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Handwritten Digit Recognition using Machine Learning

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Abstract: *Deep learning is remarkably used in vast ranges of fields because of its diverse range of applications such as surveillance, health, medicine, sports, robotics, drones, etc. In deep learning, Convolutional Neural Network (CNN) is at the Centre of spectacular advances that mixes Artificial Neural Network (ANN) and up to date deep learning strategies. It has been used broadly in pattern recognition, sentence classification, speech recognition, face recognition, text categorization, document analysis, scene, and handwritten digit recognition. The goal of this Project is to observe the variation of accuracy of CNN to classify handwritten digits using various numbers of hidden layers and epochs and to make the comparison between the ac-curacies. For this performance evaluation of CNN, we performed our experiment using Modified National Institute of Standards and Technology (MNIST) datasets. Further, the network is trained using VGG61 model*

Objective

The objective for this project is to create a system that could detect and extract hand written digit from images or scanned documents which can be converted into an editable format with maximum accuracy.

The main objectives of the project are as follows:

- *To design an image classifier model for implementing the handwritten detection algorithm to detect digits.*
- *To make an easy-to-use user interface to predict the handwritten digits.*
- *Evaluate the results from trained model.*

Scope

Data Collection: Gathering a dataset of handwritten digit images is an essential part of developing a machine learning model for digit recognition. This may involve collecting samples from different sources, such as publicly available datasets or creating a custom dataset.

Data Preprocessing: Preprocessing the collected data is crucial to ensure the quality suitability of the dataset for training the model. This step may involve tasks like resizing images, normalizing pixel values, removing noise, and augmenting the dataset through techniques like rotation, scaling, or adding noise

The rapid proliferation of the Internet of Things (IoT) has led to the integration of numerous smart and interconnected devices in various domains. To ensure seamless communication in IoTnetworks with mobile devices, efficient and adaptive routing protocols are essential. This paperpresents a comprehensive study on optimizing routing protocols for IoT networks with mobile devices. We analyze the challenges posed by mobility in IoT networks and propose novel solutions to enhance the performance of routing protocols. The proposed optimizations are evaluated through simulations and real-world experiments, by demonstrating significant improvements in network efficiency, scalability,and reliability

Keywords: Internet ofThings

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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. 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.Forthis, 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

II. LITERATURE SURVEY

[1] R. B. Arif, M. A. B. Siddique, M. M. R. Khan, and M. R. Oishe, "Study and Observation of the Variations of Accuracies for Handwritten Digits Recognition with Various Hidden Layers and Epochs using Convolutional Neural Network," in 2018 4th International Conference on Electrical Engineering and Information & Communication Technology (iCEEiCT), 2018.Nowadays, deep learning can be employed to a wide ranges of fields including medicine, engineering, etc. In deep learning, Convolutional Neural Network (CNN) is extensively used in the pattern and sequence recognition, video analysis, natural language processing, spam detection, topic categorization, regression analysis, speech recognition, image classification, object detection, segmentation, face recognition, robotics, and control. The benefits associated with its near human level accuracies in large applications lead to the growing acceptance of CNN in recent years. The primary contribution of this paper is to analyze the impact of the pattern of the hidden layers of a CNN over the overall performance of the network. To demonstrate this influence, we applied neural network with different layers on the Modified National Institute of Standards and Technology (MNIST) dataset. Also, is to observe the variations of accuracies of the network for various numbers of hidden layers and epochs and to make comparison and contrast among them. The system is trained utilizing stochastic gradient and back propagation algorithm and tested with feed forward algorithm.

[2] D. C. Ciresan, U. Meier, J. Masci, L. M. Gambardella, and J. Schmidhuber, "Flexible, high performance convolutional neural networks for image classification," in Twenty -Second International Joint Conference on Artificial Intelligence,2011.We present a fast, fully paramaterizable GPU implementation of Convolutional Neural Network variants. Our feature extractors are neither care-fully designed nor pre-wired, but rather learnedin a supervised way. Our deep hierarchical architectures achieve the best published results on bench- marks for object classification (NORB, CIFAR10) and handwritten digit recognition(MNIST), with error rates of 2.53%, 19.51%, 0.35%, respectively. Deep nets trained by simple back propagation per- form better than more shallow ones. Learning is surprisingly rapid. NORB Handwritten digit recognition using ML Page 5 is completely trained within five epochs. Test error rates on MNIST drop to 2.42%, 0.97% and0.48% after 1, 3 and 17 epochs, respectively.

