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RECOGNITION OF HANDWRITTEN DIGIT USING DEEP LEARNING AND CNN

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Abstract:
Handwritten recognition is the noteworthy and important. All the handwriting digits are not in same size, same thickness, same position and direction. We have to face different problems while we are writing handwritten digits. The written digits has the uniqueness and importance for the various styles of different industries for the extra influence in presence of digits. The handwritten digits is mainly used in many real time programs like bank cheques and tax documents. The main purpose of the project is to detect the handwritten digits is used in machine learning algorithms like TKINTER, NAVIE BAYES, PLOTTED algorithms and so on. And we are using deep learning calculations like CNN by utilizing keras with numpy tensor flow and pillows. By using these libraries we have to get some different accuracy values like 97.50%, 90.01%, 85.60% by obtaining Navi bayes and plotted algorithms.

Handwritten digit recognition will have to gain more attention in various methods of pattern recognition and machine learning algorithms due to the various applications of various fields. Handwritten digit recognition has specific domain has to be applied. Various techniques has to be proposed for symbol recognition in handwritten digit recognition. In coming years for character recognition is a server key to create paper less works by processing the existing documents. This project presents a detailed view of handwritten digit recognition.

Keywords—Scikit-learn, Classifier, keras, TensorFlow, MNIST, Python, Deep learning, Neural networks, Digit recognition, Navi bayes, Plotted algorithms.

Introduction

Character recognition is very basic, but it is in the difficult subject of pattern recognition that most valuable applications are found. It is a large field of research that dates back to the early days of computer science and is based on the natural differences between computers and people. Character recognition is the technique of identifying and detecting characters from an input picture to other equivalent machine editable method. This technique has to be used for which computer system has to recognize the characters and other symbols has been writing the hand digits is called hand written recognition method. It has been divided into two methods like offline and online handwritten digit recognition method. If handwritten digit is scanned by the computer and the computer has been understood by this method is called offline handwritten digit recognition. The handwritten digit recognition has been written by the touch pad by using stylish pen is online handwritten digit recognition. The character recognition is divided into different categories like global segmentation and analytic segmentation. The handwritten character recognition of processing systems and using specific applications.

This project has been done in different European languages and Arabic languages like Hindi, Punjabi, Urdu, Telugu, Gujaratietc.

Handwritten character recognition is nothing more than the ability to identify digits in other papers. The capability of a computer to read manually scribbled digits from various sources is known as handwritten digit recognition.The handwritten digits is mainly used like messages, bank cheques, pictures etc. It is a web based handwritten digit recognizing the pc tablets, identifying the number plates on vehicles, bank cheques and other digits on different forms. Deep learning is a machine learning method that has to been trained by computers that easily fall in place for the people. The handwritten digit recognition has to used large datasets for recognize the digits for different sources. The handwritten character recognizing has been using since 1980. The main aim of the project by using different classifiers such as online digit recognition on Various computer tablets, recognition of zip codes on mail, bank check amounts, and so forth. The handwritten digits do not all have the same size, thickness, location, or orientation. When writing handwritten numerals, we have to deal with a variety of issues.

The fundamental goal of handwritten digit pattern recognition is to detect the handwriting digits that have been categorised in the MNIST collection of pictures by handwritten digit (0-9).

Literature Survey

In this study, AnujDutt describes how he was able to obtain a high level of accuracy by applying Deep Learning systems. He achieved 98.72 percent accuracy by using the Convolutional

Neural Network with Keras and Theano as a backend. Furthermore, CNN performance with Tensor flow is 99.70 percent superior. Despite the fact that the method and codes appear to be more sophisticated than traditional machine learning algorithms, the accuracy gained is becoming increasingly apparent. The Multilayer Perceptron (MLP) Neural Network was used to recognise and forecast handwritten digits from 0 to 9 in a research published by Saeed AL-Mansuri. MNIST data was used to train and test the proposed neural system. A. The Current System Images are now being used to communicate data by a rising number of individuals. It is also the primary distribution for separating vital info from photos. For your most utilised apps, image recognition is an essential study topic. In general, one of the most challenging jobs in the realm of pattern recognition is the exact computer recognition of human writing. Without a sure, this is a challenging subject to study because handwriting differs so much from person to person. Despite the fact that these distinctions are meaningless to humans, teaching computers to understand typical handwriting is becoming increasingly challenging. It is used in image recognition, such as handwriting categorization.

