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Sign Language Recognition Using Machine Learning

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Abstract: This study proposes a method for recognising motions through image processing. In this project, we create a sign detector that can be readily enhanced to recognise a wide range of various signs and hand gestures, such as the alphabets, and that can recognise numbers from 1 to 10.. We used the Python Keras and OpenCV libraries to create this project. Applications for this project are incredibly diverse. Machine learning is used to build models, extract key features, and construct applications since it has access to enormous databases. Machine learning can be used in our daily lives to make living easier. Deep learning is used to detect signs in sign language, which is a complicated process.

Index Terms: CNN, openCV, Keras, Machine learning.

I. INTRODUCTION

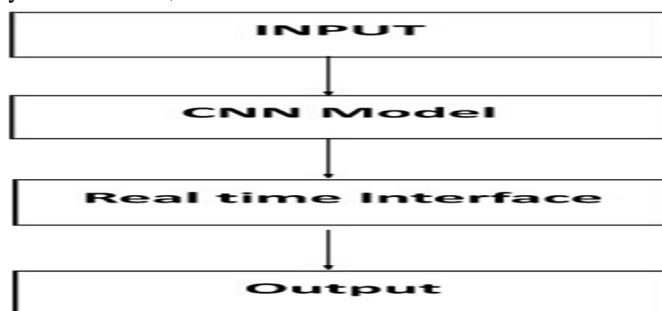
In many ways, sign language is highly beneficial. Here, we are accepting input in the form of signs and sending them through an interface that, depending on the sign's recognition threshold value, launches an application. To create an interface that truly aids in taking real-time input and launching the required application, we use OpenCV. Using the newly produced dataset, we will first train the data.

II. MODEL

A. Convolutional Neural Networks

We will first generate our own dataset of images of hand movements including the digits 1 to 10 using numpy and a number of tools and methods. The dataset can be produced using a wide variety of photos. The data is then trained using the Keras library. To extract the features, or indicators, from the image, we employ convolutional neural networks (CNN).

Identify applicable funding agency here. If none, delete this.



III. OUR MODEL DEVELOPMENT

Regarding Deep Learning The most well-known neural network method and a common approach for image/video tasks is convolution neural networks (CNN). LeNET- 5 and MobileNetV2, two cutting-edge designs for Convolution Neural Networks (CNN), are among the architectures we can apply to achieve the State of the Art (SOTA). These are all employable architectures that can be combined using neural network ensemble techniques. By doing this, we can create a hand gesture recognition model that is almost entirely correct.

This model will be implemented in standalone applications or embedded devices that use standalone web frameworks like Django to recognise hand motions in real-time video, calculate the appropriate threshold value, and launch the appropriate application.

A. Abbreviations and Acronyms

CNN - "Convolution Neural Networks" RTI - "Real time Interface" SOTA - "State Of the ART"

IV. LITERATURE SURVEY

Around the world, there are numerous research projects aimed at creating recognition systems for sign languages. Our main goal is to create a hand gesture recognition-based programme for PCs, mobile devices, tabulators, and other devices. There are numerous systems that employ various methodologies to apply this recognition-type concept. They deal with the alphabet, numeric numerals, and unusual signs.

A. Real-Time Sign Language Fingerspelling Recognition Using Convolutional Neural Networks From Depth Map [5].

The focus of this project is American Sign Language static fingerspelling, a technique for putting into practise a sign language to text/speech conversion system without the use of handheld gloves and sensors, which involves continually recording the gestures and turning them into voice. Only a small number of photos were used in this method to identify objects. The layout of a device to let physically unable people communicate.

B. Real-Time Sign Language Fingerspelling Recognition Using Convolutional Neural Networks From Depth Map [5].

C. Design Of A Communication Aid For Physically Challenged [6]

The MATLAB environment was used for the system's development. The training phase and the testing phase make up the majority of it. The author used feed-forward neural networks during the training stage. The issue here is that MATLAB is not very effective, and it is also challenging to integrate the concurrent qualities as a whole.

D. American Sign Language Interpreter System for Deaf and Dumb Individuals [7].

Twenty of the static ASL alphabets could be recognised using the approaches we explained. The occlusion issue prevented the recognition of the letters A, M, N, and S. There aren't many images that they've used.

