

Developing an application to recognize hand Written digit using GUI tool kit

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Abstract— The ability of computers to recognize numbers written by humans is called handwritten digit recognition. This is one of the practically significant problems in pattern recognition applications. Applications for digit recognition include form data entry, bank check processing, mail sorting, and more. Since handwritten digits are imperfect and can be generated with a variety of flavors, it is a difficult job for the machine. The answer to this problem is handwritten digit recognition, which uses an image of a digit to identify the digit contained in the image. Using a deep neural network called CNN, we will develop handwritten digit recognition in this project by using the MNIST dataset that contains photos of handwritten digits from zero to nine (Convolutional Neural Network). The handwritten features and much prior knowledge form the basis of traditional handwriting recognition systems. An optical character recognition (OCR) system must be trained using these prerequisites, which is a difficult process. Deep-learning approaches have been the focus of handwriting recognition research in recent years, leading to breakthrough results. An example of a deep-learning algorithm is convolutional neural networks, which use filters to learn the different features of an image as they are fed into the algorithm. Finally, a graphical user interface is created to draw the figure.

Keywords— *Handwritten Character Recognition, Optical Character Recognition*

I.INTRODUCTION

This chapter gives an overview of the project report's contents and an explanation of its purpose. In addition, the system's goal, objectives, context, and operating environment are described.

1.1 Purpose:

This project's major goal is to provide a detailed description of the "Handwritten Digit Reorganization." It will serve as an illustration of the project's goal and complete declaration of intent. This article is primarily designed for anyone who is interested in learning more about the process, results, and potential future applications of this project. This application aims to achieve these objectives: This application is effective, efficient and initiating for helping users. This application helps users to give handwritten digits as input to receive the correct number given in the machine This project's objective is to produce a classification algorithm that can identify handwritten numerals (0-9).

1.2 Background of Project:

The current research aims to provide an accurate output to the input written numbers by the user. Before Computers existed all the information was stored in form of papers, this is very inefficient form of storing data as we cannot guarantee that papers can last a while long. So The primary objective of this initiative is to gather information the primary objective of this project is to gather information from these papers and store the information and give us the accurate output.

1.3 Scope of Project :

Our project focuses mainly on the task of handwritten digit recognition using a classifier. This task is really important and has many applications, such as online handwriting recognition on computer tablets, sorting postal mail by zip code, processing the amounts on bank checks, and numeric entries in forms filled out here by hand (like as tax forms).

1.4 Modules Description:

This project is composed of the following modules:

1. TensorFlow: A machine learning software library named TensorFlow is free and open-source. It can be used to a variety of tasks, although it concentrates mostly on deep neural network training and inference. Dataflow and differentiable programming are the foundation of the symbolic math package TensorFlow.
2. NumPy: The NumPy library provides the Python programming language with support for huge, multi-dimensional matrices and arrays, in addition to a substantial number of high-level mathematical operations to interact on these arrays.

3. Cv2: The creation of real-time applications for computer vision is accessible due to the cross-platform OpenCV library. Image processing, recorded video, and analysis—which includes features for item and face identification the key areas of attention.
4. Matplotlib: Matplotlib is a plotting library for the Python programming language and its numerical mathematics extension NumPy. When utilizing all-purpose GUI toolkits like Tkinter, it offers an object-oriented API for embedding plots into systems.
5. Tkinter: The default GUI library for Python is called Tkinter. The integration of Python with Tkinter makes it quick and simple to build GUI apps. The Tk GUI toolkit's strong object-oriented user interface is offered by Tkinter..
6. PIL: The Python Imaging Library is a free and open-source extra library that enhances support for accessing, editing, and saving a broad range of image file types. utilizing guidelines that take into account the fact that your paper will be a component of the complete proceedings rather than a stand-alone one. Do not change any of the present designations, thank you..