[3] Y. Liu and Q. Liu, "Convolutional neural networks with large - margin softmax loss function for cognitive load recognition," in 2017 36th Chinese Control Conference (CCC) ,2017.Cognitive load recognition has been widely studied recently, but how to find the effective and robust feature representations from the electroencephalography

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(EEG) signals is still a challenge. In this paper we design lightweight 1D and 2D Convolutional Neural Networks (CNNs) with large-margin soft max loss functions for cognitive load recognition. First, we extract the frequency domain features from the EEG signals. Then, the extracted frequency feature vectors and matrices are used to train the 1D and 2D CNNs. Our approach approximately achieves 93%accuracy for 1D CNNs and 91% for 2D CNNs with shorter training time on the 4 classes of cognitive load recognition task. The results indicate that the proposed method with few parameters gets good performance and is more efficient than other deep learning methods. We find that the large-margin soft max loss function works well for EEG signal recognition, and we also find that the 1D CNNs with 3 χ 1 convolution kernel have good classification performance with few parameters and fast training rate to be more suitable for EEG signal classification than2D CNNs for small EEG dataset. However, 2D CNNs are suitable for large EEG dataset because of their fast training rate.

[4] A. Tavanaei and A. S. Maida, "Multi- layer unsupervised learning in a spiking convolutional neural network," in 2017 International Joint Conference on Neural Networks (IJCNN) , 2017.Spiking neural networks (SNNs) have advantages over traditional, non-spiking networks with respect to borealis, potential for low-power hardware implementations, and theoretical computing power. However, in practice, spiking networks with multi-layer learning have proven difficult to train. This paper explores a novel, bio-inspired spiking convolutional neural network (CNN) that is trained in a greedy, layer-wise fashion. The spiking CNN consists of convolutional/pooling layer followed by a feature discovery layer, both of which undergo bio inspired learning. Kernels for the convolutional layer are trained using a sparse, spiking auto encoder representing primary visual features. The feature discovery layer uses a probabilistic spike-timing-dependent plasticity (STDP) learning rule. This layer represents complex visual features using WTA threshold, leaky, integrate-and-fire (LIF) neurons. The new model is evaluated on the MNIST digit dataset using clean and noisy images. Intermediate results show that the convolutional layer is stack-admissible, enabling it to support a multi-layer learning architecture. The recognition performance for clean images is above 98%. This performance is accounted for by the independent and informative visual features extracted in a hierarchy of convolutional and feature discovery layers. The performance loss for recognizing the noisy images is in the range 0.1% to 8.5%. This level of performance loss indicates that the network is robust to additive noise.

[5] K. G. Pasi and S. R. Naik, "Effect of parameter variations on accuracy of Convolutional Neural Network," in 2016 International Conference on Computing, Analytics and Security Trends (CAST) , 2016.In this paper, we implement a Convolutional Neural Network especially designed for Natural Language processing. With the help of this CNN, we try to classify sentences for sentiment analysis for which the embedding's used were learned from scratch rather than using pre-trainedword2vec vectors. Here we try to vary the different parameters and learn how they effect on the performance of the CNN. From the observations we try to demonstrate that a fairly less-complex CNN that has a small amount of parameter adjustments and fine-tuning can achieve a significant growth in performance.

[6] K. B. Lee, S. Cheon, and C. O. Kim, "A convolutional neural network for fault classification and diagnosis in semiconductor manufacturing processes," IEEE Transactions on Semiconductor Manufacturing, 2017.Manual classification of particle defects on semiconductor wafers islaborintensive, which leads to slow solutions and longer learning curves on product failures while being prone to human error. This work explores the promise of deep learning for the classification of the chemical composition of these defects to reduce analysis time and inconsistencies due to human error, which in turn can result in systematic root cause analysis for sources of semiconductor defects. We investigate a deep convolutional neural network (CNN) for defect classification based on a combination of scanning electron microscopy (SEM) images and energy-dispersive x-ray (EDX)spectroscopy data. SEM images of sections of semiconductor wafers that contain particle defects are fed into a CNN in which the defects' EDX spectroscopy data is merged directly with the CNN's fully connected layer. The proposed CNN classifies the chemical composition of semiconductor wafer particle defects with an industrially pragmatic accuracy. We that merging spectral data with the CNN's fully connected layer significantly improves classification performance over CNNs that only take either SEM image data or EDXspectraldata as an input. The impact of training data collection and augmentation on CNN performance is explored and the promise of transfer learning for improving training speed and testing accuracy is investigated.

