Handwritten Digit Recognition using Deep Learning

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Abstract—The reliance of humans over machines has never been so high such that from object classification in photographs to adding sound to silent movies everything can be performed with the help of deep learning and machine learning algorithms. Likewise, handwritten text recognition is one of the significant areas of research and development with a streaming number of possibilities that could be attained. Handwriting recognition (HWR), also known as Handwritten Text Recognition (HTR), is the ability of a computer to receive and interpret intelligible handwritten input from sources such as paper documents, photographs, touch-screens and other devices [1]. Apparently, in this paper, we have performed handwritten digit recognition with the help of MNIST datasets using Support Vector Machines (SVM), Multi-Layer Perceptron (MLP) and Convolution Neural Network (CNN) models. Our main objective is to compare the accuracy of the models stated above along with their execution time to get the best possible model for digit recognition.

Keywords: Deep Learning, Machine Learning, Handwritten Digit Recognition, MNIST datasets, Support Vector Machines (SVM), Multi-Layered Perceptron (MLP), and Convolution Neural Network (CNN).

I. INTRODUCTION

Handwritten digit recognition is the ability of a computer to recognize the human handwritten digits from different sources like images, papers, touch screens, etc, and classify them into 10 predefined classes (0-9). This has been a topic of boundless-research in the field of deep learning. Digit recognition has many applications like number plate recognition, postal mail sorting, bank check processing, etc [2]. In Handwritten digit recognition, we face many challenges because of different styles of writing of different peoples as it is not an Optical character recognition. This research provides a comprehensive comparison between different machine learning and deep learning algorithms for the purpose of handwritten digit recognition. For this, we have used Support Vector Machine, Multilayer Perceptron, and Convolutional Neural Network. The comparison between these algorithms is carried out on the basis of their accuracy, errors, and testing-training time corroborated by plots and charts that have been constructed using matplotlib for visualization.

The accuracy of any model is paramount as more accurate models make better decisions. The models with low accuracy are not suitable for real-world applications. Ex- For an automated bank cheque processing system where the system recognizes the amount and date on the check, high accuracy is very critical. If the system incorrectly recognizes a digit, it can lead to major damage which is not desirable. That's why an algorithm with high accuracy is required in these real world applications. Hence, we are providing a comparison of different algorithms based on their accuracy so that the most accurate algorithm with the least chances of errors can be employed in various applications of handwritten digit recognition.

This paper provides a reasonable understanding of machine learning and deep learning algorithms like SVM, CNN, and MLP for handwritten digit recognition. It furthermore gives you the information about which algorithm is efficient in performing the task of digit recognition. In further sections of this paper, we will be discussing the related work that has been done in this field followed by the methodology and implementation of all the three algorithms for the fairer understanding of them. Next, it presents the conclusion and result bolstered by the work we have done in this paper. Moreover, it will also give you some potential future enhancements that can be done in this field. The last section of this paper contains citations and references used.

II. RELATED WORK

With the humanization of machines, there has been a substantial amount of research and development work that has given a surge to deep learning and machine learning along with artificial intelligence. With time, machines are getting more and more sophisticated, from calculating the basic sums to doing retina recognition they have made our lives more secure and manageable. Likewise, handwritten text recognition is an important application of deep learning and machine learning which is helpful in detecting forgeries and a wide range of research has already been done that encompasses a comprehensive study and implementation of various popular algorithms like works done by S M Shamim [3], Anuj Dutt [4], Norhidayu binti [5] and Hongkai

