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Real-Time Communication System Powered By Ai for Especially Abled

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ABSTRACT:The WHO says that in India there are more than 63 million peoples suffers from either complex or partial deafness. Deaf-mute people uses Sign language to communicate or to exchange information between their own community and with other people. Database were used to store different set of hand gestures are stored. Using Convolutional Neural Networks (CNN) algorithm hand gestures will be detected accurately. This algorithm is also used for analyzing visual images. This application is built using Flask UI.

KEYWORDS: Open CV, Flask, CNN, Keras, TensorFlow.

I. INTRODUCTION

The WHO says that in India there are more than 63 million peoples suffers from either complex or partial deafness, and of these, at least 50lakh are children. Deaf-mute people has challenging task to communicate with normal people. The human interaction system is helpful for dumb people to overcome the difficulty. Deaf-mute people uses Sign language to communicate or to exchange information between their own community and with other people, this become most widely used technique. In this tech era, people can easily access the application, which converts sign language into speech or text using Convolutional Neural Network (CNN).

II.RELATED WORK

[1]. Hand gesture recognition system for deaf and dumb:

It is a non vision based extended idea that will assist in reducing the communication gap. Each gesture is associated with a specific meaning and this is stored in database. In this project, one glove is fitted with the flex sensor in our hand. Then the flex sensor senses the signal and this signal given to the microcontroller whereas all the data kept in the database, then the microcontroller matches the motion of hand with the database and produces speech signal and text. The output will appear through the speaker and OLED display. Here the raspberry pi 3B+ is used as a single board computer and an Arduino nano is used as an A/D converter.

[2]. Hand gesture recognition application for physically disabled:

It accommodates a hardware module and a package module. In hardware module-The gesture recognition is completed with the assistance of a device glove that accommodates five measuring instruments sensors, a microcontroller which square measure best positioned in fingers upon analysis of sign language. The design of glove and also the idea of decryption gestures by considering the axis orientation with regard to gravity and also corresponding voltage levels area unit mentioned. The accelerations of a hand motion in three perpendicular directions are detected by accelerometers and accelerator values were transmitted to microcontroller. An automatic gesture recognition algorithm is developed to identify individual gestures in a sequence. As a final point, the gesture is recognized by comparing the acceleration values with the stored templates. According to recognized gesture, respective commands are played through speaker using voice chip.

[3]. Gesture recognition for physically challenged:

The human interaction system is helpful for dumb people to overcome the difficulty, besides it can be installed anywhere. This paper proposes the method or algorithm for an application which would help in recognizing the different signs and convert those sign gesture into voice. Different sets of hand gestures were captured using web camera and then stored in a directory. The correct signs by the user is identified by using feature extraction techniques and neural network algorithm. The sign language for different numbers in words are trained and tested. The test image is aligned correctly with training images which is based on correlation and convert the matched image into text and then text into voice. By using this system, hearing impaired people can easily interact without depending on translators.

III. METHODOLOGY

Flask UI is an web application by which user can access the application to predict their hand signs. For training and testing the data CNN algorithm is used, that consist of four layers which is used for feature extraction and classification of given input images. Image preprocessing is the first step which takes the input image and preprocess it. Database is a collection of training set and test set data which were used to recognize the given output with this database. In essence, CNNs are a subset of artificial neural networks that are skilled at identifying and interpreting patterns. CNN is therefore the most practical tool for classifying images. Filters of various shapes and counts are used in CNN models. In essence, these filters aid in pattern detection. Although they can also be utilized with one-dimensional and three-dimensional data,

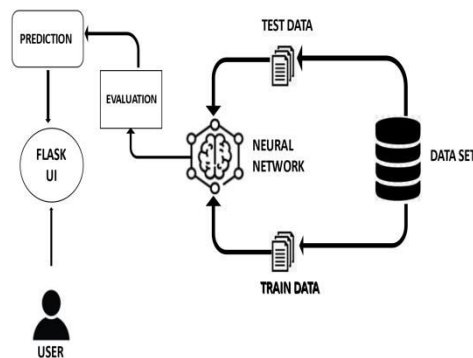


Fig 1: Data Flow Diagram

CNNs are specialized neural network models created for working with two-dimensional picture data. The convolutional layer is responsible for the name of the convolutional neural network. Convolution is an operation that is carried out in this layer. Convolutional and pooling layers are the most frequently used layers in CNN models. Since CNN performs better with data that are represented as grid structures, it is a good solution for challenges involving photo categorization. The dropout layer lessens the model's overfitting by deactivating certain neurons during training. Convolutional feature extraction and binary classification make up our model. Max pooling and convolution are used to extract the image's properties. 32 3x3 convolution filters, a max-pooling layer with a 2x2 pooling size, and a second convolution layer with 64 3x3 filters are used to process a 28x28 image.

