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HAND-WRITTEN DIGITS RECOGNITION USING MISCELLANEOUS MACHINE LEARNING AND DEEP LEARNING ALGORITHMS

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Abstract
Identification of Hand-written digits is a rational key point in pattern identification applications. There are many uses of hand-written digits identification like mail sorting in postal, cheques processing in the banks, data entry through forms, etc. The key to the issue lies in the expertise to grow a well-organized algorithm that can accept hand-written numbers and which are submitted by end-users by the scanners, tablets, and other digital devices. This paper gives a viewpoint to handwritten numbers recognition constructed on machine learning models, and deep learning models and shows the out-comes in the shape of accuracy. The primary objective of this paper is to guarantee powerful and dependable methodologies for the acknowledgment of handwritten numbers using machine learning and deep learning algorithms. Several machine learning algorithms such as Decision Tree (DT), Naïve Bayesian (NB) classifier, Multilayer Perceptron (MLP), Support Vector Machine (SVM), Random Forest (RF), and deep learning algorithms such as Convolutional Neural Network (CNN), AlexNet, and Multilayer Perceptron (MLP) have been used for recognition of hand-written digits in Jupyter Notebook and Matlab.Through some features extraction, and different experiments and analysis of Machine Learning Algorithms (MLA) and Deep Learning Algorithms (DLA), the accuracy of deep learning algorithms is better than the machine learning algorithms.

Keywords: Hand-written, Digits Recognition, MNIST Dataset, Machine Learning Models, Deep Learning Models, Algorithms, AlexNet, Features Extraction, , fc6, fc7, and fc8., Classification, Pattern Recognition, Supervised, Unsupervised Learning.

1 INTRODUCTION

The MNIST represents the “Modified National Institute of Standards and Technology. It is a huge database of physically composed digits that are used for preparing diverse picture handling systems.MNIST comprises two datasets, one for training i.e. 60,000 pictures and

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one for testing i.e. 10,000 pictures. Many examinations partition the preparation set into two sets comprising 50,000 pictures for training and 10,000 for validation. Our organization is prepared on marginally disfigured pictures, ceaselessly produced in online style; consequently, we might utilize the entire un-twisted preparing set for approval, without squandering preparing pictures. Pixel powers of the first dim scale pictures range from 0 (foundation) to 255 (max frontal area force). 28×28 = 784 pixels for every picture get planned to genuine, and are taken care of into the NN input layer. Programmed penmanship acknowledgment is of incredible scholarly and business interest [1], [2].

Intelligent picture investigation is an engaging examination region in Artificial Intelligence and is urgent for an assortment of present open examination troubles. Manually written digits acknowledgment is a well-informed subarea inside the field that is worried about learning models to recognize pre-fragmented transcribed digits. It is quite possibly the main issue in information mining, AI, and design acknowledgment alongside numerous different controls of man-made reasoning. The principle utilization of AI techniques in the last decade has decided solid in adjusting definitive frameworks which are contending to human execution and which achieve far improved than physically composed traditional man-made consciousness frameworks utilized in the beginnings of optical person acknowledgment innovation However, not all highlights of those explicit models have been recently reviewed.[3]

To perceive diverse example classes, the human perception framework has an inborn capacity to distinguish the nearby locales, where the pattern classes vary essentially. This intrinsic capacity of an individual might be imitated in any example acknowledgment framework by incorporating the capacity of finding the areas which contain the most extreme segregating data among the example classes. Accordingly, any individual needs to notice intently the lower part of the digit pictures to recognize these two Bangla digits. The easiest method to recognize the districts containing the most extreme oppressive data is to separate the example picture into a fixed number of equivalents estimated districts. These areas may have a few covers with one another. For each such district, highlights (frequently called nearby highlights) are extricated. These nearby districts are then examined haphazardly to deliver different subsets of them. The acknowledgment performance is assessed with include a set shaped with the highlights of every one of those subsets. [5]

The SVM algorithm is based on Vapnik's factual learning theory and quadratic programming optimization (QPO). And the SVM is essentially a parallel classifier, and many SVMs may be joined to provide a multi-class classification framework. An SVM classification framework is commonly referred to as an SV classifier (SVC). SVC's unequaled classification ability has been demonstrated in a variety of tests, mainly in high dimensionality,and less sample size condition. This study examines the novel implications of handwritten digit recognition using cutting-edge extraction approaches and learning/classification computations.The computations were put to the test using well-known data sets to compare them to earlier findings. The goal of this research is to see how accurate cutting-edge processes can be in transcribed digit recognition and to provide a benchmark for

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future research. CEDAR, CENPARMI, and MNIST are the datasets that have been tested. These datasets have been widely used in similar type of research as character recognition and classification [6].