Wang [8] to compare the different models of CNN with the fundamental machine learning algorithms on different grounds like performance rate, execution time, complexity and so on to assess each algorithm explicitly. [3] concluded that the Multilayer Perceptron classifier gave the most accurate results with minimum error rate followed by Support Vector Machine, Random Forest Algorithm, Bayes Net, Na¨ıve Bayes, j48, and Random Tree respectively while [4] presented a comparison between SVM, CNN, KNN, RFC and were able to achieve the highest accuracy of 98.72% using CNN (which took maximum execution time) and lowest accuracy using RFC. [5] did the detailed study-comparison on SVM, KNN and MLP models to classify the handwritten text and concluded that KNN and SVM predict all the classes of dataset correctly with 99.26% accuracy but the thing process goes little complicated with MLP when it was having trouble classifying number 9, for which the authors suggested to use CNN with Keras to improve the classification. While [8] has focused on comparing deep learning methods with machine learning methods and comparing their characteristics to know which is better for classifying mediastinal lymph node metastasis of non-small cell lung cancer from 18 F-FDG PET/CT images and also to compare the discriminative power of the recently popular PET/CT texture features with the widely used diagnostic features. It concluded that the performance of CNN is not significantly different from the best classical methods and human doctors for classifying mediastinal lymph node metastasis of NSCLC from PET/CT images. However, CNN does not make use of the import diagnostic features, which have been proved more discriminative than the texture features for classifying small sized lymph nodes. Therefore, incorporating the diagnostic features into CNN is a promising direction for future research.

III. METHODOLOGY

The comparison of the algorithms (Support vector machines, Multi-layered perceptron and Convolutional neural network) is based on the characteristic chart of each algorithm on common grounds like dataset, the number of epochs, complexity of the algorithm, accuracy of each algorithm, specification of the device (Ubuntu 20.04 LTS, i5 7th gen processor) used to execute the program and runtime of the algorithm, under ideal condition.

A. DATASET

Handwritten character recognition is an expansive research area that already contains detailed ways of implementation which include major learning datasets, popular algorithms, features scaling and feature extraction methods. MNIST dataset (Modified National Institute of Standards and Technology database) is the subset of the NIST dataset which is a combination of two of NIST's databases: Special Database 1 and Special Database 3. Special Database 1 and Special Database 3 consist of digits written by high school students and employees of the United States Census Bureau, respectively. MNIST contains a total of 70,000 handwritten digit images (60,000 - training set and 10,000 - test set) in 28x28 pixel bounding box and anti-aliased. All these images have corresponding Y values which apprises what the digit is.

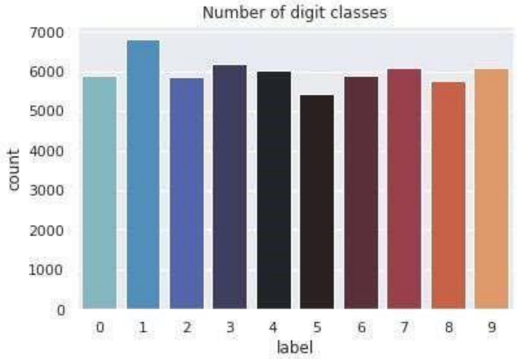


Figure 1. Bar graph illustrating the MNIST handwritten digit training dataset (Label vs Total number of training samples).

Figure 2. Plotting of some random MNIST Handwritten digits.

B. SUPPORT VECTOR MACHINE

Support Vector Machine (SVM) is a supervised machine learning algorithm. In this, we generally plot data items in n-dimensional space where n is the number of features, a particular coordinate represents the value of a feature, we perform the classification by finding the hyperplane that distinguishes the two classes. It will choose the hyperplane that separates the classes correctly. SVM chooses the extreme vectors that help in creating the hyperplane. These extreme cases are called support vectors, and hence the algorithm is termed as Support Vector Machine. There are mainly two types of SVMs, linear and non-linear SVM. In this paper, we have used Linear SVM for handwritten digit recognition [10].