[7] K. Isogawa, T. Ida, T. Shiodera, and T. Takeguchi, "Deep shrinkage convolutional neural network for adaptive noise reduction," IEEE Signal Processing Letters, 2018. The noise level of an image depends on settings of an imaging

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device. The settings can be used to select appropriate parameters for devoicing methods. But devoicing methods based on deep convolutional neural networks (deep-CNN) do not have such adjustable parameters. Therefore, a deep-CNN whose training data contain limited levels of noise does not effectively restore images whose noise level is different from the training data. If the range of noise levels of training datais extended to solve the problem, the maximum performance of a produced deep-CNN is limited. To solve the tradeoff, we propose a deep-CNN that is adjustable to the noise level of the input image immediately. We use soft shrinkage for activation functions of our deep-CNN. The soft shrinkage has thresholds proportional to the noise level given by the user. We also propose an optimization method for proportionality coefficients for the thresholds of soft shrinkage. Our method optimizes the coefficients for various noise levels simultaneously. In our experiment using a test set whose noise level is from 5 to 50, the proposed method showed higher PSNR than that in the case of the conventional method using only one deep-CNN, and PSNR comparable to that in the case of the conventional method using multiple noise-level-specific CNNs. Handwritten digit recognition using ML Introduction

[8] C. C. Park, Y. Kim, and G. Kim, "Retrieval of sentence sequences for an image stream via coherence recurrent convolutional networks," IEEE transactions on pattern analysis and machine intelligence,2018.fig.2.1We propose an approach for retrieving a sequence of natural sentences for an image stream. Since general users often take a series of pictures on their experiences, much online visual information exists in the form of image streams, for which it would better take into consideration of the whole image stream to produce natural language descriptions. While almost all previous have dealt with the relation between a single image and a single natural sentence, our
work extends both input and output dimension to a sequence of images and a sequence of sentences. For retrieving a coherent flow of multiple sentences for a photo stream, we propose multimodal neural architecture called coherence recurrent convolutional network (CRCN), which consists of convolutional neural networks, bidirectional long short-term memory (LSTM) networks, and an entity-based local coherence model. Our approach directly learns from vast user-generated resource of blog posts as text-image parallel training data. We collect more than22 K unique blog posts with 170 K associated images for the travel topics of NYC, Disneyland Australia, and Hawaii. We demonstrate that our approach outperforms other state-of-the-art image captioning methods for text sequence generation, using both quantitative measures and user studies via Amazon Mechanical Turk. Handwritten digit recognition using ML Introduction

[9] Y. Yin, J. Wu, a nd H. Zheng, "Ncfm: Accurate handwritten digits recognition using convolutional neural networks," in 2016 International Joint Conference on Neural Networks(IJCNN) , 2016.Convolutional Neural Networks(CNNs) have been confirmed as a powerful technique for classification of visual inputs like handwritten digits and faces recognition. Traditional convolutional layer's input feature maps are convolved with learnable kernel then combined for achieving better performance. The biggest drawback is that the combination of feature maps can lose features and do not apply well to large-scale neural networks. In this paper, we introduce no combination of feature maps, a novel technique to improve the performance of CNNs. By applying Ncfm technique, the input feature maps are not combined, which implies that the number of input feature maps is equal to output feature maps. The Ncfm technique converges faster and performs better than Cfm (Combination of feature maps) with fewer filters. Through the type of feature map, experimental evaluation shows that the performance is improved and we achieve the state-of-the-art performance with 99.81% accuracy rate on the MNIST datasets.

[10] L. Xie, J. Wang, Z. Wei, M. Wang, and Q. Tina, "Disturb label: Regularizing cnn on the loss layer," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition , 2016.During a long period of time we are combating over-fitting in the CNN training process with model regularization, including weight decay, model averaging, data augmentation, etc. In this paper, we present Disturb Label, an extremely simple algorithm which randomly replaces a part of labels as incorrect values in each iteration. Although it seems weird to intentionally generate incorrect training labels, we show that Disturb Label prevents the network training from overfittingby implicitly averaging over exponentially many networks which are trained with different label sets. To the best of our knowledge, Disturb Label serves as the first work which adds noises on the loss layer. Meanwhile, Disturb Label cooperates well with Dropout to provide complementary regularization functions. Experiments demonstrate competitive recognition on several popular image recognition datasets. Handwritten digit recognition using ML Introduction

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III. MOTIVATION

The task of handwritten digit recognition using a classifier has great importance and use such as online handwriting recognition on computer tablets, recognize zip codes on mail for postal mail sorting, processing bank check amounts, numeric entries in forms filled up by hand and so on. There are different challenges faced while attempting to solve this problem. The handwritten digits are not always of the same size, thickness or orientation and position relative to the margins. Our goal is to implement a pattern classification method to recognize the handwritten digits provided by the user. The general problem we predicted we would face in this digit classification problem was the similarity between the digits like 1 and 7, 5 and 6, 3 and 8, 8 and 8 etc. Also people write the same digits in many different ways. Finally the uniqueness and variety in the handwriting of different individuals also influences the formation and appearance of the digits.