Because of the great inconstancy of penmanship, acknowledgment of unconstrained penmanship is as yet thought to be an open exploration theme in the archive investigation local area. Acknowledgment of manually written digits has been read for a long time, and a few benchmark datasets have been distributed, like MNIST, USPS, Optdigits1, Semeion1 Transcribed digit acknowledgment has for quite some time been a functioning point in OCR applications, and example order/learning research. Various methodologies have been proposed for pre-preparing, highlight extraction, learning/order, and post-preparing, and a few standard picture information bases are broadly used to assess the presentation. This paper presents the most recent outcomes on three notable data sets utilizing the component extraction and order methods that address the best in class. The tried datasets are MNIST, CENPARMI and CEDAR. On every data set, we consolidated 7 classifiers with 8 element vectors to give 56 exactness.[7]

In pragmatic example acknowledgment issues one frequently attempts various classifiers and various capabilities to track down the best mix. When this mix is tracked down different classifiers and highlights are not, at this point utilized. Strategies for consolidating classifiers are to diminish the number of grouping blunders is depicted in late writing. In this paper, the helpfulness of consolidating classifiers was tried on a genuine informational index comprising of a few arrangements of highlights of transcribed digits. "When does combining classifiers result in a decrease in arrangement mistakes, and why?" are some of the topics we could wish to investigate. "How would we partition this set into subsets to achieve the best results if we have a large number of features?" and "If we have a large number of features, how would we partition this set into subsets to get the best results?" This article shows how classifiers may be combined, how our classifiers calculate back probabilities, and how our data is represented. We present the results of our experiments and our judgments [8], [9].

Yet, since penmanship relies much upon the author and because we don't continuously compose a similar person in the very same manner, assembling a general acknowledgment framework that would perceive any person with great unwavering quality in each application is unimaginable. Commonly, the acknowledgment frameworks are custom-made to explicit applications to accomplish better exhibitions. Specifically, unconstrained manually written digit acknowledgment has been applied to perceive sums composed on checks for banks or postal districts on envelopes for postal services (the USPS data set). In these two cases, great outcomes were gotten. An unconstrained transcribed digit acknowledgment framework can be isolated into several stages: preprocessing (sifting, division, standardization, diminishing. . .), highlight extraction (and determination), arrangement, and check. This paper centers around highlighting extraction and characterization[10].

The component determination issue in the mechanized plan of design classifiers alludes to the errand of distinguishing and selecting a compelling subset of highlights to be utilized

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to represent designs from a bigger arrangement of frequently commonly repetitive or then again even unessential highlights. Subsequently, the principal objective of feature determination is to lessen the number of highlights utilized in order while keeping an adequate arrangement precision. We can arrange to include determination calculations into two classes depending on whether include choice is performed freely of the learning calculation used to build the classifier. On the off chance that includes determination is done independently of the learning calculation, the procedure is said to follow a channel approach. Else, it is said to follow a Covering approach [11].

1.1 Problem Statement

Manually written digit acknowledgment has recently been a popular exploration topic due to its extensive practical uses in postal mail sorting and healthcare data administration. Due to the differences in handwriting features and styles, manually written digit acknowledgment is a tough problem.For this problem, several strategies have been proposed, including profound learning-based classification calculations (Larochelle et al., 2009; Wang, et al., 2016), fake neural organizations (Goltsev and Gritsenko, 2012; Kang and Palmer-Brown, 2008), and SVM classifiers (Larochelle et al., 2009; Wang et al., 2016), Lauer et al., 2007, and Niu and Suen, 2012). Even though these procedures have yielded acceptable identification results, a few digit miss-recognitions are unavoidable due to non-standard composing proclivities and snares[4].

The Identification of Hand Written Digits on MNIST Dataset using machine learning and deep learning algorithms to improve the accuracy on the basis of Training-Test ratio and feature extraction using AlexNet.

1.2 Purpose of Study

The purpose of study is to find the accuracy of Hand Written Digits Recognition on MNIST Dataset using machine and deep learning algorithms in Python and Matlab.

1.3 Research Method

First download the MNIST Dataset, then apply the machine learning algorithms on MNIST Dataset in the form of .csv and apply deep learning models on images MNIST Dataset after features extraction using AlexNet to find the accuracy of the identification of digits in Python and Matlab.

1.4 Expected Outcome

The Deep Learning Algorithms (DLA) shouldproduce better results than Machine Learning Algorithms (MLA) in term of accuracy for identification of hand-written digits. The accuracy should be improved due to some features extraction and applying models.

Section 2 of this paper comprises a literature review, section 3 contains methodology, its subsections contain experiments and results and discussion is section 4, and section 5 contains the conclusion. The section 6 is for future work and after this list of references is mentioned.

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2 LITERATURE REVIEW

TheMNIST comprises two datasets, one for preparing (60,000 pictures) and one for testing (10,000 pictures). Numerous investigations partition the preparation set into two sets comprising 50,000 pictures for preparing and 10,000 for approval. Our organization is prepared on somewhat deformed pictures, consistently produced in online design; thus we may utilize the entirety of un-distorted preparing set for approval, without squandering preparing pictures. Pixel intensities of the first dim scale pictures range from 0 (foundation) to 255 (max closer view power). 28×28 = 784 pixels for each picture get planned to the genuine qualities pixel power 127.5 −1.0 and are taken care of into the NN input layer [1].