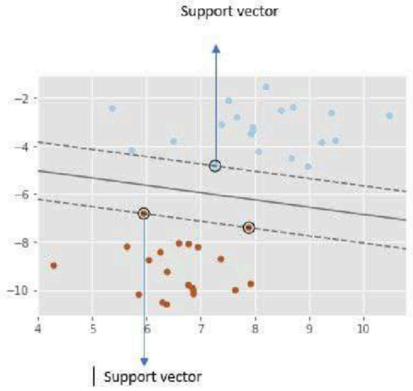


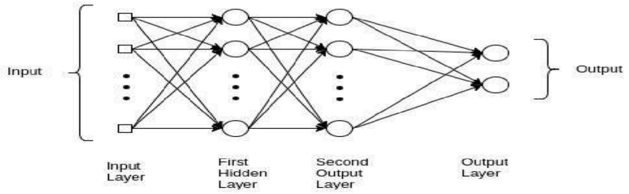
Figure 3. This image describes the working mechanism of SVM Classification with supporting vectors and hyperplanes.

C. *MULTILAYERED PERCEPTRON*

A multilayer perceptron (MLP) is a class of feedforward artificial neural networks (ANN). It consists of three layers: input layer, hidden layer and output layer. Each layer consists of several nodes that are also formally referred to as neurons and each node is interconnected to every other node of the next layer. In basic MLP there are 3 layers but the number of hidden layers can increase to any number as per the problem with no restriction on the number of nodes. The number of nodes in the input and output layer depends on the number of attributes and apparent classes in the dataset respectively. The particular number of hidden layers or numbers of nodes in the hidden layer is difficult to determine due to the model erratic nature and therefore selected experimentally. Every hidden layer of the model can have different activation functions for processing. For learning purposes, it uses a supervised learning technique called backpropagation. In the MLP, the connection of the nodes consists of a weight that gets adjusted to synchronize with each connection in the training process of the model[11].

Figure 4. This figure illustrates the basic architecture of the Multilayer perceptron with variable specification of the network.

D. *CONVOLUTIONAL NEURAL NETWORK*



CNN is a deep learning algorithm that is widely used for image recognition and classification. It is a class of deep neural networks that require minimum pre-processing. It inputs the image in the form of small chunks rather than inputting a single pixel at a time, so the network can detect uncertain patterns (edges) in the image more efficiently. CNN contains 3 layers namely, an input layer, an output layer, and multiple hidden layers which include Convolutional layers, Pooling layers(Max and Average pooling), Fully connected layers (FC), and normalization layers [12]. CNN uses a filter (kernel) which is an array of weights to extract features from the input image. CNN employs different activation functions at each layer to add some non-linearity [13]. As we move into the CNN, we observe the height and width decrease while the number of channels increases. Finally, the generated column matrix is used to predict the output [14].

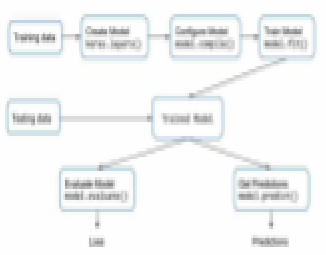


Figure 7. Detailed architecture of Convolutional Neural Network with apt specifications of each layer

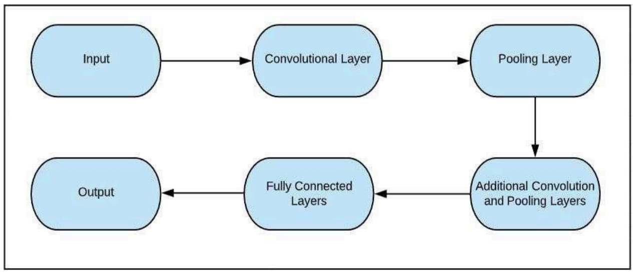


Figure 5. This figure shows the architectural design of CNN layers in the form of a Flow chart.

E. *VISUALIZATION*

In this research, we have used the MNIST dataset (i.e. handwritten digit dataset) to compare different level algorithm of deep and machine learning (i.e. SVM, ANN-MLP, CNN) on the basis of execution time, complexity, accuracy rate, number of epochs and number of hidden layers (in the case of deep learning algorithms). To visualize the information obtained by the detailed analysis of algorithms we have used bar graphs and tabular format charts using module matplotlib, which gives us the most precise visuals of the step by step advances of the algorithms in recognizing the digit. The graphs are given at each vital part of the programs to give visuals of each part to bolster the outcome.