We finally have 7x7 photos that we can flatten. The flattening of the 7x7 images into a set of 128 values will produce a dense layer of 128 neurons connected to the category output layer of 10 neurons. The dot product method of multiplication is used to combine an input patch the size of the filter with the filter since the input data is larger than the filter. To create the dot product, the filter-sized patch of the input and filter is multiplied element by element. The elements of this result are then concatenated to yield a single value.

Because it produces a single result, the operation is frequently referred to as the "scalar product." Because it allows

the same filter (set of weights) to be multiplied by the input array several times at different positions on the input, it is intentional to use a filter that is smaller than the input. To be more specific, the filter is constantly applied to each overlapping area or filter-sized patch of the incoming data from top to bottom, left to right. The filter is multiplied once by the input array to give a single value. A two-dimensional array of output values—which serves as a representation of input filtering—is produced as the filter is repeatedly applied to the input array. This process generates a "feature map," a two-dimensional output array.

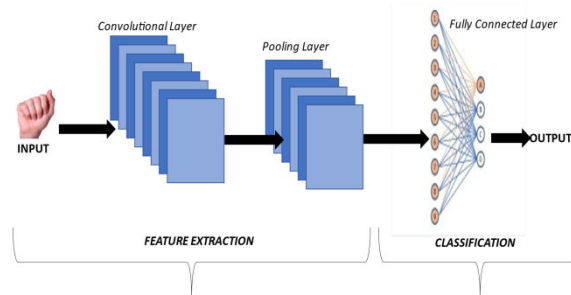


Fig 2:CNN Layers

CNN Layers:

These layers repeatedly recurring demonstrates how deep our network is, and this structure is referred to as a deep neural network. Input: raw pixel values are given as the input. Convolutional layer: The output of the neuron layer is translated by the input layers. The filter that will be applied must be specified. Only 5*5 windows that move across input data and capture pixels with maximum intensities are allowed for each filter. Rectified linear unit [ReLU] layer: offered activation feature for image data that was captured. ReLU function is employed in the back propagation scenario to prevent changes in pixel values. Pooling layer: carries out a volume down sampling procedure along the dimensions (width, height). Fully connected layer: The maximum score of the input digits is discovered after concentrating on the scoring class. There is a significant rise in complexity as we dig further and deeper into the layers. However, it would be worthwhile to go since while accuracy might improve, time consumption does, unfortunately, too.

A. Convolutional layer:

This layer was used to extract the various features from the input images initially. At this layer, a $M \times M$ -dimensional filter and the input picture go through a mathematical process called convolution. By swiping the filter over the input image in relation to the filter's size, the dot product between the filter and the elements of the input image is obtained ($M \times M$). The image's corners and edges are described in detail by the feature map. Later, other layers are given access to this feature map so they can add new features from the original image.

B. Pooling layer:

A pooling layer is typically used after a convolutional layer. This layer's main goal is to scale down the convolved feature map in order to save money on computing. This is done by independently changing each feature map and utilising fewer linkages between layers. Depending on the method employed, there are many pooling operations. The most significant contribution to Max Pooling is made by the feature map. The average of the components in a section of a picture with a predetermined size is obtained by average pooling. Sum Pooling determines the cumulative

sums of the components inside the specified segment. The Pooling Layer often serves as a link between the Fully Connected Layer and the Convolutional Layer.

C. Fully connected layer:

Using the Fully Connected layer neurons are connected between two layers, which also includes weights and biases. These layers, which make up the final few in a CNN architecture, are frequently positioned before the output layer. This gives the Fully Connected layer with a flattened version of the input image from the layers below. The flattened vector is then subjected to the standard operations on mathematical functions after passing through a few additional Fully Connected levels. The classification procedure starts to take place at this point.

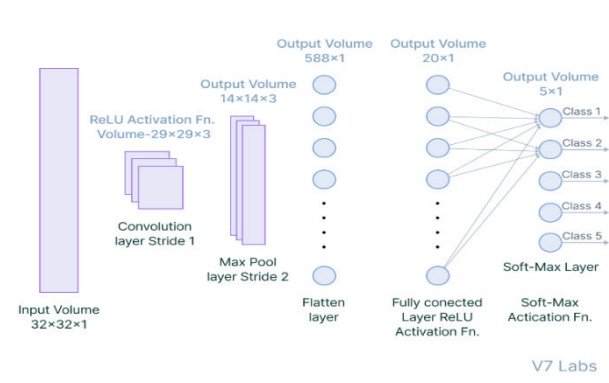


Fig3:Fully Connected Layer

D. Dropout:

The neurons between two layers are connected by the Fully Connected (FC) layer, which also employs weights and biases. These last few layers are usually placed before the output layer in a CNN configuration. This gives the FC layer with a flattened version of the input image from the layers below. The flattened vector is then subjected to the standard operations on mathematical functions after passing through a few additional FC levels. The classification procedure starts to take place at this point.