It's crucial to understand how the information is presented in the visuals. The MNIST Database's Handwriting Recognition is well-known among sAnujDutt in his article indicating that he was able to obtain a high degree of accuracy utilising Deep Learning methods. He achieved 98.72 percent accuracy by using the Convolutional Neural Network with Keras and Theano as a backend. Furthermore, CNN performance with Tensorflow is 99.70 percent better. Despite the fact that the method and codes appear to be more sophisticated than traditional machine learning algorithms, the accuracy gained is becoming increasingly apparent. A Multilayer Perceptron (MLP) Neural Network was used to recognise and forecast handwritten digits from 0 to 9 in a research published by Saeed AL-MansooriA.The Current System Images are now being used to communicate data by a rising number of individuals. It is also the primary distribution for separating vital info from photos. For your most utilised apps, image recognition is an essential study topic. In general, one of the most challenging jobs in the realm of pattern recognition is the exact computer recognition of human writing. Without a sure, this is a challenging subject to study because handwriting differs so much from person to person.

Despite the fact that these distinctions are meaningless to humans, teaching computers to understand typical handwriting is becoming increasingly challenging. Fragmentation by hand, for example, is used in picture recognition.Handwriting recognition using the MNIST database is well-known among scientists, since the mistake rate may be lowered by using classification parameters, for example, from linear (1-layer NN) by 12 percent to 0.23 percent using 35-board neural convolution board systems.

The goal is to think about several kinds of dividers and different tactics by focusing on how to produce an approach to human performance utilising the Handwriting Digital Recognition framework. The most prevalent difficulty to be handled in multi-digit design work (0-9) for various persons is the issue of digit order and the proximity between digits such as 1 and 7, 5 and 6, 3 and 8, 9 and 8, and so on. Furthermore, people write the same digit with various thoughts, and the handwriting of different people contributes to the creation and existence of digits., from linear phase (1 NN layer) to 12 percent to 0.23 percent by 35 neural convolution systems board The goal is to use the Handwriting Digital Recognition framework to come up with new class separators and tactics while focusing on how to get as near to human performance as possible. The most common difficulty to be handled in the work of identifying various numbers (0-9) for different persons is the issue of digit order and the proximity between the digits, such as 1 and 7, 5 and 6, 3 and 8, 9 and 8, and so on.. In addition, people create the same digit with different ideas, the diversity and diversity in the handwriting of different people also contributes to the development and existence ofdigits.

In 1959, Grimsdale made the first noteworthy attempt in the subject of symbol recognition research. The so-called analytical method-by-synthesis, introduced by Eden in 1968, formed the cornerstone of the significant scientific activity in the early 1960s. The work of Eden was significant since it formally established that all the texts were fakes.

There are only a few systemic aspects, which has been explained explicitly in previous volumes. Later on, this idea was extended to include all elements of symbol production. K. Gaurav, P. K.

Bhatia, et al. Various pre-processing strategies are described in this respect, including skew detection and repair, picture enhancement techniques that lengthen the difference, both integration, sound removal
techniques, familiarity and separation, and morphological processing techniques. We've come to the conclusion that because we're just employing one processing method, we won't be able to properly process the image. However, even with all of the approaches outlined, complete precision in the pre-processing process may not be feasible. In this hybrid study, Salvador Espaa-Boquera et al [6] offer a Hidden Markov Model (HMM) modelIn this example, Markov chains make up part of the optical model structure, and the Multilayer Perceptron is employed to calculate the probability of release. [7] proposes a quadratic classifier-based approach for identifying the offline handwriting numbers of six prominent Indian novels using a quadratic classifier. To recognise English letters written in handwriting, a multilayer perceptron is utilised [8]. Boundary tracing features and associated Fourier Descriptors have been provided. By examining his or her circumstance and comparing his or her distinctive qualities, a sign might be identified. In order to obtain optimal performance of the back distribution network, analyses have also been undertaken to estimate the number of hidden layer nodes. 94 percent accuracy in With short training time, recognition was reported in English handwritten letters. To identify offline characters, the diagonal feature output is enhanced in [9]. The model is based on the ANN model. This Neural Network identification system is made up of two approaches that employ 54 features and 69 features respectively. The neural network recognition system is trained using horizontal and vertical element output techniques to compare the visual acuity of the proposed diagonal output method. The diagonal approach of feature extraction revealed 97.8% recognition in 54 aspects and 98.5 percent recognition in 69 features.

