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Intelligent Handwritten Digit Identification System for Computer Applications Using IBM Watson Studio

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ABSTRACT: Handwriting recognition is one of the most interesting areas of research because everyone has their own way of writing. It means that the computer can automatically read and understand handwritten numbers or letters. Because science and technology are getting better, everything is becoming digital to make less work for people. So, there are many real-time applications that need to be able to read handwritten numbers. This process of recognising is often done with the MNIST data set, which has 70000 handwritten digits. We train these images and build a deep learning model using artificial neural networks. A web app is made where the user can upload a picture of a handwritten number.

KEYWORDS: Handwriting recognition, MNIST, Artificial neural networks.

I. INTRODUCTION

Machine learning researchers should focus their efforts on improving the accuracy of handwritten digit recognition. It's a great approach to learn about pattern-recognition-based applications. Uses for handwritten number recognition include processing bank checks, filling out forms and distributing mail. In order to stay up with the ever-growing demands of the IT business, machine learning is one of the most significant concepts. In order to create a system that can decipher handwritten digits, we turned to machine learning techniques. For our own education in machine learning and problem solving, we conducted this experiment. Machine learning methods may be employed in a variety of ways to benefit both individuals and organisations, and this challenge is a great place to start. In machine learning, there are a variety of models for learning. They're as follows:

This dataset was created by Yann LeCun, Corinna Cortes, and Christopher Burges and is referred to as the MNIST dataset. Researchers have long been interested in using machine learning methods to create systems that can read handwritten numbers.



This dataset was created by Yann LeCun, Corinna Cortes, and Christopher Burges and is referred to as the MNIST dataset. Handwritten number recognition systems based on machine learning methods have long been a favourite of researchers. As a result, this database was ideal for testing these models since the scanned numerals were all the same size and centre. Using various classifiers for different methods and parameters may greatly reduce the mistake rate. Different handwritten digits are utilised as training examples in the MNIST dataset. Each picture in the dataset is divided into two categories: training and testing. The training dataset has 60,000 images, while the testing dataset contains 10,000. Both sets of data include photographs of the 0–9 digits that have been appropriately labelled. Grayscale photographs of the numerals written by hand are exhibited. Handwritten digits are represented by a target label and a picture, both of which are included in every MNIST data point. There isn't much data cleaning required while working with the MNIST dataset, so you may concentrate on your machine learning or deep learning model's aim.



Fig: Various styles of handwritten labels within the dataset

II. LITERATURE SURVEY

Automated systems that can read human-handwritten numbers can be built using machine learning methods. There are a variety of ways to handle this issue, and each one has its own advantages and disadvantages. There is generally a trade-off between speed and accuracy when putting these sorts of systems together using various algorithms. In order to train a model more quickly, some methods sacrifice accuracy. Other algorithms require a long time to train, but the final results are more accurate. Many implementations of this technology need a high level of precision, while others may require the model to be trained more quickly but with greater error margins. It is possible to compare the outcomes of various algorithms since they differ in terms of how long it takes and how effectively it works. More emphasis is being placed on accuracy in our studies, and we'll be comparing the methods used by various algorithms to achieve this goal. In our suggested project, we used a Convolutional Neural Network to construct a system that can read numbers written by hand, using this technology. We used a lot of convolution and pooling layers in our model's training to ensure that it was very accurate. The task we want to undertake requires a high level of proficiency in recognising digit strings in order to be able to transform the recognised decimal number into the binary, octal, or hexadecimal number system. According to our findings, CNN is the algorithm of choice for obtaining the most precise results.