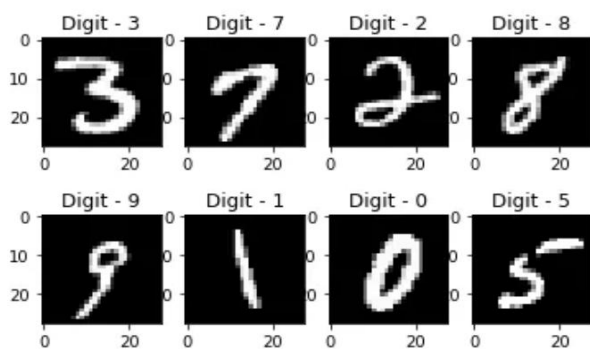


Fig.1 Example of MNIST Database

II.LITERATURE SURVEY

The identification of handwritten digits has attracted the attention of scholars. These include These days, A lot of papers and publications on this subject are being published. In compared to the most popular machine learning algorithms, such as SVM, KNN, and RFC, research has revealed that deep learning methods, such as multilayer CNN utilising Kera's with Theano and TensorFlow, provide the greatest accuracy. Convolutional Neural Network (CNN) is used frequently in image classification, video analysis, and other applications due to its high accuracy[1]. Sentence sentiment recognition is a goal of many researchers. By adjusting various parameters, CNN is utilised for sentiment analysis and natural language processing. Given that the large-scale neural network requires more parameters, it might be difficult to achieve acceptable performance.

Numerous scholars are working to improve CNN's accuracy while reducing inaccuracy. Another study has demonstrated that deep networks perform better when trained using straightforward backpropagation. Comparing their design to that of NORB and CIFAR10, they have the lowest error rate on MNIST. It suggested a quicker execution with 99.65% accuracy. A loss function that works with lightweight 1D and 2D CNN was developed. The accuracy in this instance was 93% and 91%, respectively[2]. An rising number of people are using images to transfer info these days. It is also common practise to isolate important information from images. For its many uses, image recognition is a vital study topic. The exact computer recognition of human handwriting is one of the challenging tasks in the realm of pattern recognition in general. Given the huge range in handwriting patterns that exist among people, there is no doubt that this is a very difficult subject. However this distinction has little bearing on people, it is getting harder to educate computers to read normal handwriting. For the image recognition issue, such as handwriting categorization, understanding information representation on a screen is essential. [3]. As an example, a board of 35 convolution neural networks was able to reduce the failure rate from a linear classifier (1-layer NN) with 12% to 0.23% by using many classifiers with different parameters using the MNIST dataset for handwritten recognition. The objective is to develop a framework for handwritten digit recognition that takes into account a variety of classifiers and 4 techniques while concentrating on how to achieve performance that is as close to human as possible. The difficulty with digit position and order, such is 1 and 7, 5 and 6, 3 and 8, 9 and 8, and so on, would be the most frequent issue when making distinct numbers (0-9) for different people[4]. The Numerous machine learning algorithms may be used to construct handwritten digit recognition systems. When several methods are applied to solve this problem, the amount of time needed to build the model and the end The assessed model's accuracy can differ. There is typically a trade-off between time and accuracy when building such systems using different methods. Compared to other algorithms, certain techniques take less time to train the model entirely, but as a result, they offer less accuracy. On the other hand, many alternative methods require a lot of time to fully train the model yet ultimately produce results that are more accurate. Due to the variety of applications for this technology, While some of them have no time limits and require