3.1 Problem Statement

Following are the constraints faced when computers approach to recognize handwritten digits:

1. The Handwritten digits are not always of the same size, width, orientation and justified to margins as they differ from writing of person to person.
2. The similarity between digits such as 1and 7, 5 and 6, 3 and 8, 2 and 7 etc. So, classifying between these numbers is also a major problem for computers.
3. The uniqueness and variety in the handwriting of different individuals also influence the formation and appearance of the digits.

3.2 Methodology

Deep Learning has emerged as a central tool for self-perception problems like understanding images, voice from humans, robots exploring the world. The project aims to implement the concept of Convolutional Network which is one of the important architecture of deep learning. Understanding CNN and applying it to the handwritten recognition system, is the major target of the proposed system. This project is divided into 3 sections:

[1] Image Feature Extraction During our method, we use CNN LeNet-5 [5] to obtain more diverse features from each handwritten digit image. The Le Net architecture is considered as the first architecture for convolutional neural networks. We can easily see from the LeNet-5 in Fig. 1 that many feature maps are generated in each layer. So we can obtain more diverse features than using other 14 common methods. The LeNet-5 is an excellent architecture for handwritten digit recognition. The LeNet-5 has two parts, one is feature extraction, whereas the other one is classification which is used to classify objects. Given an image of 32 × 32 × 1, firstly, a convolution layer with six 5 × 5 filters with the stride of 1 is used and an output matrix of 28 × 28 ×6 is generated. With the stride of 1 and no padding, the feature map is reduced from 32 × 32 to 28 × 28. Then average pooling with the filter width of 2 and the stride of 2 is taken and the dimension is reduced by the factor of 2 and ends up with 14 × 14 × 6. Furthermore, another convolution layer with sixteen 5 × 5 filters is used leading to an output matrix of 10 × 10 × 16. Then another pooling layer is involved and ends up with an output matrix of 5 × 5 × 16. Therefore, we extract sixteen 5 × 5 feature maps from each image, and each feature map (5 × 5) is treated as a column vector (25 × 1). Overall, there are two convolution layers, two sub sampling layers, and two fully connected layers in the LeNet-5.

[2] Image Classification Once the feature extraction has been done, Pooled Feature Map is flattened to get fully connected layer. This fully connected layer has 120 feature maps each of size 1x1. Each of the 120 units is connected to all the 400 nodes (5x5x16) in the fully connected layer. Sixth layer is a fully connected layer with 84 units in order to reduce number of trainable parameters from 48120 (with 120 units layer 5) to 10164. Finally, there is a fully connected soft max ouput layer y^ with possible values corresponding to the digits from 0 to 9.

[3] GUI development for digits prediction After we get the desired testing input, an interface is developed for the purpose of enabling users with a choice to detect the digits depicted or written in images or drawer respectively. When users opens up the interface, they will be provided with an option to choose whether they wants to draw the digits all by themselves or insert image files from their local directory containing digits. If users chooses first option, he will be guided to a drawer interface where he can draw digits by themselves and get their digits recognized along with their accuracy. If user chooses second option, he will be asked to insert image file from their local directory and can get their

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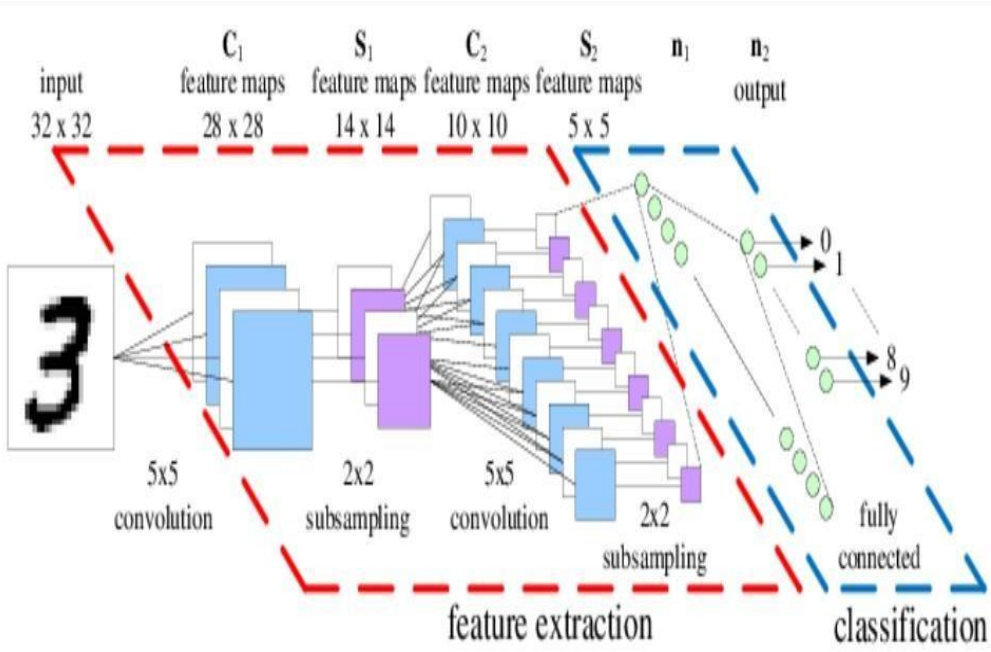
digits written in image files predicted with optimum accuracy and along with percentage. So by giving recognized digits as a results against inputs made by users to its users, this project fulfills all its objective.



