FEATURE EXTRACTION TECHNIQUE BASED CHARACTER RECOGNITION USING CONVOLUTIONAL NEUTRAL NETWORK

Ayush Gupta[1] , Ritesh Anand[2] and Dr. N. Arunachalam[3]
[1, 2] UG Students, [3]Assistant Professor
Department of Computer Science and Engineering,
School of Computing, College of Engineering and Technology,
Faculty of Engineering and Technology, SRM Institute of Science and Technology,
SRM Nagar, Kattankulathur, Chengalpattu – 603203, Chennai, Tamil Nadu, India
ak8122@srmist.edu.in, rr7904@srmist.edu.in, arunachn@srmist.edu.in

Abstract

Character recognition which is Handwritten is the capacity of a PC to get and decipher clear written by hand input information. Handwritten character recognition is an arising and creating innovation regarding picture handling. Text recognition is the one of the marvels of enabling a PC machine to consequently know the characters which is written in a picture or pdf. Text Character extraction has ended up being truly outstanding among the advancement in the field of example recognition, Artificial Intelligence and profound learning. In the proposed method, we present a written by hand character and digit recognition framework dependent on various. Deep learning strategy which is convolutional Neural Network. Text character recognition assumes a significant part due to potential applications in helping innovation for daze and outwardly hindered clients, programmed information passage, human–robot collaboration for business records, and some more. We propose an approach/method in this proposed work for perceiving text characters and digits using profound learning approaches like the Convolutional Neural Network (CNN). The proposed framework was prepared on the basis of huge data base photos of alphabets and numbers, and experiments on the customer information index examples and the result of this study were exceptionally high. These experimental results are contrasted with the calculation of other neural organisations and then we check for better framework.

I. INTRODUCTION

Character recognition is a model which recognize evidence that has been the subject of broad in the midst of the current many years. Physically, text content shows wide assortments. Character Recognition System (CRS) is utilized to recognize print picture. These print picture can be in any way similar to alphabetic, numeric, image, etc. These print pictures are either printed or made out of different size and literary style. All character recognition is the path toward recognizing and seeing character from instructive picture and convert it into American Standard Code for Information Interchange(ASCII) or into other looking at PC editable structure. Character recognition completely isolates into two sorts: manually written and PC printed. The printed character reference is uniform and effectively reasonable.

Fake Neural Network and Deep learning Techniques have been viably applied to different zones like picture arrangement, walker identification, Medical Images location, satellite pictures, perceiving traffic signs ,discourse recognition, face recognition, etc. The result of Artificial Neural Network and profound learning methods is noticeable, and sometimes the outcomes are smarter to human specialists. From most recent couple of years the greater part of the issues are additionally being re-explored different avenues regarding profound learning methods with the perspective on accomplishing improvement in the current disclosures. Different kind of structures of profound learning have been presented as of late, like profound organizations, convolutional neural organizations, and repetitive neural organizations. The engineering has shown the aptitude in different territories. Written by hand Character recognition is one of those spaces where AI and Artificial Intelligence procedures have been broadly use or tested. The absolute first profound learning procedure is one of the main AI strategies, was proposed for manually written character recognition on MNIST information base in 1998.

The profound learning and neural organization strategies are made out of different hidden layers, and those hidden layer comprises of different neurons, which register the loads for the profound organization. Weighty processing power is needed to figure these loads, and an extremely incredible architecture was required, which was not effectively accessible. Since the analysts have attracted their consideration discovering the method which needs less force by changing over the pictures into highlight vectors. Over the most recent couple of many years, a ton of highlight extraction strategy have been proposed like HOG (histogram of situated angles) and numerous others procedures are utilized as unmistakable component extraction techniques, that have been tried for some, issues like face location, picture acknowledgment, character recognition, and so forth

Highlight extraction is one kind of dimensionality decrease method that addresses the significant pieces of an enormous picture into an element vector. These highlights are hand tailored and plainly planned by the examination local area. There are the situations where some crucial highlights might be concealed by the analysts while extricating the highlights from the picture and this may bring about a high order blunder. Profound learning upsets the way toward handcrafting and planning highlights for a specific issue into a programmed interaction to process the best highlights for that issue. A convolutional neural organization has different convolutional layers to separate the highlights naturally. The highlights are draw out just a single time in learning models, yet on account of profound learning models, different convolutional layers, for example, level layer, Max-pooling layer, sequence layer, and so on, have been received to separate segregating highlights on numerous occasions. This is one reason that profound learning models are for the most part effective. And furthermore, in Deep feed forward neural organizations the highlights are figure consequently by utilizing diverse number of covered up layer in it. Attributable to their extraordinary achievement, many driving organizations have additionally presented profound models.