This study covers machine learning and in-depth learning algorithms like CNN, as well as the Plot digital digital recognising recognition system. It also includes details on an efficient method for executing the digital recognition function. To better comprehend what will be addressed in the next sections of this article, the related work in this topic is followed by the operation and application of all algorithms. After that, provide the conclusion and the result. The last section of this article covers all of the references and quotes that were utilised in this work. To detect and analyse the accuracy of different periods, the authors of the study [10] utilised a 7-layer convolutional neural network with 5 hidden layers, a gradient drop, and a background prorogation model. The same authors briefly reviewed the many components of CNN, its evolution from LeNet-5 to SE Net, and comparisons between other models such as Alex Net, Dense Net, and Res Net in their study [11]. The test error rate for LeNet-5 and LeNet-5 (in reverse) in the MNIST data set was 0.95 percent and 0.8 percent, respectively. Alex Net's architecture and accuracy level are identical to LeNet-5, however it is too large. The "Squeeze-and-Excitation network" (SE Net) network won the ILSVRC-II competition by roughly 4096000 parameters.

In 2017, they used the most powerful CNN model available to lower the error rate from 5% to 2.25 percent.

Methodology

Usually handwriting recognition is divided into six categories namely image acquisition, pre-processing, classification, feature extraction, classification and post processing. A diagram of the key symbol recognition block is shown in fig1.

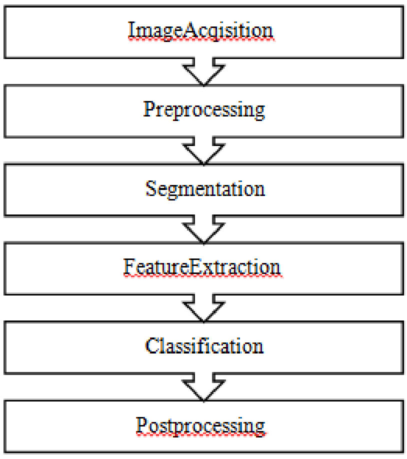


Fig 1 : Block Diagram of Character Recognition

A.) The digital picture was used as input for the image capture. Electronic tablets are the name for these gadgets. For digital nature, these gadgets are mostly employed in pen. Other ways, such as scanners and directly writing on the computer for stylus, are utilised in handwriting devices.

B.) The initial phase of digit recognition is pre-processing, which has a high recognition rate. The primary goal of pre-processing is to eliminate variances and lower the recognition rate. These variances include inconsistent text size, missing points from pen motions, and a small bend in the hand to the left or right writing from the vantage point of a neighbour The five processes of pre-processing include size normalisation and centring, missing points, smoothing, slant correction, and point resampling.

C.) Segmentation is mostly applied to the image's individual characters. All papers in segmentation are arranged in a hierarchical order. All of the lines in the first level were segmented using the histogram row. The histogram column is used to extract all words for each row, and the characters are then converted to words..

D.) Feature extraction is mainly used in the extraction of pattern classification. Feature extraction techniques is used in different methods like principal component analysis, linear discriminant analysis and chain code. For this method we have to extract the features for individual character by using histogram.

E.) Classification is used in input image to present the HCR method. The features are extracted from the input data from the training classifier like ANN. When the classifier It gets the best matching for input class by comparing input from a stored pattern data.

F.)In order to utilise linguist expertise, post-processing is needed to rectify misclassified findings. Shape recognition produces a post-processing result. Shape recognizers are employed in single string characters for the handwriting approach.

Each research endeavour necessitates some type of measurement, and the MNIST database is utilised to assess the accuracy and performance of the handwritten digits. MNIST is a commonly used handwriting digital recognition standard. MNIST is a huge and well-known website that contains handwritten digits. The MNIST database is frequently used to evaluate algorithms for distinguishing handwriting digital recognition systems.