IV. IMAGE FUNDAMENTALS

Pixels: The Building Blocks of Images Pixels are the raw building blocks of an image. Every image consists of a set of pixels. There is no finer granularity than the pixel. Normally, a pixel is considered the "color" or the "intensity"of light that appears in a given place in our image. If we think of an image as a grid, each square contains a single pixel. For example, take a look at Figure 3.1.Handwritten digit recognition using ML Introduction

The image in Figure 3.1 above has a resolution of 1000_750, meaning that it is 1000 pixels wide and 750 pixels tall. We can conceptualize an image as a (multidimensional) matrix. In this case, our matrix has 1000 columns (the width) with 750 rows (the height). Overall, there are1000_750 = 750000 total pixels in our image. Most pixels are represented in two ways:

1. Grayscale/single channel
2. Color

In a Grayscale image, each pixel is a scalar value between 0 and 255, where zero corresponds to "black" and 255 being "white". Values between 0 and 255 are varying shades of gray, where values closer to 0 are darker and values closer to 255 are lighter. The Grayscale gradient image in Figure 3.2 demonstrates darker pixels on the left-hand side and progressively lighter pixels on the right-hand side. Color pixels; however, are normally represented in the RGB color space. Figure 3.1: This image is 1000 pixels wide and 750 pixels tall, for a total of1000x750=750000 total pixels. Handwritten digit recognition using ML I Pixels in the RGB color space are no longer a scalar value like in a Grayscale/single channel image – instead, the pixels are represented by a list of three values: one value for the Red component, one for Green, and another for Blue. To define a color in the RGB color model, all we need to do is define the amount of Red, Green, and Blue contained in a single pixel. Each Red, Green, and Blue channel can have values defined in the range [0;255] for a total of256 "shades", where 0 indicates no representation and 255 demonstrates full representation. Given that the pixel value only needs to be in the range [0;255], we normally use 8-bit unsigned integers to represent the intensity. As we'll see once we build our first neural network, we'll often preprocess our image by performing mean subtraction or scaling, which will require us to convert the image to a floating point data type. Keep this point in mind as the data types used by libraries loading images from disk (such asOpenCV) will often need to be converted before we apply learning algorithms to the images directly. Given our three Red, Green, and Blue values, we can combine them into an RGB tuple in the form (red, green, blue). This tuple represents a given color in the RGB

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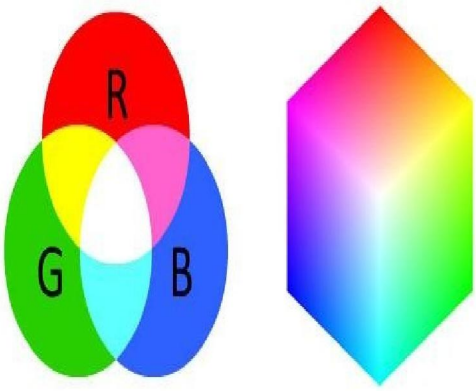
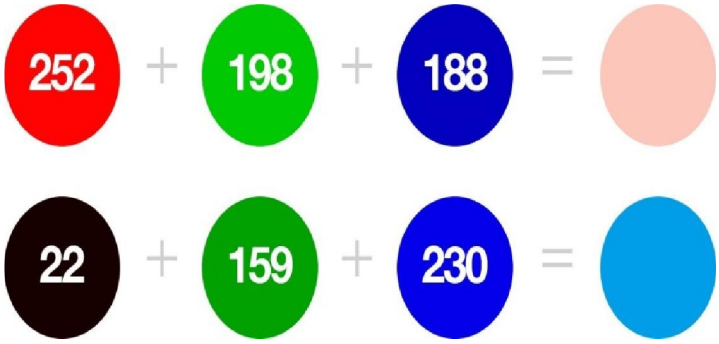
color space. The RGB color space is an example of an additive color space: the more of each color is added, the brighter the pixel becomes and closer to white. We can visualize the RGB color space in Figure3.3 (left). As you can see, adding red and green leads to yellow. Adding red and blue yields pink. And adding all three red, green, and blue together, we create white.