The recognition of the character is a field in which the picture is perceived and transformed into an apparatus that can be discerned. As we have talked about over, the profound learning strategies and convolutional neural organizations method have been utilized for discovery of picture and acknowledgment of character. In Roman (MNIST), Chinese, Bangla and Arabic, this method was also applied effectively. For transcribed English characters and digital recognition, a convolutional neural organisation is applied in this paper.

II. Proposed Algorithm

This part gives outline of proposed framework, its architecture design, modules, dataset for implementation, algorithm used and UML designs.

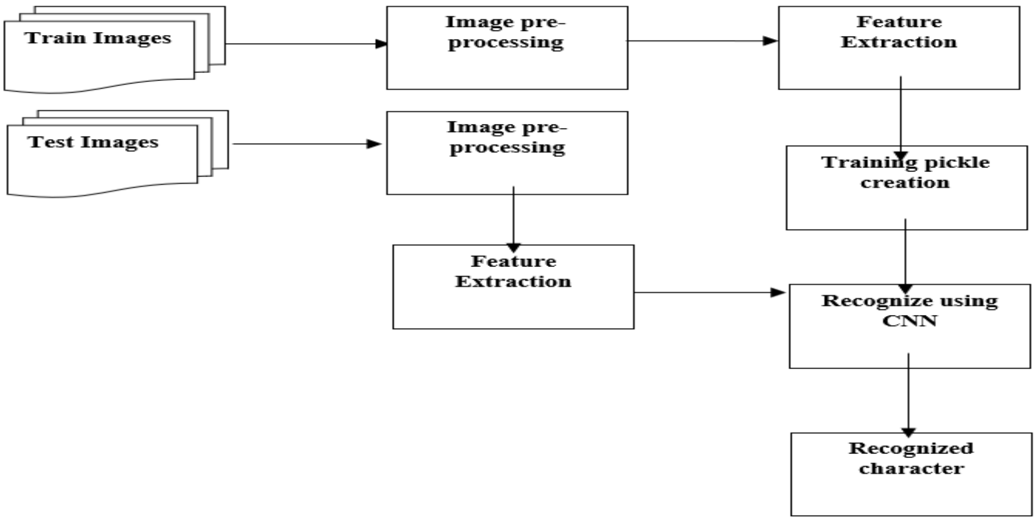

Figure 1: System Architecture

The above figure addresses System Architecture of proposed framework, where all modules required through recognition measure is addressed. The proposed framework contains two significant stages, for example, preparing stage and test stage. Preparing stage is directed and pickle document is produced. The proposed recognition framework utilizes OpenCV for picture preparing and Neural Network for character recognition.

1.1 MODULES

The proposed system can be achieved by implementing the following modules

- Image pre-processing
- Text localization
- Feature extraction

- Character recognition

1.2 IMAGE PRE-PROCESSING

Picture pre-processing is completed into steps, for example, shading transformation and Gaussian obscuring. Shading transformation work changes over input picture from one shading space to other, here we utilized BGR2GRAY for changing the info picture over to Gray scale picture. The following stage of pre-measure is Gaussian obscuring of pictures. Gaussian obscuring eliminates clamors from pictures and smoothest the pictures. For picture division, Adaptive Gaussian Threshold is applied and Threshold is determined for each little locale of pictures.

1.3 TEXT LOCATION

Text restriction should be possible through picture shapes. Forms are utilized to dissect shape, object discovery and recognition. Forms can be applied on parallel pictures just, so picture pre-interaction, for example, thresholding is performed prior to applying discover Contours (). cv2.CHAIN_APPROX_SIMPLE () work is utilized to get the co-ordinate focuses for text confinement.