E. A Framework for Hand Gesture Recognition and Spotting Using Sub-gesture Modeling [10].

With the only difference that in this scenario, we add a gesture model (each gesture will have a gesture completion model) between the start state and exit state of the filler model, gesture-completion models are built in a manner identical to filler models.

F. Research On Optimization Of Static Gesture Recognition Based On Convolution Neural Network [11].

The image-based information vector sequence that serves as the foundation for gesture modelling includes features like the hand contour, the vector feature, the area histogram, and the motion vector track feature, to name just a few.

The image-based information vector sequence that serves as the foundation for gesture modelling includes features like the hand contour, the vector feature, the area histogram, and the motion vector track feature, to name just a few. The two fundamental subcategories of static gesture recognition are static gesture recognition and dynamic gesture recognition. Due to the deep neural network's potent ability to assess the effective qualities, several researchers began researching the static gesture recognition method based on depth learning.

V. PROPOSED METHODOLOGY

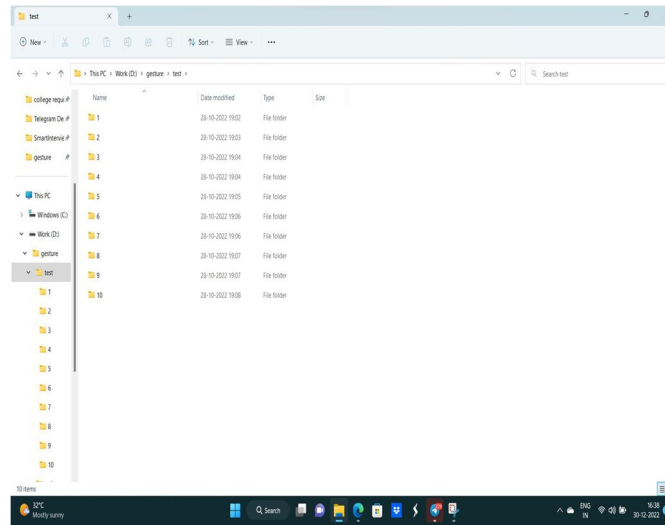
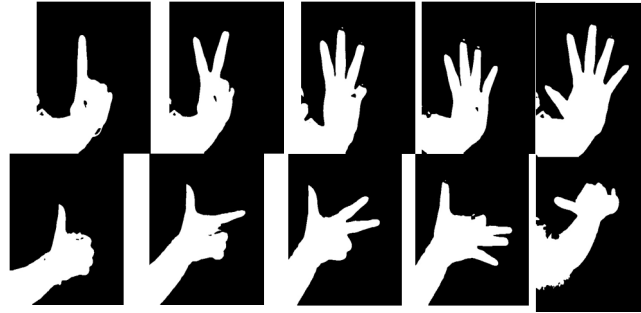
This model will be used to recognise hand gestures in real-time video, determine the proper threshold value, and launch the proper application. It will be implemented in standalone apps or embedded devices that employ standalone web frameworks like Django.

A. Mission

The goal is to create a system that can accept a sign and process it to a real time interface that opens the application respectively.

B. Corpus

The data set that we produced served as the corpus that we employed. We have produced a data set with various indicators in it. The data set we require may be found online, however for this project, we will be building the data set ourselves. Every frame that recognises a hand in the predetermined region of interest will be saved in the "gesture" directory, which also contains the folders "train" and "test," each of which contains 10 folders of images that were captured using the application "generate gesture using data.py".



C. Data Pre-processing

An image, in its most basic form, is a 2-dimensional array of pixels with values ranging from 0 to 255. Typically, 0 indicates black and 255 indicates white. The mathematical function $f(x, y)$ defines an image, where x in a coordinate plane denotes the horizontal and y the vertical. An image's pixel value at every position is given by the value of $f(x, y)$ at that location. Algorithms are used in image pre-processing to manipulate pictures. Prior to delivering the photos for model training, it is crucial to preprocess the photographs. For instance, all of the photos should be 200x200 pixels in size. If not, it is impossible to train the model.

D. Model

The model we developed trains the data sequentially. The train and test data are first loaded using the keras programming language. Now we use a variety of hyperparameters to create the CNN. The model is now fitted, and it is saved for future usage. This model will be implemented in standalone applications or embedded devices that use standalone web frameworks like Django to identify hand motions in real-time video, calculate the appropriate threshold value, and launch the appropriate application.