III. SYSTEM DESIGN

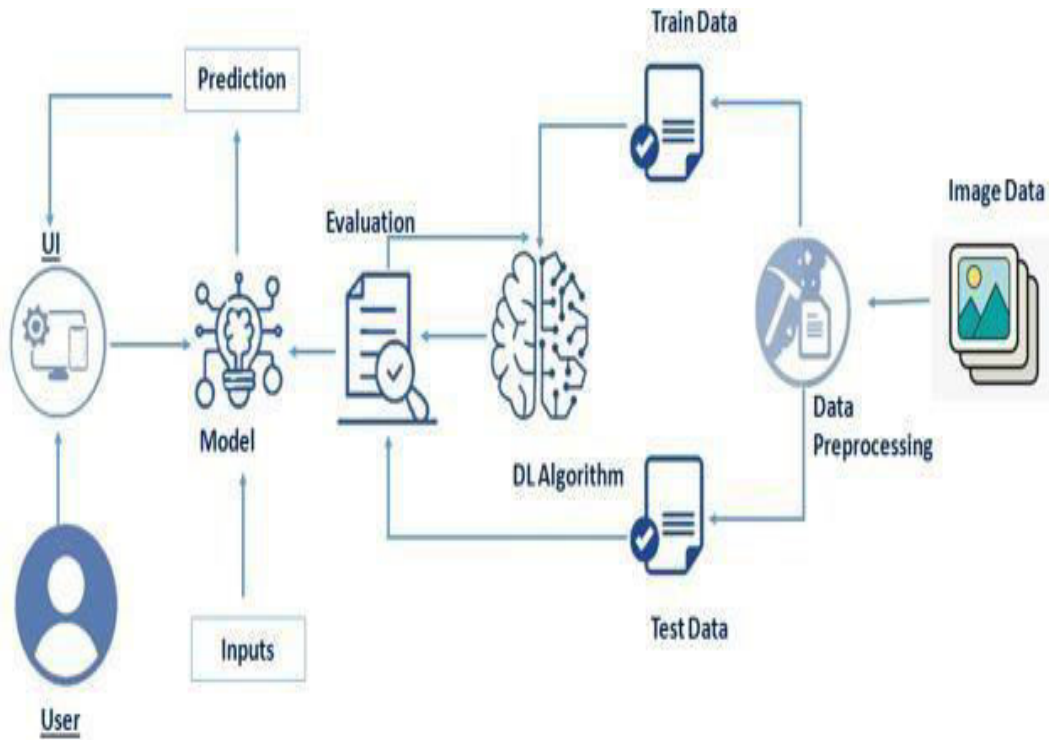


Fig:ArchitectureDiagram

Data Pre-Processing: The pre-processing step does different things to the image that comes in. It basically improves the picture by making it easier to divide into parts. The main reason for pre-processing is to pull an interesting example out of the background. During this stage, most of the noise filtering, smoothing, and standardising will be done. The example is also shown in a smaller way because of the pre-processing. Binarization turns a grayscale picture into a binary picture.

Train and Test Data: When training a model, we first divide it into two parts called "Training data" and "Testing data." The "training data set" is used to teach the classifier how to work, and the "test data set" is used to see how well it works. Training set: The training set is what a computer uses to learn how to handle information. The training part of machine learning is done by algorithms. The training data set is used to learn and adjust the classifier's settings.

Testset: A set of unknown data that is only used to test how well a fully-specified classifier works.

Evaluation: Model evaluation is a key part of the process of making a model. It helps figure out which model best fits the data and how well the model chosen will work in the future. You can tune the model's hyperparameters and improve its accuracy to make it better. By adding more true positives and true negatives, the confusion matrix can be used to make things better. The output is predicted by looking at both the input and output test data. The output is then shown.

Model Selection: Model selection is the process of choosing one final machine learning model for a training dataset from a group of candidate models. Model selection is a process that can be used with different kinds of models and with the same kind of models that have been set up with different model hyper parameters.

Algorithm identifier:

DL Algorithm: DL algorithms look at how information is processed in patterns to see if they can find patterns like our brains do and then classify the information based on those patterns. DL works with bigger sets of data than ML, and machines take care of the prediction mechanism.

CNN: A convolutional neural network, or CNN, is a deep learning neural network that was designed to process structured arrays of data, like pictures. At the moment, these algorithms are the best ones we have for automatically processing images. Many businesses use these algorithms to do things like figure out what's in a picture. Images have information in the form of RGB values.

