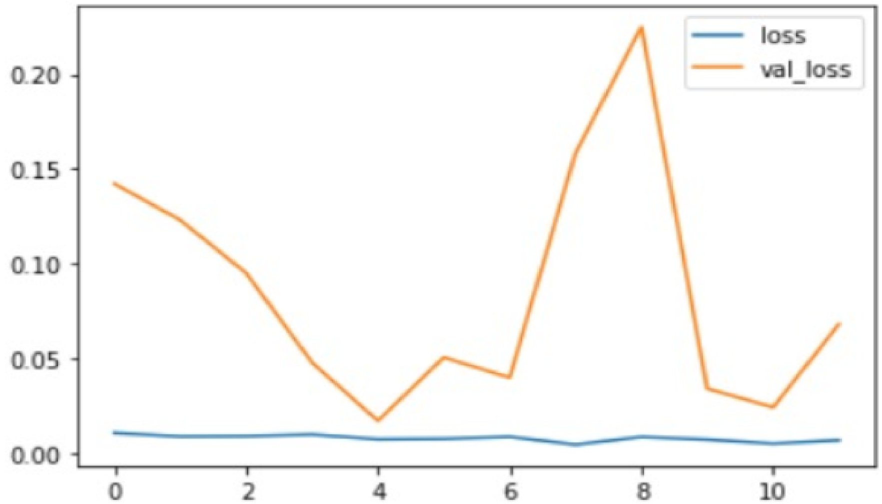




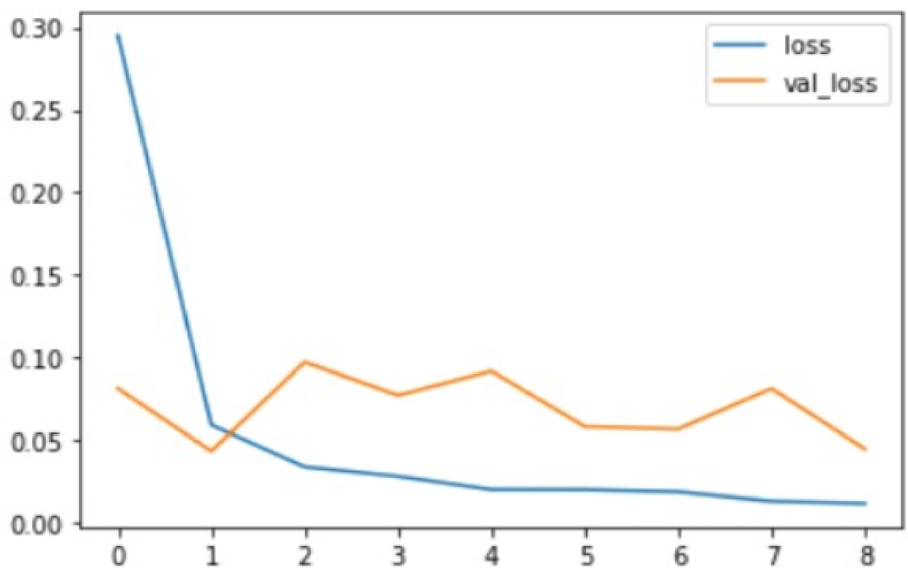
```
[22] metrics[['loss','val_loss']].plot()
     plt.show()
```



```
[22] metrics[['loss','val_loss']].plot()
     plt.show()
```




```
[18] metrics[['loss','val_loss']].plot()
     plt.show()
```



Future Works

1. It very well may be incorporated with different web crawlers and messaging applications like Google, WhatsApp. So that even unskilled individuals might visit with different people, or inquiry something from the web just with the assistance of motions.

2. In future work, the proposed framework can be created and carried out utilizing Raspberry Pi. The picture Processing part ought to be improved so the System would have the option to convey in the two ways i.e.it ought to be fit for changing typical language over to gesture-based communication and the other way around. We will attempt to perceive signs which incorporate movement. In addition, we will zero in on changing over the arrangement of motions into text for example word and sentences, and afterward changing over it into the discourse which can be heard.

3. We can have a next word prediction integrated with it to make things simpler.

4. There can be an option for creating your gestures, as well as a scanner to check the correctness of the sentences formed.

5. This project is working on an image currently, further development can lead to detecting the motion of video sequence and assigning it to a meaningful sentence with TTS assistance

6. Moreover, an export to file module can also be furnished with TTS(Text-To-Speech) help meaning whatever the sentence was framed a client will actually want to hear it out and afterward rapidly trade alongside noticing what signal he/she made during the sentence development.

Conclusion

From this task/application, we have attempted to eclipse a portion of the serious issues looked at by handicapped people as far as talking. We discovered the main driver of why they can't put themselves out there all the more openly. The outcome that we got was that the opposite side of the crowd can't decipher what these people are attempting to say or what is the message that they need to pass on.

Subsequently, this application serves the individual who needs to learn and talk in communications through signing. With this application, an individual will rapidly adjust different signals and their significance according to ASL norms. They can rapidly realize what letter set is appointed to which signal. Concerning the execution, we have utilized the TensorFlow system, with Keras Programming interface. Fitting easy to understand messages are provoked according to the client's activities alongside what motion implies what character window.

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