IV. IMPLEMENTATION

To compare the algorithms based on working accuracy, execution time, complexity, and the number of epochs (in deep learning algorithms) we have used three different classifiers:

- Support Vector Machine Classifier
- ANN - Multilayer Perceptron Classifier
- Convolutional Neural Network Classifier

We have discussed in detail about the implementation of each algorithm explicitly below to create a flow of this analysis to create a fluent and accurate comparison.

I. *PRE-PROCESSING*

Pre-processing is an initial step in the machine and deep learning which focuses on improving the input data by reducing unwanted impurities and redundancy. To simplify and break down the input data we reshaped all the images present in the dataset in 2-dimensional images i.e (28,28,1). Each pixel value of the images lies between 0 to 255 so, we Normalized these pixel values by converting the dataset into 'float32' and then dividing by 255.0 so that the input features will range between 0.0 to 1.0. Next, we performed one-hot encoding to convert the y values into zeros and ones, making each number categorical, for example, an output value 4 will be converted into an array of zero and one i.e [0 ,0,0,0,1,0,0,0, 0,0].

II. *SUPPORT VECTOR MACHINE*

The SVM in scikit-learn [16] supports both dense (numpy.ndarray and convertible to that by numpy.asarray) and sparse (any scipy.sparse) sample vectors as input. In scikit-learn, SVC, NuSVC and LinearSVC are classes capable of performing multi-class classification on a dataset. In this paper we have used LinearSVC for classification of MNIST datasets that make use of a Linear kernel implemented with the help of LIBLINEAR [17].

Various scikit-learn libraries like NumPy, matplotlib, pandas, Sklearn and seaborn have been used for the implementation purpose. Firstly, we will download the MNIST datasets, followed by loading it and reading those CSV files using pandas.

After this, plotting of some samples as well as converting into matrix followed by normalization and scaling of features have been done. Finally, we have created a linear SVM model and confusion matrix that is used to measure the accuracy of the model [9].

V. CONVOLUTIONAL NETWORK

III. The implementation of handwritten digit recognition by Convolutional Neural Network [15] is done using Keras. It is an open-source neural network library that is used to design and implement deep learning models. From Keras, we have used a Sequential class which allowed us to create model layer-by-layer. The dimension of the input image is set to 28(Height), 28(Width), 1(Number of channels). Next, we created the model whose first layer is a Conv layer [20]. This layer uses a matrix to convolve around the input data across its height and width and extract features from it. This matrix is called a Filter or Kernel. The values in the filter matrix are weights. We have used 32 filters each of the dimensions (3,3) with a stride of 1. Stride determines the number of pixels shifts. Convolution of filter over the input data gives us activation maps whose dimension is given by the formula: ((N + 2P - F)/S) + 1 where N= dimension of input image, P= padding, F= filter dimension and S=stride. In this layer, Depth (number of channels) of the output image is equal to the number of filters used. To increase the non-linearity, we have used an activation function that is Relu [21]. Next, another convolutional layer is used in which we have applied 64 filters of the same dimensions (3,3) with a stride of 1 and the Relu function.

Next, to these layers, the pooling layer [22] is used which reduces the dimensionality of the image and computation in the network. We have employed MAX-pooling which keeps only the maximum value from a pool. The depth of the network remains unchanged in this layer. We have kept the pool-size (2,2) with a stride of 2, so every 4 pixels will become a single pixel. To avoid overfitting in the model, Dropout layer [23] is used which drops some neurons which are chosen randomly so that the model can be simplified. We have set the probability of a node getting dropped out to 0.25 or 25%. Following it, Flatten Layer [23] is used which involves flattening i.e. generating a column matrix (vector) from the 2-dimensional matrix. This column vector will be fed into the fully connected layer [24]. This layer consists of 128 neurons with a dropout probability of 0.5 or 50%. After applying the Relu activation function, the output is fed into the last layer of the model that is the output layer. This layer has 10 neurons that represent classes (numbers from 0 to 9) and the SoftMax function [25] is employed to perform the classification. This function returns probability distribution over all the 10 classes. The class with the maximum probability is the output.