E. Activation function:

The way a node or nodes in a layer of a neural network convert the output from the weighted sum of the inputs is described by the network's activation function. The term "transfer function" can also be used to describe the activation function. If the output range of the activation function is restricted, it may be referred to as a "squashing function." The term "nonlinearity" in this case refers to the fact that a lot of the activation functions in the layer or network architecture are nonlinear. Different activation functions may be used in different regions of the model, and the choice of activation function has a significant impact on the neural network's capacity and performance.

Although networks are built to utilize the same activation function for all nodes in a layer, technically the activation function is applied before or after the internal processing of each node in the network. A network may have three different kinds of layers: output levels that produce predictions, hidden layers that receive data from one layer and transfer it to another, and input layers that take raw input directly from the domain. Typically, the same activation function is used by all buried levels. The sort of prediction needed by the model will determine what activation function is used in the output layer, which is often different from the hidden layers.

A given input value can be used to derive the first-order derivative for activation functions that are typically differentiable. Given that neural networks are frequently trained using the backpropagation of error algorithm, which needs the derivative of the prediction error to update the model's weights, this is necessary. Although there are many different kinds of activation functions utilized in neural networks, possibly only a few functions are really used for the hidden and output layers in actual practice. The activation function is one of the most crucial elements of the CNN model. They are employed to discover and approximation any type of

continuous and complex link between network variables. In layman's terms, it determines which model information should shoot ahead and which should not at the network's end.

IV.RESULT

The proposed procedure was implemented and tested with set of images. ASL dataset were used to test and train the data. The set of 15750 images of alphabets from “A” to “Z” are used for training database and a set of 2250 images of Alphabets from “A” to “Z” are used for testing database. By using CNN we can classify and predict these signs with high accuracy and with less time. Once the gesture is recognized the equivalent Alphabet is shown on the screen.

This web application will predict the hand sign with 96% accuracy and it predicted the output from alphabet ‘A’ to ‘Z’. Here we have predicted few hand gestures.

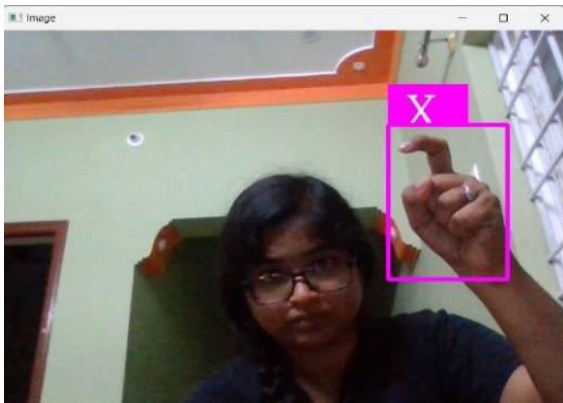


Fig 4: Output X

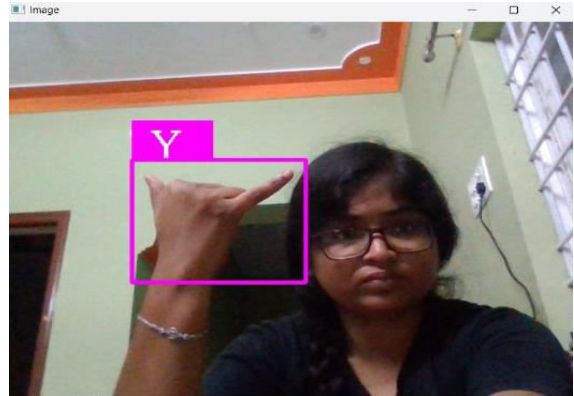
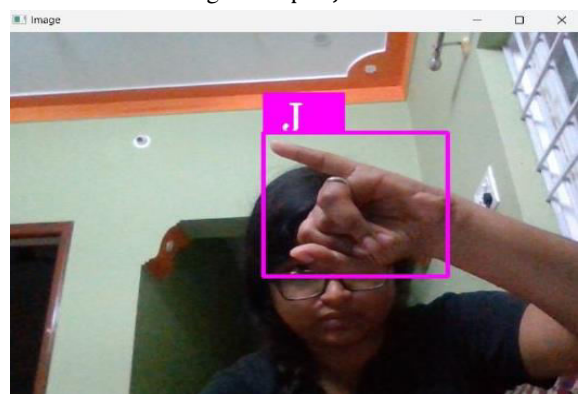


Fig 5: Output Y

Fig6: Output H



Fig 7: Output J



V.CONCLUSION

Sign language is a useful tool for facilitating communication between deaf and hearing people. The system aims to bridge the communication gap between deaf people and rest of society. The proposed methodology translates language into English alphabets that are understandable to humans. This system sends hand gestures to the model, who recognize them and displays the equivalent alphabet on the screen. As we have used ASL signs which is easy to learn and use of only one hand is required. Deaf-mute people can use their hands to perform signs, which will then be converted into alphabet.

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