IV. RESULTS AND DISCUSSION

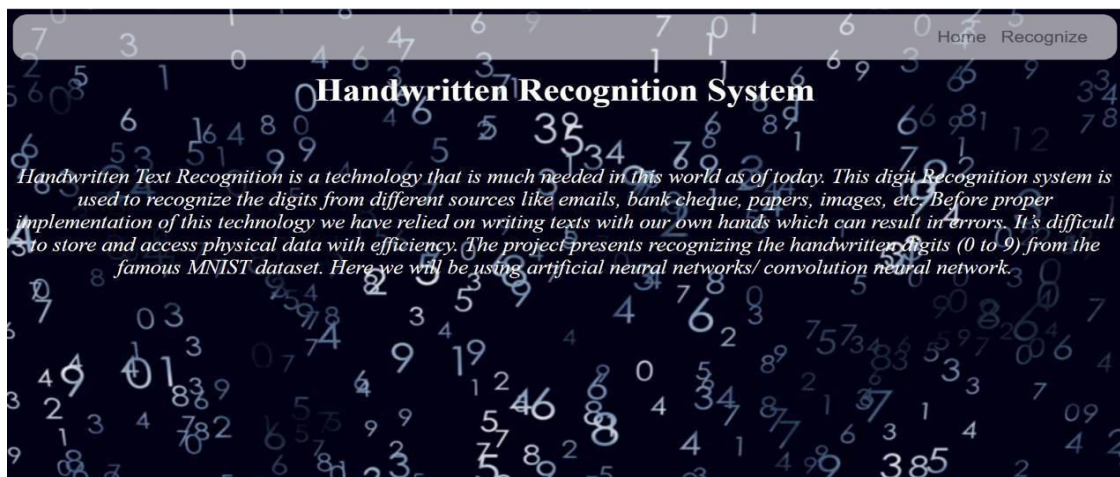


Fig : HomePage

We use HTML to create the front-end part of the web page. Here, we created 2 html pages-index.html, web.html. This how our index.html file looks like and here is the main page which describes about the **handwritten recognition system** and summarizes it.

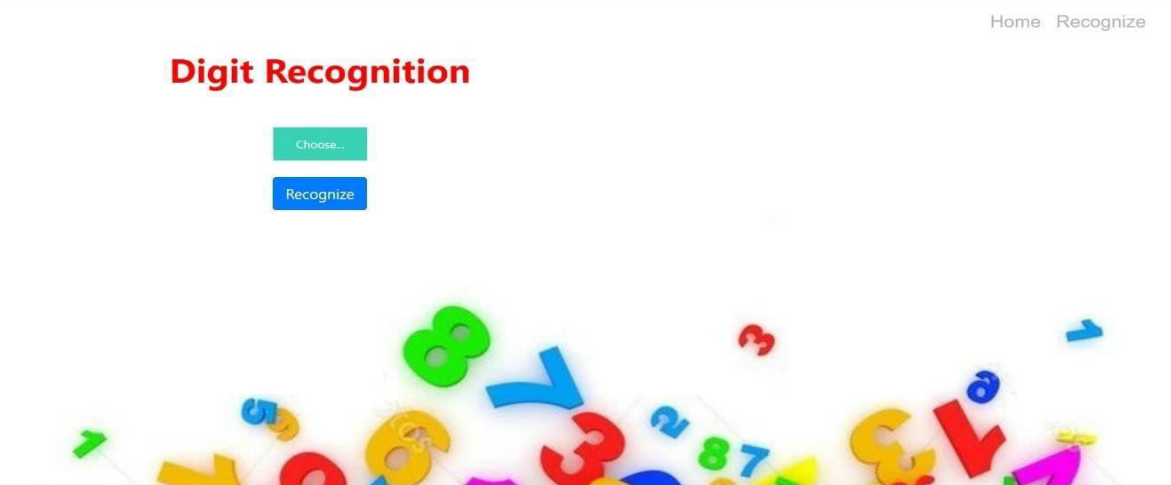


Fig: Digit Recognition Page

This is how our web.html page looks like and here is the prediction page where we get to choose the image from our local system and predict the output.