VI. RESULT

After implementing all the three algorithms that are SVM, MLP and CNN we have compared their accuracies and execution time with the help of experimental graphs for perspicuous understanding. We have taken into account the Training and Testing Accuracy of all the models stated above. After executing all the models, we found that SVM has the highest accuracy on training data while on testing dataset CNN accomplishes the utmost accuracy. Additionally, we have compared the execution time to gain more insight into the working of the algorithms. Generally, the running time of an algorithm depends on the number of operations it has performed. So, we have trained our deep learning model up to 30 epochs and SVM models according to norms to get the apt outcome. SVM took the minimum time for execution while CNN accounts for the maximum running time.

Figure 8. This table represents the overall performance for each model. The table contains 5 columns, the 2nd column represents model name, 3 rd and 4th column represents the training and testing accuracy of models, and 5th column represents execution time of models.

Figure 9. Bar graph depicting accuracy comparison (SVM (Train: 99.98%, Test: 93.77%), MLP (Train: 99.92%, Test: 98.85%), CNN (Train: 99.53 %, Test: 99.31%)).

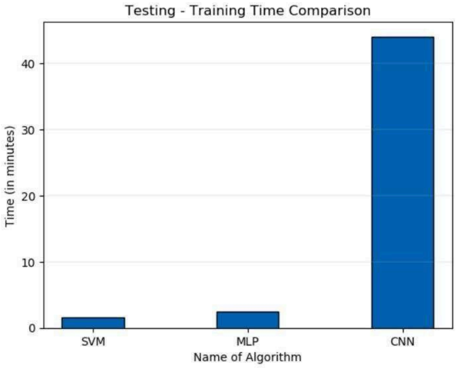


Figure 10. Bar graph showing execution time comparison of SVM, MLP and CNN (SVM: 1.58 mins, MLP: 2.53 mins, CNN: 44.05 mins).

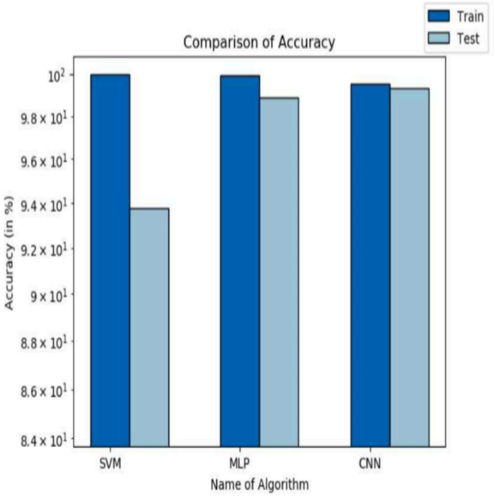
Furthermore, we visualized the performance measure of deep learning models and how they ameliorated their accuracy and reduced the error rate concerning the number of epochs. The significance of sketching the graph is to know where we should apply early stop so that we can avoid the problem of overfitting as after some epochs, change in accuracy becomes constant.

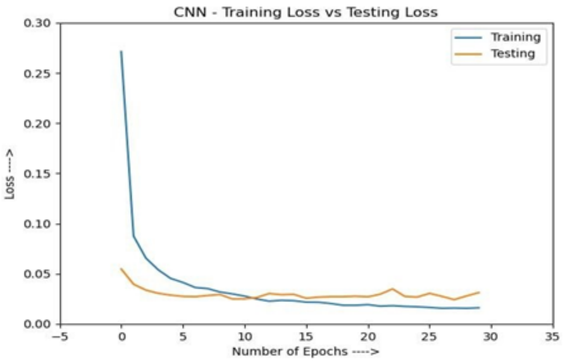
Figure 12. Graph illustrating the transition of training accuracy with increasing number of epochs in Multilayer Perceptron (Accuracy v/s Number of epochs).