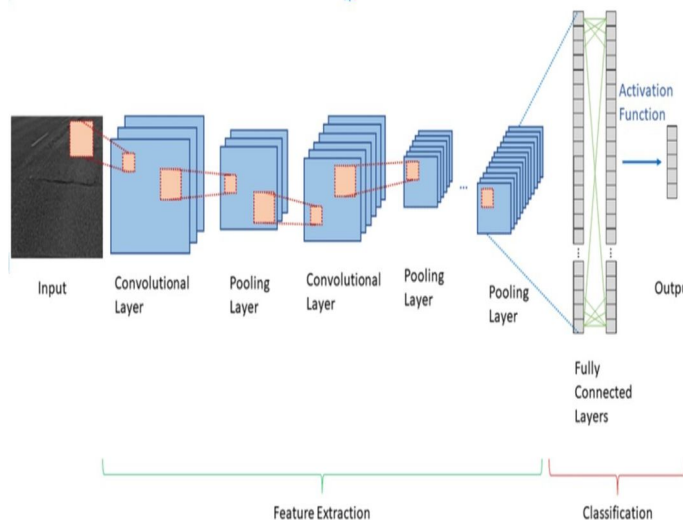
In our Sequential Model we have used 4 convolutional neural layers and pooling layers with different filters. In order to edit images, algorithms are utilised in image pre-processing. Preprocessing the images is essential before providing them for model training. For instance, each photo should have a dimension of 200x200 pixels. If not, training the model is not possible.

A 2-dimensional array of pixels with values ranging from 0 to 255 constitutes a picture in its most basic form. Normally, 0 represents black and 255 represents white. The mathematical function $f(x, y)$, which represents the horizontal in a coordinate plane as x and the vertical as y , defines a picture. The value of $f(x, y)$ at a particular place determines the value of each pixel in a picture.

VI. CONVOLUTIONAL NEURAL NETWORK

Convolutional neural networks are deep neural networks that have been specifically created to analyse data with input forms approximating a 2D matrix. Images might be represented by a straightforward 2D matrix. CNN is crucial while utilising images. It takes an image as input, gives various elements and objects in the image weights and biases, and then separates them out depending on relevance.

The CNN uses filters (also known as kernels) to help with feature learning and identify abstract ideas such as blurring, edge detection, sharpening, etc., similar to how the human brain recognises objects in time and space. Because weights may be reused and there are fewer factors involved, the architecture fits the picture dataset more accurately (2048 to 256).

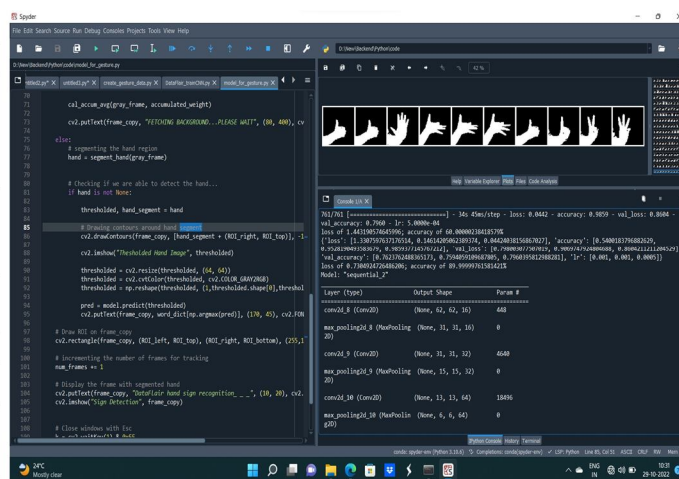


In this study, a convolutional neural network (CNN) is employed to convert an RGB picture into a visual feature vector. The three most often used CNN layers are convolution, pooling, and fully connected. ReLU $f(x) = \max(0, x)$, a nonlinear active function, is also used. ReLU is faster than the common equation $f(x) = \tanh(x)$. The use of a dropout layer prevents overfitting. Each hidden neuron's output is set to zero with probability 0.5 by the dropout. The "dropped out" neurons are neither a part of the backpropagation or the forward pass. [5]

Due to the millions of parameters that both the CNN and the RNN include, there are special convergence concerns when they are merged. For instance, Vinyals et al. found that fixing the convolutional layer's parameters to those learnt from ImageNet is optimal. The only CNN parameters that are really learnt from caption instances are the RNN parameters and the non-convolution layer parameters.