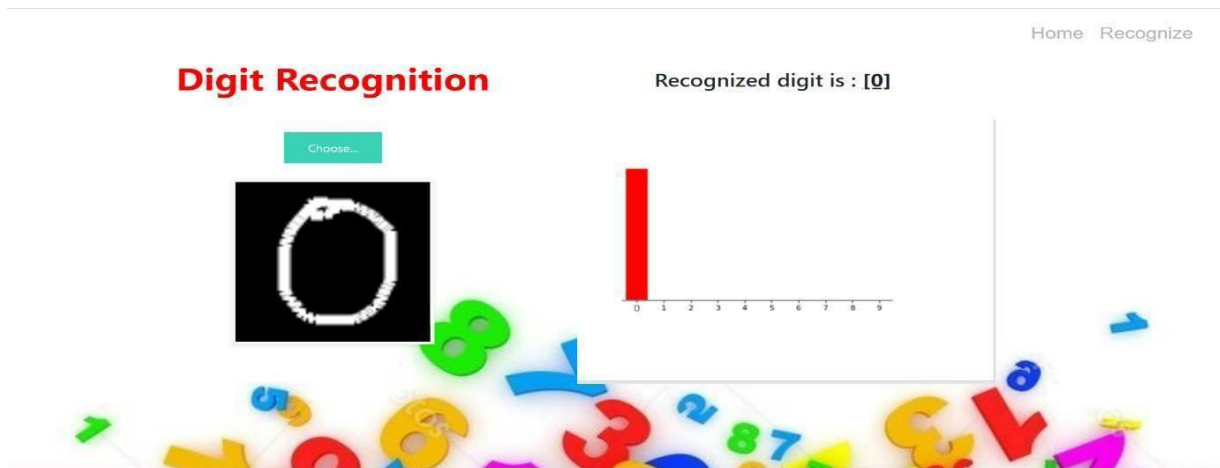


Fig: Digit Recognition of 0

After uploading an image here, we can see the predicted output. Digit recognition of 0 has been shown in the above figure.

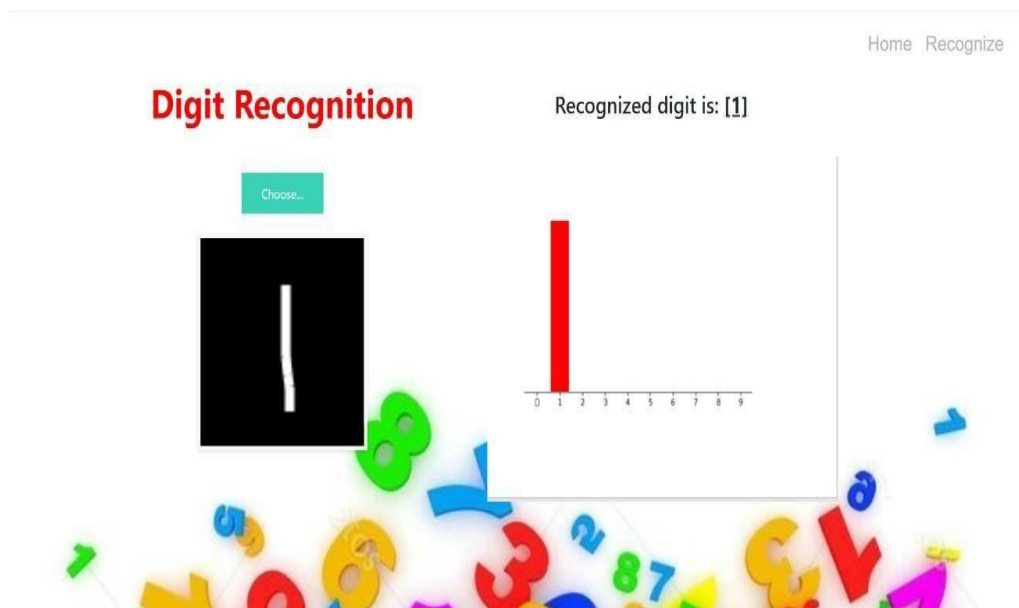


Fig: Digit Recognition of 1

In the above figure, handwritten digit recognition of 1 has been shown, and the output of handwritten digit 1 has been predicted in the graphical representation.

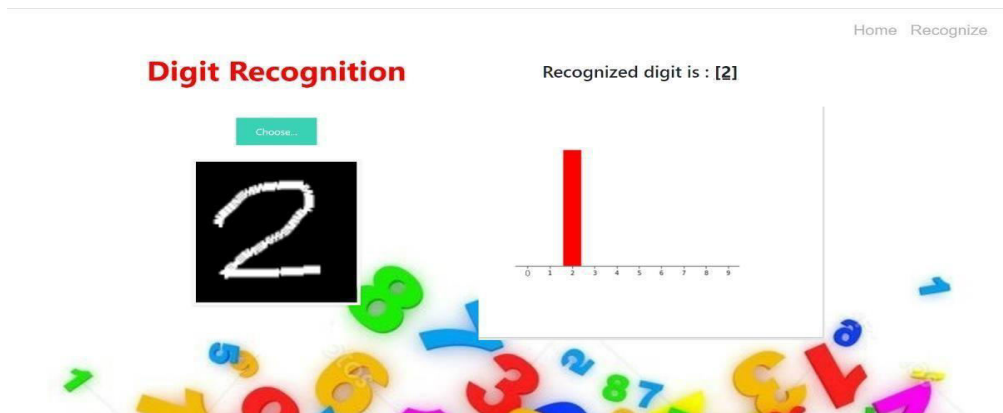


Fig: DigitRecognitionof2

In the above figure handwritten digit recognition of 2 has been shown and the output of handwritten digit 2 has been predicted in the graphical representation.