Figure 13. Graph illustrating the transition of training loss of CNN with increasing number of epochs (Loss rate v/s Number of epochs).

TABLE I
COMPARISON ANALYSIS OF DIFFERENT MODELS.

MODEL	TRAINING RATE	TESTING RATE	EXECUTION TIM
SVM	99.98%	94.005%	1:35 min
MLP	99.92%	98.85%	2:32 min
CNN	99.53%	99.31%	44:02 min





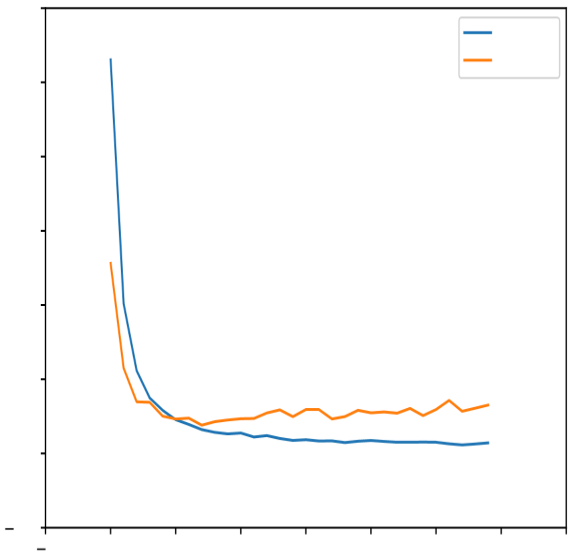
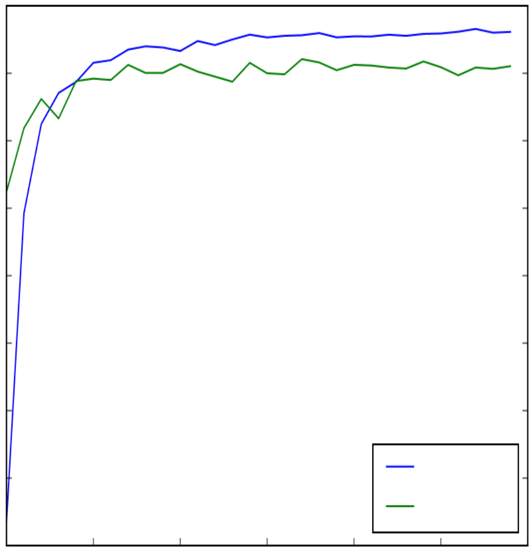


Figure 11. Graph illustrating the transition of training loss with increasing number of epochs in Multilayer Perceptron (Loss rate v/s Number of epochs).

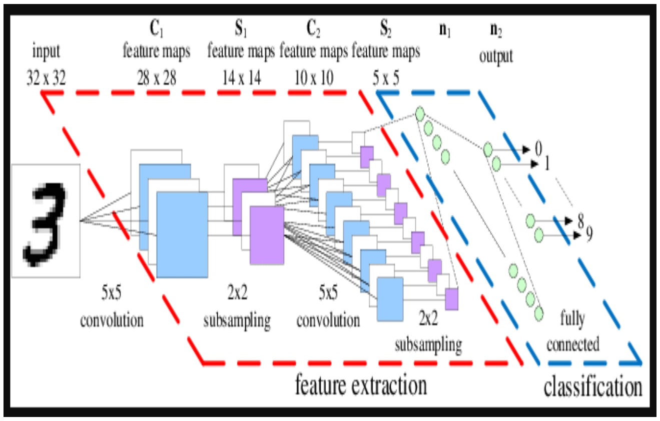


VII. SIMULATION

Working model prototype diagram of this project:

```
+---------------------------------+
|                                 |
|          Input Image            |
|                                 |
+-------+-------------------------+
        |
        |
        v
+-------+---------+
|  Preprocessing  |
|  Module         |
+-------+---------+
        |
        |
        v
+-------+---------+
| Convolutional   |
| Neural Network  |
| (CNN)           |
+-------+---------+
        |
        |
        v
+-------+---------+
| Fully           |
| Connected       |
| Neural Network  |
| (FCNN)          |
+-------+---------+
        |
        |
        v
+-------+---------+
| Softmax         |
| Classifier      |
+-------+---------+
        |
        |
        v
+-----------------+
| Output          |
| (Predicted      |
| Digit)          |
+-----------------+
```

Fig 12:



EXPLANATION:

Input Image: This represents the handwritten digit image that needs to be recognized.