better accuracy to work well, other applications can require the model. [5]. These algorithms may be compared since the outputs of these algorithms differ in terms of timing and accuracy. The focus of our research is accuracy, and we will be evaluating several methods. About the same. In our suggested project, a handwritten digit recognition system has been implemented using the advantages of a convolutional neural network. Our model was trained using a number of convolution and pooling layers to achieve high accuracy. For our planned effort to convert a recognised decimal number to a binary, octal, or hexadecimal number system, digit strings must be identified extremely precisely. Our research revealed that CNN is the most accurate algorithm that can be used to achieve maximum accuracy[6]. The Proximal Support Vector Machine (PSVM), Multilayer Perceptron, Support Vector Machine (SVM), Random Forest, Bayes Net, Naive Bayes, J48, and Random Tree are a few of the techniques used to develop handwritten digit recognition systems. Some applications based on this technology may find these algorithms useful, but many others, such as those in the financial industry, find them to be less useful. Call for superior results that may be obtained utilising alternative algorithms in comparison to the algorithms that have already been described. Compared to other algorithms, certain techniques take less time to train the model entirely, but as a result, they offer less accuracy. On the other hand, many alternative methods require a lot of time to fully train the model yet ultimately produce results that are more accurate[7]. Convolutional Neural Networks (CNN) are able to build handwritten digit recognition systems as a result of this technology, which lowers error and increases overall efficiency. Our suggested method combines CNN with a 3x3 kernel, numerous pooling layers, and convolutional layers to achieve this. 60,000 28*28 grayscale pictures are utilised to train our algorithm. Our model, which is used to develop handwritten digit recognition systems, undergoes normal training for accuracy on the order of 99.16% over 5 epochs, which is significantly higher than that of traditional techniques like Bayes Net, Support Vector Machine, Multilayer Perceptron, Random Forest, etc. [8].



Fig.2 Different styles of handwritten labels across the data set.

III.PROPOSED WORK

Handwritten digit recognition structure can be made with Convolutional Neural Networks (CNN) to reduce error and boost overall effectiveness. Our suggested approach makes use of a 3x3-sized kernel and CNN with numerous pooling and convolutional layers to accomplish this. In order to train our model, 60,000 28*28 grayscale photos are used. Our model, which is used to create handwritten digit recognition systems, is taught through a typical 5 epochs to reach precision of the order of 99.16%, which is significantly greater than that of classic methods like SVM, Multilayer Perceptron, Bayes Net, Random Forest, etc.

IV.PROCESS OF PROPOSED WORK

Our objective in the proposed work is to recognise the entire number that the user inputs while also detecting user-defined handwritten digits (by default, in the decimal number system), which is then translated to the user's preferred binary, octal, or hexadecimal number system. For this, a graphical user interface (GUI) will be developed in which the user will see a widget for canvas that can be used to draw handwritten digit strings that will be recognised and converted appropriately. After that, the area may be cleaned up to continue. Let's discuss about the steps of system that we proposed.

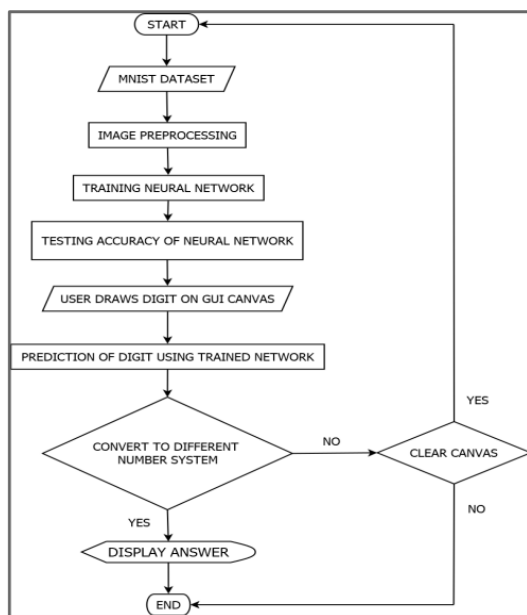


Fig.3 Activity diagram

V.METHODOLOGY

Computer Vision: Computer vision research focuses on re-creating some of the complexity of the human visual system so that computers can detect and understand items in photos and videos similarly to how people do it. One of the major factors affecting the development of computer vision is the volume of data that we currently collect and use for training as well as improving it.

Process of computer vision and how it works:

Pattern recognition methods are primarily utilized in computer vision to self-train and comprehend visual input. DL professionals have been able to use this data to make the process more precise and quicker due to the abundance of data and businesses' willingness to share it. We use a large quantity of visual details to train computers, which then process photos, identify the things in them, and look for patterns. For instance, if we send a million flowers photographs, the system will examine them, recognize patterns which are shared by all flowers, and then produce a model "flower" as a result of its investigation. As a result, each time we submit them a photo, the computer will be able to recognize a certain image as a flower with accuracy.