To make this example more concrete, let's again consider the color "white" – we would fill each of the red, green, and blue buckets up completely, like this: (255, 255, 255). Then, to create the color black, we would empty each of the buckets out (0, 0, 0), as black is the absence of color. To create a pure red color, we would fill up the red bucket (and only the red bucket)completely:(255, 0, 0).The RGB color space is also commonly visualized as a cube (Figure 3.3, right) Since an RGBcolor is defined as a 3-valued tuple, which each value in the range [0;255] we can thus think ofthe cube containing 256_256_256 = 16;777;216 possible colors, depending on how much Red,Green, and Blue are placed into each bucket. As an example, let's consider how "much" red, green and blue we would need to create a single color (Figure 3.4, top). Here we set R=252, G=198, B=188 to create a color tone similar to the skin of a Caucasian (perhaps useful when building an application to detect the amount of skin/flesh in an image). As we can see, the Red component is heavily represented with the bucket almost filled. Green and Blue are represented almost equally.



Combining these colors in an additive manner, we obtain a color tone similar to Caucasian ski the Image Coordinate System As mentioned in Figure 3.1 earlier in this chapter, an image is represented as a grid of pixels. To make this point more clear, imagine our grid as a piece of graph paper. Using this graph paper, the origin point (0;0) corresponds to the upper-left corner of the image. As we move down and to the right, both the x and y values increase. Figure 3.6provides a visual representation of this "graph paper" representation. Here we have the letter "I "on a piece of our graph paper. We see that this is an 8_8 grid with a total of 64 pixels. It's important to note that we are counting from zero rather than one. The Python language is zero indexed, meaning that we always start counting from zero

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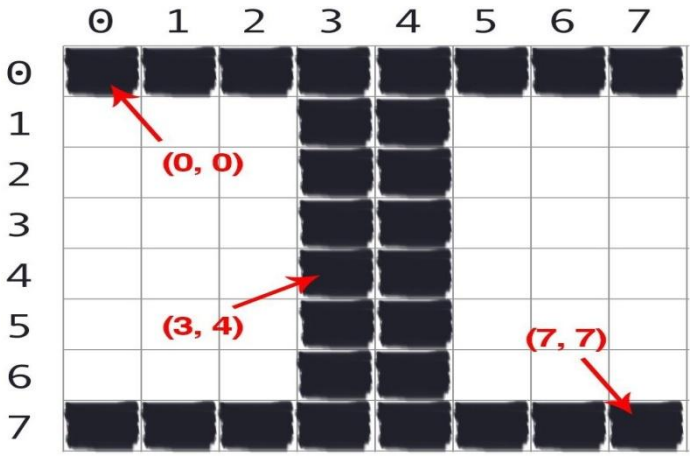

Evaluation Metrics

Report on Classification

The classification report displays the classification metrics accuracy, recall, and f1- score on aper-class basis. The measurements were based on true or false negatives, as well as both true and false positives. Positive and negative are merely names for the projected class in this case. There are four methods for figuring out if the forecasts are correct or not.

Confusion Matrix

A confusion matrix, sometimes known only as an error matrix, is a specific type of table structure that is used to analyze the performance of algorithms. Such a technique is frequently used it for supervised methods (in unsupervised learning it is usually called a matching matrix).The literature contains descriptions of both variants of the matrices, where each row denotes cases in a pure quality and each column denotes instances in a prediction model. Since it is simple to tell whether the system is confusing class labels, the name was picked (i.e. commonly mislabeling one as another).Here we analyze and measure the effectiveness of our classification model on our prepared image database. We apply precision on screen for proficiency classifier to dissect the exhibition of our fabricated order and contrast it with current strategies. Knowing force of expectation figure of a new instance following figure development becomes an essential matter. At the point when a prescient representation, fabricated utilizing chronicled data, it's normal to consider how it will perform over information that it hasn't seen previously. Some may attempt various form kinds of a similar expectation issue and afterward contrast their forecast execution with figure out which form is awesome to utilize over a certifiable dynamic situation(e.g., precision).Exactness, review, and other execution markers, generally employed surveying an indicator's exhibition. Frequently utilized exhibition estimates will be spoken about initially, trailed with clarification &examination of specific notable assessing approaches. "Performance Metrics for Predictive Modeling", a coincidence matrix (contingency table or classification matrices) are significant wellspring of execution measurements for order issues & for a 2 categorycharacterization problem. The qualities that are slantingly from upper-left to bring down right reflect exact choices, while the qualities outside this corner to corner address blunder. "A classifier's actual positive rate (otherwise called hit rate or review) is determined by partitioning the quantity of accurately arranged up-sides (the genuine positive count) by the absolute number of up-sides. The classifier's by dividing the quantity of incorrectly classified negative (overall fake negative counts) by the overall number of negatives, the bogus positive rate, also known as the bogus alertrate, is calculated. The complete precisely arranged up-sides and negatives separated by the absolute number of tests yields the exactness consequences of a classifier. Similar to the networkof neuron in the human brain, the connection of the vision cortex has an impact on a ConvNe structure. In the Receptive Field, a small area of the visual field, individual neurons can respond to advancements. To occupy the entire visual field, different comparative fields might be layeredon base of one another.