Preprocessing Module: This module performs preprocessing steps on the input image, such as resizing, normalization, and possibly noise removal, to prepare it for deep learning model input.

Convolutional Neural Network (CNN): This module consists of multiple convolutional layers followed by activation functions (e.g., ReLU) and pooling layers. The CNN is designed to automatically extract relevant features from the input image through convolution and pooling operations.

Fully Connected Neural Network (FCNN): This module consists of one or more fully connected layers that take the features extracted by the CNN and perform higher-level abstractions and classifications. The FCNN layers connect all neurons from the previous layer to the next, allowing for complex patterns and relationships to be learned.

Softmax Classifier: This module applies the softmax function to the output of the FCNN, which produces a probability distribution over the possible digit classes. The highest probability corresponds to the predicted digit.

Output (Predicted Digit): The final output of the system is the predicted digit, which represents the recognized handwritten digit from the input image.

A picture of the output from the model when '8' was drawn as a human digit drawing on GUI:

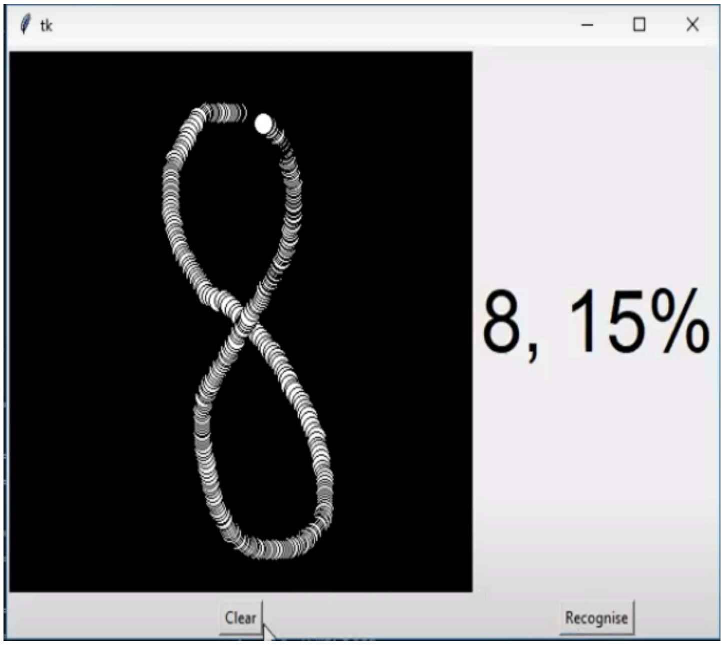


Fig13

VIII. CONCLUSION

In this research, we have implemented three models for handwritten digit recognition using MNIST datasets, based on deep and machine learning algorithms. We compared them based on their characteristics to appraise the most accurate model among them. Support vector machines are one of the basic classifiers that's why it's faster than most algorithms and in this case, gives the maximum training accuracy rate but due to its simplicity, it's not possible to classify complex and ambiguous images as accurately as achieved with MLP and CNN algorithms. We have found that CNN gave the most accurate results for handwritten digit recognition. So, this makes us conclude that CNN is best suitable for any type of prediction problem including image data as an input. Next, by comparing execution time of the algorithms we have concluded that increasing the number of epochs without changing the configuration of the algorithm is useless because of the limitation of a certain model and we have noticed that after a certain number of epochs the model starts overfitting the dataset and give us the biased prediction.

IX. REFERENCES

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