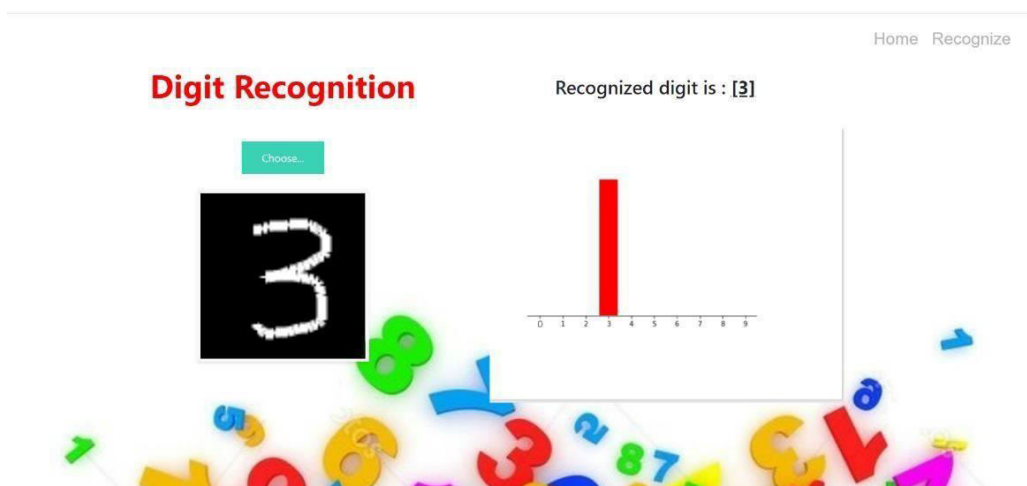


Fig:DigitRecognitionof3

In the above figure handwritten digit recognition of 3 has been shown and the output of handwritten digit 3 has been predicted in the graphical representation.

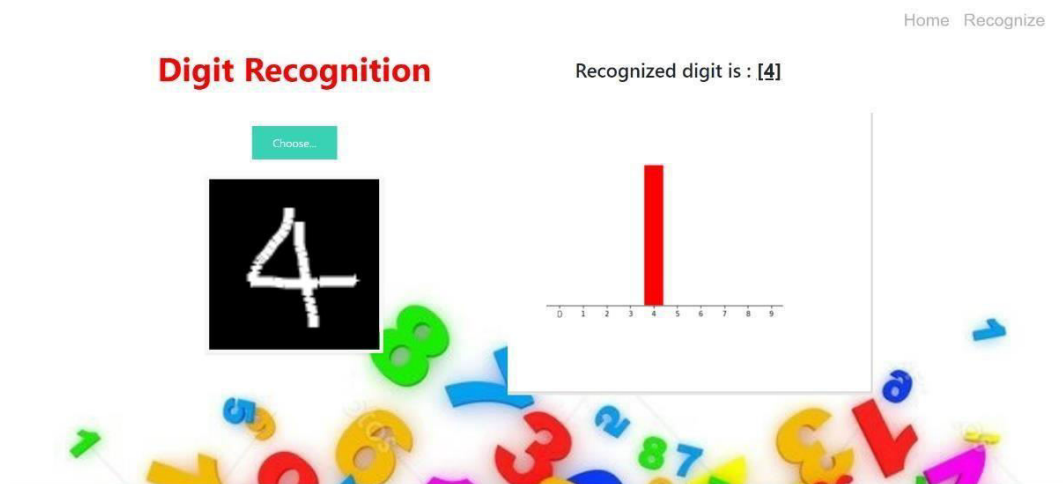


Fig:DigitRecognitionof4

In the above figure handwritten digit recognition of 4 has been shown and the output of handwritten digit 4 has been predicted in the graphical representation.

V. CONCLUSION

Deep learning methods have been used to make Handwritten Digit Recognition work. KNN, SVM, RFC, and CNN, which are the most popular Machine Learning algorithms, have been trained and tested on the same data so that they can be compared. With these deep learning techniques, you can get a high level of accuracy. Unlike other research methods, this one focuses on figuring out which classifier works best by making classification models more accurate by more than 99 percent. When Keras is used as the backend and TensorFlow is used as the software, a CNN model can be about 98.72 percent accurate. In this first test, CNN is 98.72% accurate, KNN is 96.67% accurate, and RFC and SVM are not that great.

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