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V. RESULTS

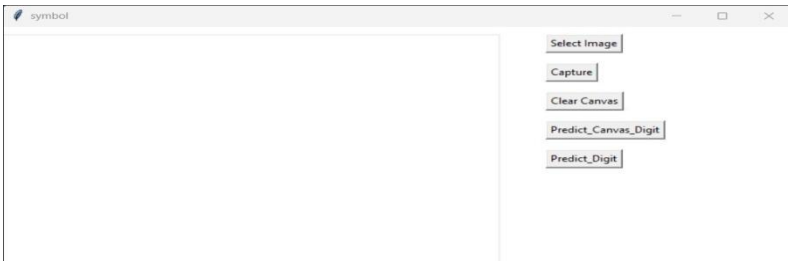

Fig.7.1

Fig.7.1.2

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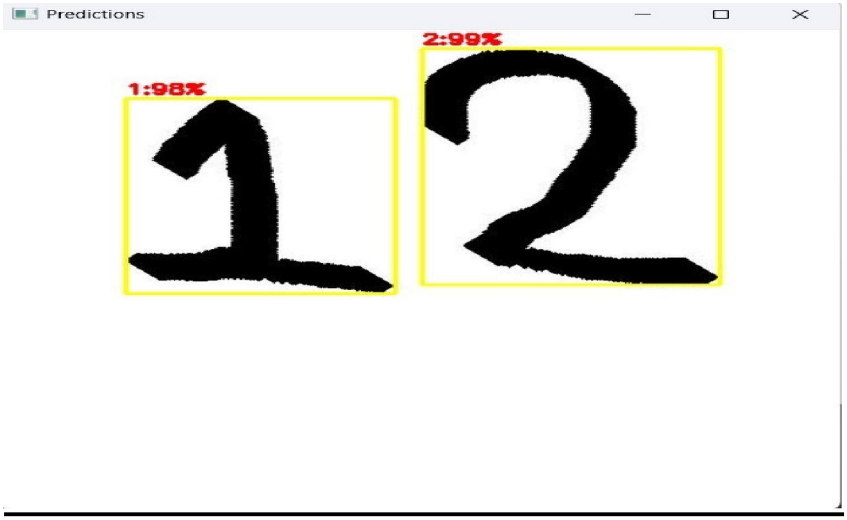