1.4 FEATURE EXTRACTION

Utilizing the above module, forms are recognized, from which shape guess is applied at that point jumping square shape is distinguished as form region. The portioned picture is put away as brief picture, in which OpenCV capacity, for example, resize and reshape are applied to get y Value_images. The showed up y Value_images are considered as extricated highlight.

3.4.1 Adding 2D Convolutional layer

To process the images of 2D information, add a 2D convolutional layer. The main contention to recognise the number of outputs directly is the Conv2D() layer work, which includes 32 output channels for this situation. In this instance we have decided to have a 5/5 moveable window tracked by the steps in the x and y covers The following information is the kernel size (1, 1). Then we have to supply the model with the size of the layer contribution. the implementation of the enactment is a modified direct unit. The information form of the main layer is expected - Keras is sufficient to determine the size of the tensors running via the model from then on.

3.4.2 Adding 2D max pooling layer

Add a max layer of 2D pooling. For this situation and the steps, we simply indicate the size of the bundle in the x and y directions (2,2).

3.4.3 Adding another convolutional + max pooling layer

Then, we add a new + max layer of pool with 64 output channels. The Conv2D() work's default steps contain (1, 1) in Keras, so we may forget. The default steps contention in Keras is used to make it equivalent to the pool dimensions. This layer's info tensor is (Bunch size 28, 28, 32) — the size 28 x 28 and the quantity of the last layer yielding channels are the 32.

3.4.4 Flatten and adding dense layer

Next is to level the yield from these to enter our completely associated layers. The following two lines pronounce our completely associated layers – utilizing the Dense () layer in Keras, we indicate the size – in accordance with our design, we determine 1000 hubs, each actuated by a ReLU work. The second is our delicate max characterization.

3.4.5 Training neural network

In the training model, we need to indicate the misfortune work, or mentioned to the system what kind of optimiser to utilize (for example slope drop, Adam optimiser and so on)

Young lady capacity of standard cross entropy for downright class arrangement (keras. misfortunes. categorical_crossentropy). We utilize the Adam analyzer (keras.optimizers.Adam). At long last, we can determine a metric that will be determined when we run assess() on the model.

We first pass in the entirety of our preparation information – for this situation x_train and y_train. The following contention is the cluster size. For this situation we are utilizing a bunch size of 32. Then, we pass the quantity of preparing ages (2 for this situation). The verbose banner, set to 1 here, indicates on the off chance that you need nitty gritty data being imprinted in the reassure about the advancement of the training.

3.4.6 Test data input

Finally, we review the evaluation data to the fitness capacity so that Keras can understand the data to be tested when assessing () on the model.