Table 1: Architectures of CNN:

YEAR	CNN	DEVELOPED BY	FEATURES	IMPORTANCE	NO. OF LAYERS	NO. OF PARAMETERS
1998	LeNet	Yann LeCun	1. Average pooling layer with subsampling 2. Activation of the tanh 3. MLP is used as the final classifier. 4. Layer connections that are sparse will simplify calculations.	1. Character Recognition 2. Classify handwritten numbers on banks and other financial institutions.	7 layers	60 thousand
2012	AlexNet	Geoffrey Hinton, Ilya Sutskever, Alex Krizhevsky	1. ReLU Activation function. 2. Batch size is 128 3. Ensembling of models to achieve the greatest outcomes.	1. object_detection task	8 layers	60 million
2014	GoogleNet	Google	1. 1x1 convolution 2. Inception module 3. Auxiliary Classifier for training	1. Image classification 2. Object recognition 3. Quantization	27 layers	4 million
2014	VGG Net	Zisserman, Simonyan	1. Has 2 networks i.e., VGG-16, VGG-19	1. Large scale Image Recognition	16 layers 19 layers	138 million
2015	ResNet	Kaiming He	1. Skip Connection technique is used 2. Residual mapping	1. efficient backbone model	34 layers	25 million
2020	Xception	Francois Chollet	1. Depthwise separable Convolutions 2. Takes the tenets of Inception for logical conclusion.	1. Image recognition	71 layers	22 million



Even though new deep models are constantly being developed, deep learning has long captured the interest of the scientific community. Finding and choosing the best model from the many that are accessible in the literature is difficult. A simple task is choosing optimizers and adjusting optimization hyperparameters. This study evaluates the performance of two deep models that have already been trained, four adaptive gradient-based optimizers, and the tuning of their associated hyperparameters on a static dataset of Indian sign language. InceptionResNetV2 and Adam optimizer may be used for transfer learning-based static sign language recognition, according to experimental results. The Inception-ResNetV2 model outperformed even the most sophisticated machine learning methods by a wide margin.

VII. RESULTS

The initial training had poor results; with 45 epochs, the training accuracy ranged from 0.00 percent to 20.00 percent. Because we believed something went wrong, we halted that. The training accuracy then improved to 89 percent with 761 epochs. Loss of 1.443190574645996; value accuracy of 60.00000238418579. A final accuracy of 89.99999761581421 percent is recorded. It contains a final layer of conv2d(Conv2D) has an output shape of (None, 62, 62, 16). Contains maxpooling2d(MaxPooling2D) layers with an output shape of (None, 31, 31, 16). 4 convolutional layers, including input and output, make up 3D Inception. There are 9 modules for inception. The inception module's details are displayed. We divide the dataset into a 6:2:2 ratio for training. 300 videos would thus be used for the training set, 100 for the validation set, and 100 for the testing set.

These results led us to believe that our model was overfitting. It acquired too much knowledge before it could even categorise the signer. The next step is to test our hypothesis. So, using a new dataset structure, we retrained. We currently use two signers for ten classes with a total of one hundred videos, two signers for twenty classes with one hundred videos, and four signers for forty classes with two hundred videos. The two signers' training accuracy ranged from 50.00 to 80.00 percent for the first ten lessons, 100.00 percent for the following ten lessons, and 20.00 percent for the final ten lessons.

VIII. CONCLUSION AND FUTURE WORK

Since we considered that 3D Inception without modification was too overfit according to the findings after several trainings, we trained the model with 10 signers and 100 classes during 751 epochs. The model's validation accuracy is quite low despite its reasonable training accuracy. With this model, we are capable of a great deal more, including layer freezing, the removal of some inception modules, the removal of transfer learning, and the transformation of the completely linked layer into a different deep learning model. The completely linked layer is not really the issue, in our perspective. Since the convolutional neural network layer is the detector, we believe that we should pay greater attention to it.

The dataset itself may have contributed to these outcomes in another way. The overfitting may be due to the LSA64's different backdrop lighting. Considering that the variations in backdrop lighting could be a benefit for machine learning. As a result, machine learning would be trained on the incorrect feature.

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