Fig.7.2

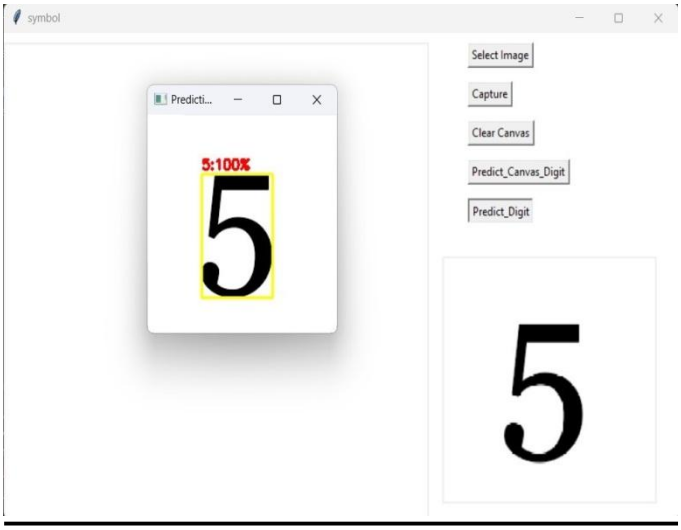

Fig.7.2.1

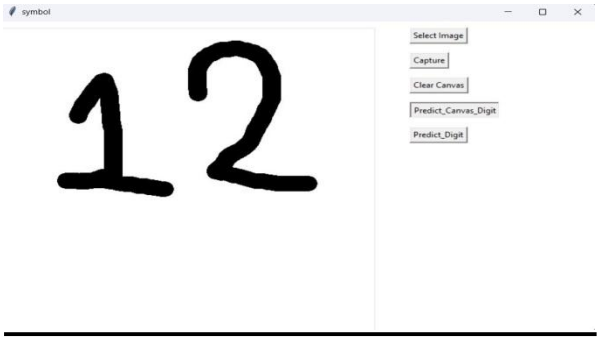

Fig.7.3

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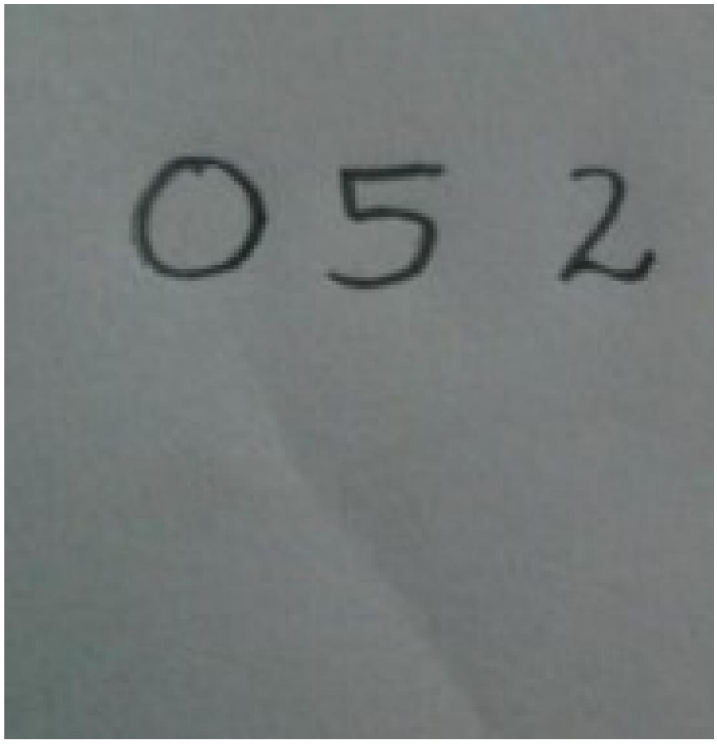

Fig.7.4

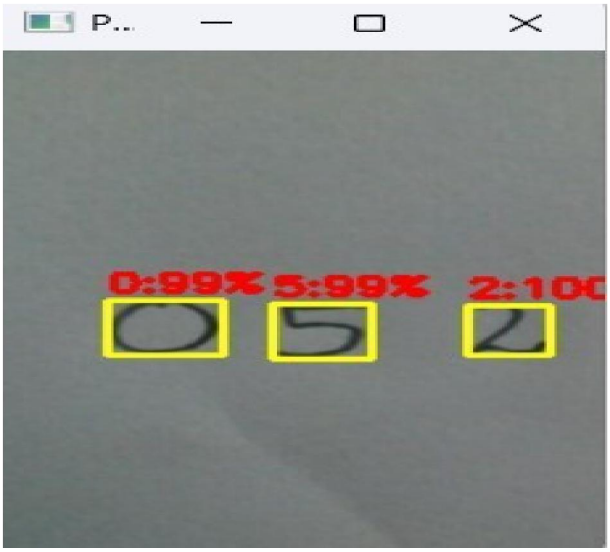

Fig.7.4.1

VI. CONCLUSION

In conclusion, machine learning techniques can be used to predict stock market prices with varying degrees of accuracy. These techniques involve analyzing historical market data and identifying patterns and trends that can be used to make predictions about future prices. There are several different machine learning algorithms that can be used for this purpose, including regression, decision trees, and neural networks. Each of these algorithms has its own strengths and weaknesses, and the choice of algorithm will depend on the specific problem being addressed and the available data.

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The objectives with which this project was initiated such as to develop handwritten digit recognizing system that enables users to recognize their handwritten digits using this deep learning model, less compuatation intensive efficient model has been achieved. The model which I built got an average accuracy of 98.23%. Also the underlying problems of not having the same size ,width, orientation, and margin always has been taken care of with the help of computer vision's opencv library's functionalities.

The problem of difficulty in distinguishing the difference between digits such as 1 and 7, 5 and 6, 3 and 8 etc has been resolved to a great extent with the opencv's edge detection and contour features. Also problems of dim lighting and blurry or unclear edges in 27 images are corrected with the help of Gaussian blur technique. Now users can find their handwritten digits in one go without much complications. This project is based on a deep neural network where users are going to get an interface for recognition of their digit images. On the top of this model, this project can be extended to append various functionalities which can be used to filter the desired results based on digits recognized by this model.

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