USE CASE DIAGRAM

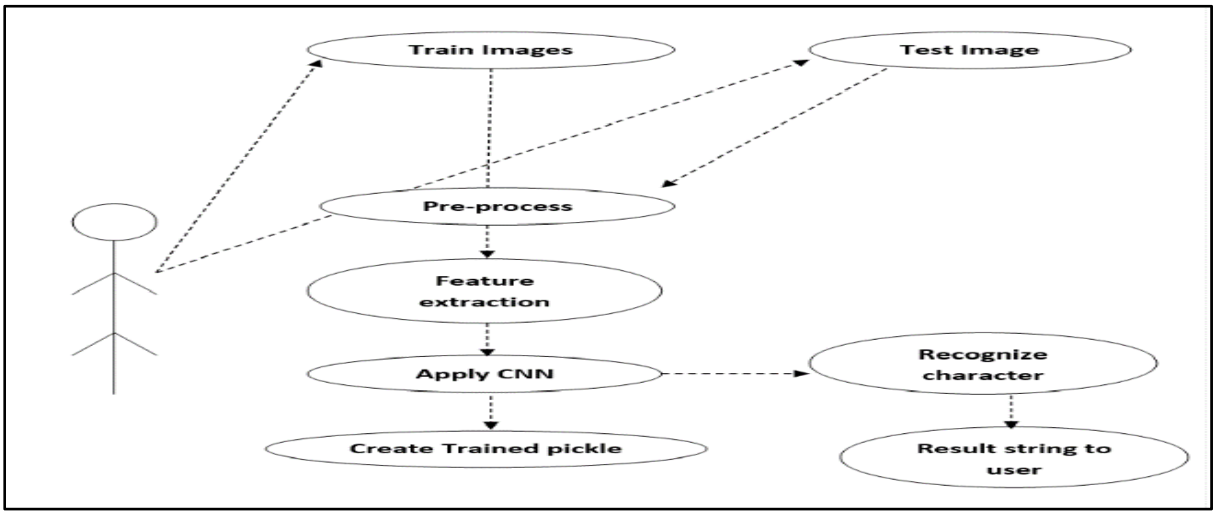

Figure 2: Use case Diagram

The above figure addresses use case diagram of the proposed framework, in which client transfer train pictures and train the framework, gets yield pickle record of prepared information. Client additionally transferred test picture, Neural organization classifier is applied for character acknowledgment

SEQUENCE DIAGRAM

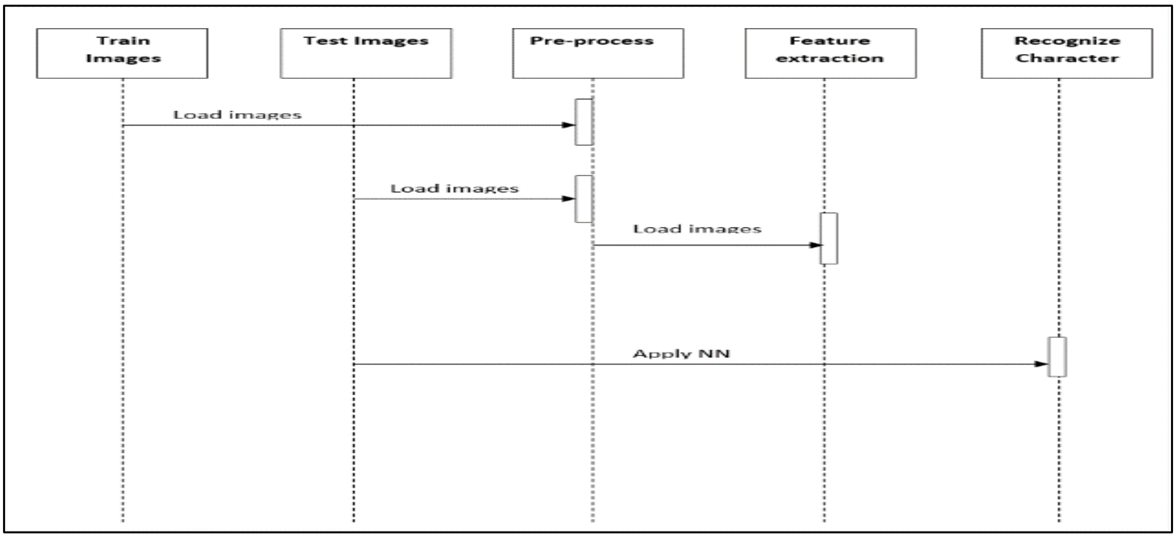

Figure 3: Sequence Diagram

The above figure addresses Sequence Diagram of proposed framework. The figure portrays the succession of cycle and pre-measure associated with the written by hand character recognition system.