3.1 Convolutional Neural Network:

A popular deep learning method for classifying and recognizing images is CNN. A class of deep neural networks in this category only need very little pre-processing. Instead of entering an image one pixel at a time, it enters the image in tiny pieces, which helps the network recognize ambiguous patterns (edges) in the image more effectively. An input layer, an output layer, and many hidden layers, including convolutional layers, pooling layers (max and average pooling), fully connected layers (FC), and normalizing layers, are the three layers that make up CNN. The filter (kernel) used by CNN to extract features from the input picture is an array of weights. For certain non-linearity, CNN uses several activation functions at each layer. Images of 28 by 28 pixels make up the input layer. This implies that the input data for the network includes 784 neurons. Grayscale input pixels with a white value of 1 and a black value of 0. There are five hidden layers in this CNN model. The top-level hidden layer is convolution. Function of Layer 1 in Feature Extraction from Entry Data This layer applies convolution to incredibly small, localized regions by fusing a filter with the convolution approach of the preceding layer. Layer. A few feature maps with corrected linear units and learnable kernels are also included (ReLU). The size of the kernel determines where the filters are placed. It decreases the output data from the convolution layer in addition to reducing the model's parameter count and computational complexity. 7 The many types of pooling include L2 pooling, Max pooling, Min pooling, and Average pooling.

In this instance, max pooling is used to subsample each feature map's dimension. Convolution layer 2 and pooling layer 2 carry out the identical operations as convolution layer 1 and pooling layer 1, with the exception of differing feature maps and kernel sizes. The 2D feature map matrix is converted into a 1D feature vector using a flatten layer after the pooling layer, allowing the output to be handled by the fully linked layers

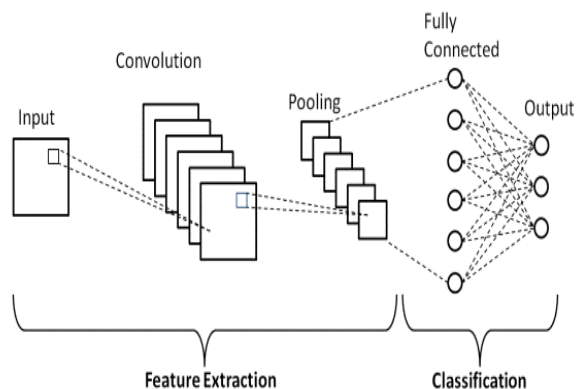


Fig.4 Layers of Convolution Neural Network

Convolution Network Layer:

The first layer utilized to extract the different characteristics from the input photos is this one. Convolution is a mathematical process that is carried out at this layer between the input picture and a filter of a specific size, $M \times M$. The dot product is obtained between the filter and the input picture's components with regard to the filter's size by sliding the filter over the input image ($M \times M$). The result is known as the Feature map, and it provides details about the image, including its corners and edges. This feature map is later supplied to further layers to teach them more features from the input picture. Once the convolution operation has been applied to the input, CNN's convolution layer passes the result to the following layer. The spatial relationship between the pixels is preserved thanks to convolutional layers in CNN.

Fully Connected Layer:

The neurons between 2 layers were connected using the Fully Connected (FC) layer, that also includes weights and biases. These layers, that make up the final few layers of a CNN architecture, are frequently placed before the output layer. This straightens the input image from the layers underneath and sends it to the FC layer. The normal operations on mathematical operations are performed after the flattened vector has gone through a few more FC levels. At this stage, the categorising process begins. Two layers are joined because they will perform better together than separately. The requirement for human monitoring is reduced by these CNN levels.