The first step will be to build up the database, which can be accomplished with ease using the Keras interface. The MNIST database has images in the form of a collection that contains the 28x28 values that make up the picture as well as their labels. If there is a case for experimental photos, this is great. Pixels are measured in 784-d pixels and range from 0 to 255, with 0 being black and 255 denoting white.

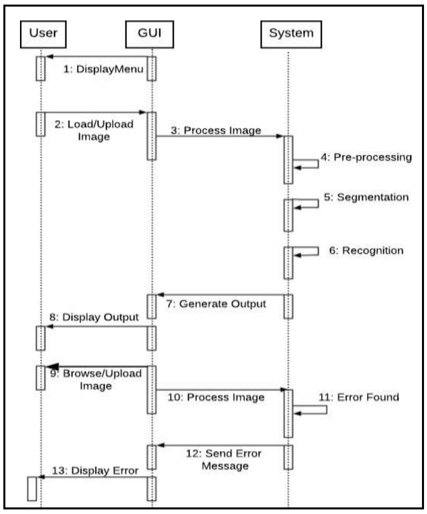


Fig 2 : Sequence Diagram of the System

The system model's sequence is depicted in the diagram above. The diagram above depicts the order in which the stages must be completed during execution. In this system, the convolution neural network model is used. The user must first supply a picture of the digit they wish to view. The image will be processed by the system. The output will be created when the code has been executed. The system will display the digit that the user has supplied, as well as the accuracy rate projected by the model. If the user uploads a picture with a resolution that differs from the code's specified resolutions, the code will not create any output and the user will receive an error notice.

Figure 3 depicts the data flow diagram for the proposed system model. Data may be entered into the system in two ways. A digital image or data from the MNIST database can be obtained by the user. Before being utilised, images are pre-processed. Different class dividers are used to compare the precision of known digits, and the results are compared.

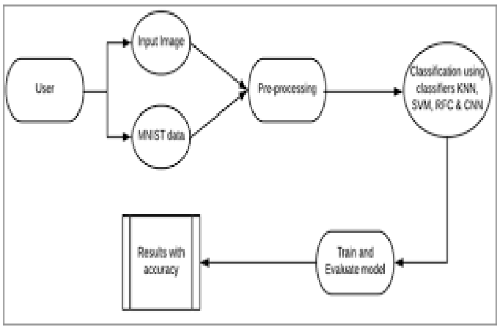


Fig 3 : Data Flow Diagram of System Model

The data flow diagram of the suggested system of the provided model is depicted in the diagram above. There are two methods for providing input to the system. The user may either design a picture that he wishes to detect in the interface window or utilise data from the MNIST collection. The system pre-processes the specified input photos. To recognise the digits, many classifiers are utilised. The accuracy of the results produced by the system is compared.

The accuracy of the results is presented beside the results.

The MNIST dataset:

It is probably most popular data set in deep

learning and machine learning algorithms. The data set contains 60000 trained images for handwriting digits from 0-9 and we have 10000 images for testing purpose in the present data set. The data set having 10 different classes. In the data set images are represented as 28 cross matrix and each image having gray scale pixelvalue.

Below are the steps to implement the handwritten digit recognition project:

1. Load the dataset and import libraries.:

First, import all of the libraries into the data set, then train our model. The keras library is already included in the data set that we must use in our model. As a result, we may import the data collection and begin working on the project. The training and testing data are returned by the mnist load data method.

2. Pre processing thedata:

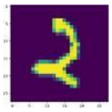
Because picture data cannot be utilised directly in this model for this project, we must employ certain functions to analyse data that has previously been presented in neural networks. This data has a dimension of 6000,28,28. One extra dimension is required for the CNN model to reshape the matrix to form.

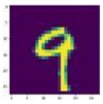
3. Construct the model:

In Python, we must design a CNN model. The pooling layers in the CNN model are mostly convolutional. The data is mostly represented as grid structures, which is why CNN is so effective in picture categorization. When the data is in the training stage, we mustdeactivate some dropout layers and then we will compile this model for Adadeltaoptimizer

4 Train themodel:

This model must begin with training data, and it will employ certain Keras functions as well as training data, validation data, and batch size.And it takes some time to train the data after training it will used the model.





5 Evaluate themodel:

We must employ 10,000 photos in our dataset, which will be assessed in relation to our model and how it performs. Because the testing data is not included in the training data, it is novel to our model. The MNIST data is nicely balanced, allowing us to achieve an average accuracy of 95%.