COLLABORATION DIAGRAM

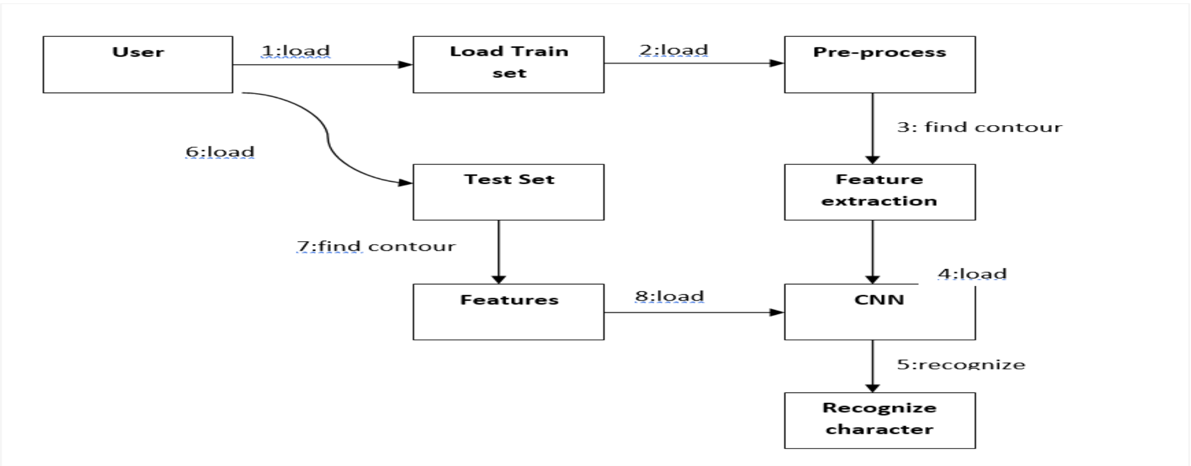

Figure 4: Collaboration Diagram

The above figure addresses Collaboration diagram of proposed framework, which portrays the follow of modules and its joint effort is addressed with grouping number

ACTIVITY DIAGRAM

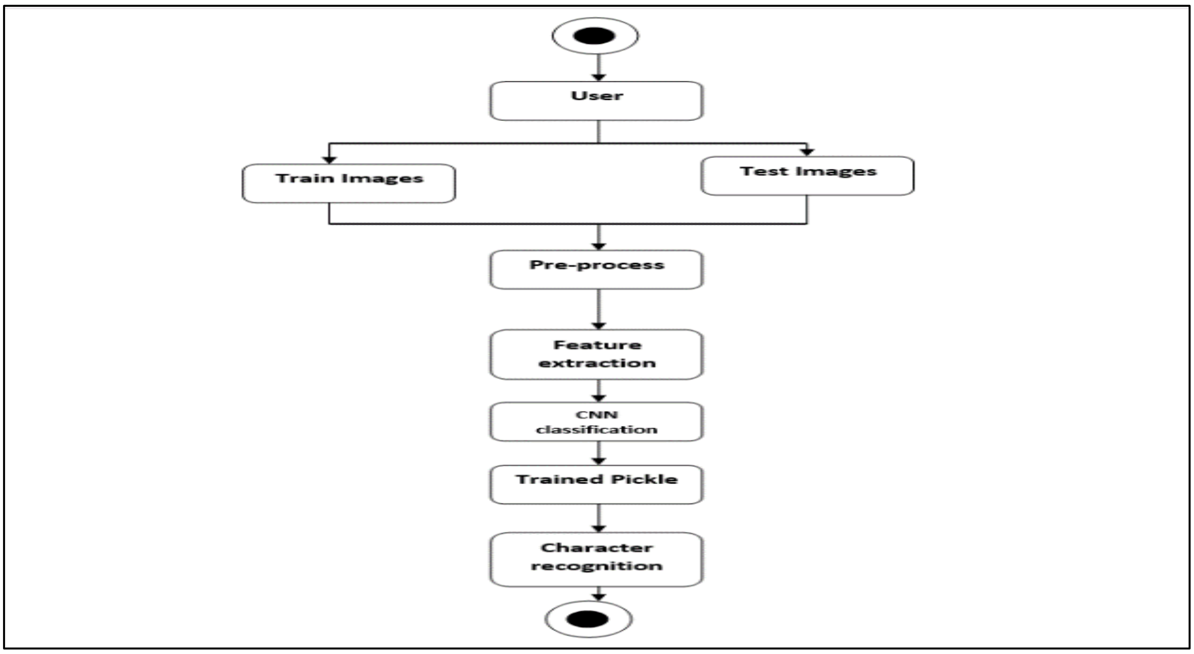

Figure 5: Activity Diagram

The above figure represents activity diagram of proposed system.