Pooling Layer:

A convolutional layer is frequently followed by a pooling layer. The primary objective of this layer is to reduce the size of the convolved feature map in order to reduce computing costs. This is done individually on each feature map and by reducing the links between layers. There are several sorts of pooling operations, depending on the mechanism utilized. Essentially, it is a summary of the characteristics produced by a convolution layer. The greatest component in Max Pooling is obtained from the feature map. The average of the components in a predetermined sized Image portion is determined via average pooling. Sum Pooling computes the total of the elements in the chosen segment. Usually, the Pooling Layer serves as a conduit between the Convolutional Layer and other layers

Dropout:

The FC layer would typically be connected to all attributes, which might overwhelm the training dataset. When a model works so well on training data that it suffers when applied to new information, this is referred to as overfitting. This problem is addressed by a dropout layer, which reduces the size of the model by removing a small number of neurons from the neural network during training. 30% of the neural network's nodes are randomly removed after passing a dropout of 0.3. Dropout enhances the performance of a machine learning model by adjusting parameters by simplifying the network. During training, neurons are deleted from neural networks.

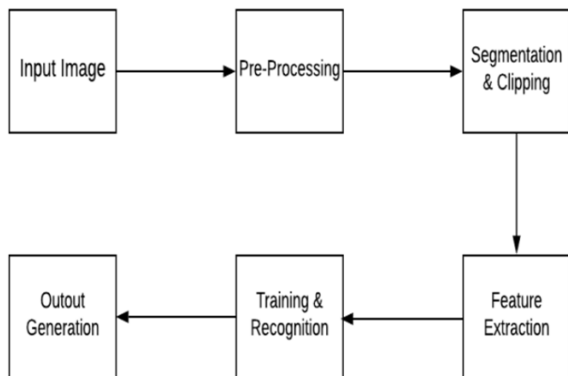


Fig.5 shows the process of digit recognition.

The suggested system's architectural diagram is shown in Figure 3.2 above. The suggested model includes the following four phases for detecting and classifying into number:

- A. Pre-Processing
- B. Segmentation
- C. Feature Extraction
- D. Recognition and Classification

A. Pre-Processing:

The pre-processing step's function to carry out different operations on the input picture. By making the picture suitable for segmentation, it essentially improves the image. Pre-primary processing's goal is to remove an interesting sample from its backdrop. The main tasks at this level are noise filtering, smoothing, and standardization. A more condensed representation of the example is also characterized by the preprocessing. A grayscale image is converted into a binary image using binarization, the initial step in processing the practice set photos is thresholding them into a binary image to decrease the amount of information. An example of a picture from the MNIST database

B. Segmentation: After the input photos have been pre-processed, the sequence of images is used to create sub-images of individual digits. A sub-image of unique digits is generated using pre-processed digit photographs, and each of those digits is assigned a number. The size of each digit is converted into pixels. Using an edge detection approach, the pictures from the dataset are segmented in this stage.

C. Feature Extraction: The pre-processed images are shown after the pre-processing and segmentation processes are finished as a matrix made up of incredibly large-sized pre-processed image pixels. The representation of the digits in the pictures that have the relevant data will be useful in this way. Feature extraction is the process in question. Redundancy from the data is removed during the feature extraction stage.

D. Classification and Recognition: Each of the following classifiers receives an individual input of the retrieved feature vectors during the classification and recognition stage. Extracted characteristics are integrated and specified using the following three classifiers to demonstrate the working system model:

- ❖ K-Nearest Neighbor
- ❖ Random Forest Classifier
- ❖ Support Vector Machine

VI.EXPERIMENTAL RESULTS

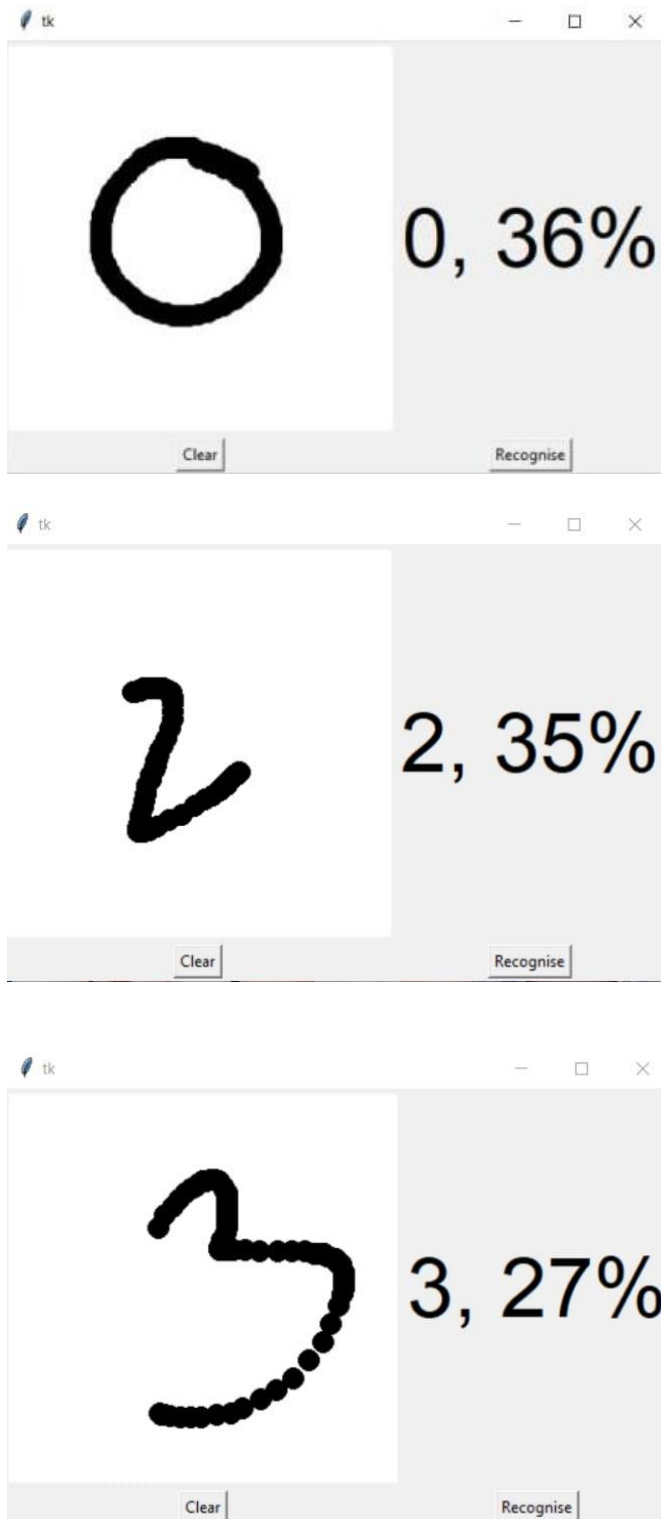


Fig.6. Shows the recognized number with accuracy value

VII.CONCLUSION

One might draw the conclusion that machine learning algorithms are quite effective at identifying trends throughout various writing styles. Handwritten digits may be recognized using a variety of techniques. It may be said that CNN recognizes and predicts handwritten digits with the highest degree of accuracy. By removing the ensemble features and adjusting the pure CNN architecture's hyperparameters, the accuracy of these conventional CNNs may be increased even further. Additionally,

by doing this, the model's implementation will be less expensive overall and computationally difficult. This method can be applied to the GPU as well as the CPU to boost efficiency by accelerating computation. Due to the reduction in training time caused by employing CUDA, a Unified Device Architecture that is computed on GPUs, the suggested machine learning model performs better overall. When it comes to the promise of this technology based on machine learning, it is extremely adaptable, has numerous uses in the banking, shipping, and postal sectors, and can help automate a few operations that are present in these specific sectors. Some of these involve automating the banking procedure and saving time by reading the cash slips' value and account number. The postal and shipping sectors may potentially profit from automated address recognition. In general, this technology may handle a wide range of complicated applications. Convolutional neural networks are trained using real-time data, which simplifies the model by cutting down on the number of variables while yet providing adequate accuracy. To get the highest level of accuracy in our project, we combined CNN with libraries like Keras, Matplotlib, CV2, and TensorFlow. CNN's accuracy was shown to be 99.63% accurate in a review of several algorithms for machine learning, including Support vector machines, K-Nearest Neighbors, Linear Regression, Convolutional Neural Networks, and Random Forest Classifier. The project might move on to the following phase by broadening its scope to incorporate different writing emphases.

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