6 Create GUI to predictdigits:

We need to construct a new file in the GUI to establish an interactive window for drawing digits on the canvas with a button to recognise the appropriate digit. The Tkinter library is the standard Python library. We must design a function predict digit that takes an image as input and predicts the digit using the training value. After that, we must design an app class that is in charge of creating the GUI. To capture the digit, we must first construct a canvas and then use the predict digit method to display the results.

Result and Discussion

When testing different recognition

models, some features of the MNIST database were developed (Figure 4):

- all digital images have a clearly defined boundaryarea;
- gray images, pixel brightness varies across digital image width;number pictures focused on the 28x28area.

Fig 4 : Sample images of MNIST Dataset

Fig 5 : Border width 20% of the maximum image size. Recognition accuracy is100%.

To test the causes of recognition failure, a Python test system was developed that allows for visual representation of numbers and monitoring the location of the recognition and effect (Fig. 6).

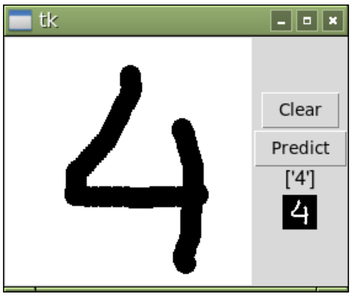
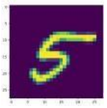
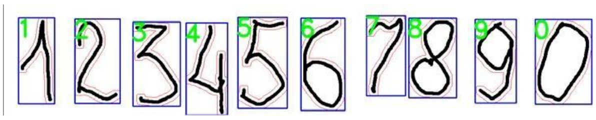


Fig 6 : Appearance of the program window for testing handwritten character recognition

After constructing recognition models using all the above- mentioned algorithms, the accuracy rate of the recognized handwritten digits in the test system appeared in the range of 98-100% (one error or none with 50 digit drawn). recognition accuracy sets the basis for building models to work with black and white images. In this case, the images from MNIST dataset have been converted to black and white. The output obtained are closely related to the features of



highlighting interesting areas that contain



digits in the image. Account selection (find Contours function in OpenCV) is performed right next to the established container boundary. The selected area in the rectangular position defined next to the digital counter, other than the region for further processing interest, differs significantly from the MNIST base. The same effect has been achieved in industrial photography. Regardless of which version of the neural network was used, the accuracy of the detection was 96-98%. In the case of ladle car numbers and morphological "closing" functions (MORPH_CLOSE according to the OpenCV library) were created before detection. Figure 10 shows the result produced by CNN training.

Fig 7 : Output generated by CNN

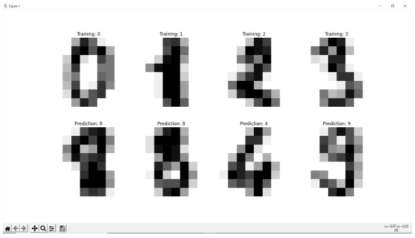


Fig 8

The above fig 8 tells us how the MNIST data set is trained with the digits we give.Above fig easily tells us about the training of numbers 1 to 9.

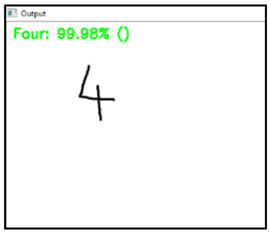
Fig 9

The above fig(9) tells us that when we give the number as input then the trained data will recognize the number and gives the output with same number.

S.No	Methods	Accuracy
1	CNN	99%
2	Navie Bayes	70%
3	Plotted Algorith m	77%

Table 1 : Acuuracy Percentages

The above table 1 tells us about how much accuracies we get in all the 3 methods that we have used in our project.



Classification	Report for precision	Classifier recall	SVC F1-score	Support
0	1.00	0.99	0.99	88
1	0.99	0.97	0.98	91
2	0.99	0.99	0.99	86
3	0.98	0.87	0.92	91
4	0.99	0.96	0.97	92
5	0.95	0.97	0.96	91
6	0.99	0.99	0.99	91
7	0.96	0.99	0.97	89
8	0.94	1.00	0.97	88
9	0.93	0.99	0.95	92

Table 2 : Report of Classification for all digits using Plotted Algorithm

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