ER DIAGRAM

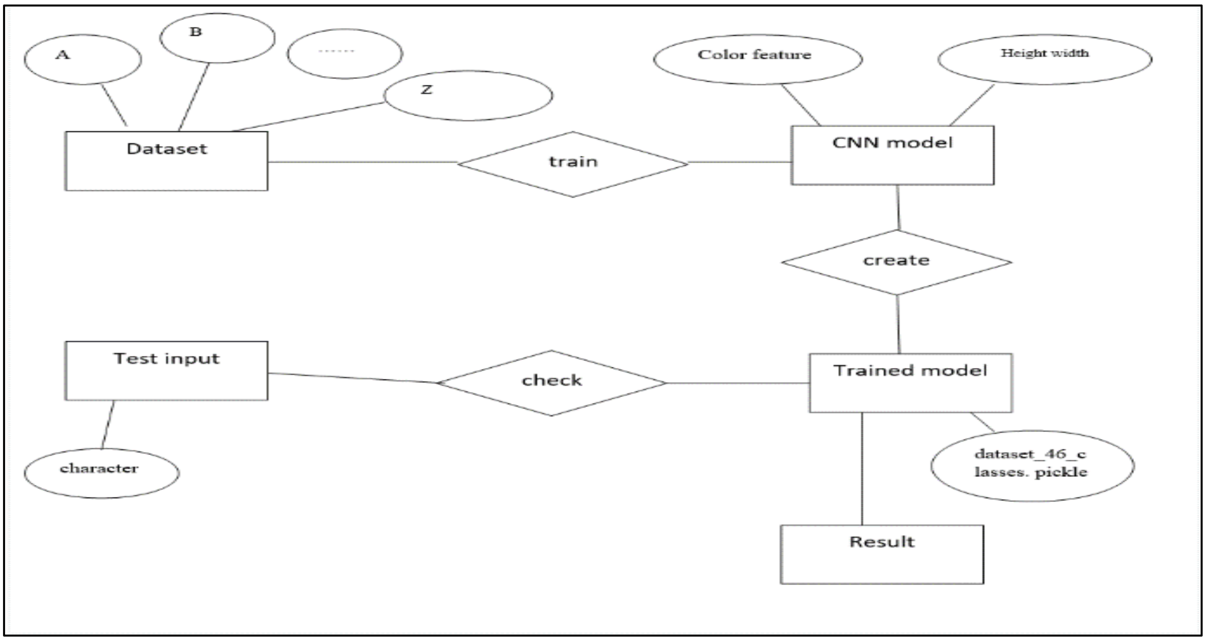

Figure 6: ER Diagram

The above figure addresses ER outline of proposed framework. All Oval formed shows the contribution of dataset to the framework. Square model addresses modules.

III. Result and Discussion

The Neural Network generally consists of different layers hidden. In the majority of Conv2D, there will be 2 secret layers with 16 or 32 neurons and the sky will be the limit from there. Hidden layers are reproduced by different arbitrary pixel loads, from 0 to 1. However, in the Conv2D Neural Network the plan consists of the same two secret layers and each secret layer consists of huge neuron layers. For example, we used 128 thick, irregularly loaded neurons. We achieved promising results through the use of this deep organisation. Here are some characters naming in Table 1.

Table 1: Sample data representation of labeling.

Layer Type	Layer operation	No of feature map	Feature map size	Window size	Total parameters
C1	Conv2D	42	50 X 50	5X5	2500

In this test phase, we used the Adam Optimization model of 5 layered Convolutional Neural Networks (CNN). On them we used five layers of Convolutional Neural Networks (CNN) model for convolutional, one layer for maximum pooling or sub-testing, a flatten layer that changes during this test stage.

IV. CONCLUSION

We proposed in this paper a diverse approach to neural organisation for handwritten characters and image digits. We assessed the submission using the CNNs with improvements and the Deep Feed Forward Neural Network. We evaluated the submission. These methods are used to train and test the data set from various customers on a standard customer. Explorative outcomes show the best accuracy for handwritten characters contrasted with optional methods for the DFFNN, CCN-Adam and SoftMax. We have achieved promising results in a highly accurate strategy.

V. FUTURE ENHANCEMENT

The future tasks must be productive and each word without covering or lacking parts can be fragmented. We can utilize some more neural organization idea and boundary varieties can be utilized for the division and arrangement which may improve our outcomes.

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