It's also known as a feed-forward network in this context. The number of information layer hubs is determined by the number of qualities in the dataset. The yield layer's number of hubs is determined by the number of obvious classes in the dataset. The optimal number of hubs or the beneficial number of covered layers it’s tough to choose a hidden layer for any explicit problem. Nonetheless, when everything is said and done, these figures are picked based on a hunch. The relationship between two hubs in a multi-facet perceptron is made up of the weight. It essentially learns the specific weight change that is related to each association when preparing the measure. It's not a controlled learning technique called Back engendering calculation for the learning purpose [2] [3].

A typical deep learning model, the versatile profound auto-encoder (ADAE), can gradually extract the key highlights from the information images. Because of its flexible learning pace, the ADAE, in particular, can complete union in less time. The Limited Boltzmann-Machine is the fundamental element of the ADAE, and the insights gained from it will be discussed in this section. [4].

It comprises 53 highlights on the whole. These highlights are framed with 24 changed shadow highlights, 16 octant centroid highlights, 8 distance-based highlights, 1 component addressing the number of circles, and 4 longest run highlights [11] registered on the whole digit picture. For extraction of highlights, every digit picture is scaled to such an extent that the negligible jumping box walling it in is square. Portrayals of that load of highlights are given in the accompanying subsections [5].

CENPARMI, Concordia University, provided the CENPARMI digit data set. It comprises 6000 digit images culled from USPS envelope images and filtered at 166DPI. In this data set, 4000 images (400 test each class) are designated for preparation, while the remaining 2000 images (200 examples per class) are designated for testing. CEDAR CDROM-1, issued by CEDAR, and SUNY Bua, contains the CEDAR digit information base. The images were filtered at a resolution of 300 DPI. There are 18468 digit photos in the preparation in-formational index (br) (the quantity of tests fluctuates from one class to another, for the test informational index). There are 2711 digit photos in the test informational collection. Because some of the images in the test set were not properly fragmented, a subset of 2213 images was created [6].

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As far as anyone is concerned, this dataset is the first to give records in RGB. In the planning cycle of the information base, uniform dissemination of the events of every digit was guaranteed. For the opposition, the pictures are conveyed in unique size with a goal of 300 dpi. As opposed to other datasets, the digits are not size-standardized since in genuine cases, contrasts in an author's penmanship remember variety for size just as composing style [7].

The CENPARMI digit data set consists 6,000 digits pictures gathered from the envelope pictures of USPS, checked in 166DPI. The preparation dataset has 4,000 examples, and test-dataset have 2,000 pictures. The dataset of CEDAR digitsis contained in the CDROM-1. The pictures were examined in 300 (DPI) from the live mail pictures of USPS. The training dataset has 18,468 examples and the test dataset has 2,711 examples. A subset containing 2,213 very much divided pictures was sorted out for testing [8].

To classify the hand-written digits, a classifier based on Neural-Network (NN) called Multi-Layers Perceptron (MLP) is used widely. It has some input layers,output layers, and some hidden layers. Every layer can contain a specific number of neurons, and each layer neuronis connected to any the next layer neurons. It is also called as a feed-forward network in this context. It is tough to evaluate if a useful numerous hidden layers or a beneficial number of hubs in a secret layer is better for a certain problem. Nonetheless, when everything is said and done, these figures are picked based on a hunch. The relationship between two hubs in a multi-facet perceptron is made up of the weight. It happens while you're preparing a measure[9], [10].

There are two normal strategies to take care of a multi-class issue with parallel classifiers like SVMs: one-against-all (or one-versus rest) and one-against-one. In the one-against-all plan, a classifier is worked for each class and relegated to the partition of this class from the others. For the one-against-one technique, a classifier is worked for each pair of classes to isolate the classes in pairs. Another way to deal with the acknowledgment of n various digits is to utilize a solitary n-class SVM rather than n paired SVM sub-classifiers with the one-against-all technique, in this way taking care of a solitary compelled streamlining issue. Multi-class SVMs have been concentrated by various creators. A multi-class SVM was contrasted with a gathering of double SVMs on the USPS datasets. The multiclass SVM gave lower exactness rates than the normal strategies. In any case, multi-class SVMs gave promising outcomes and beat other combinatory strategies in the forecast of protein optional designs [11].

To defeat such troubles, Pareto-based evolutionary advancement has gotten an option to classical procedures, for example, weighted whole strategy. This approach was first proposed by Goldberg and it explicitly utilizes Pareto strength to decide the reproduction likelihood of every person.. To stay away from such an issue, Goldberg and Richardson in propose the extra utilization of wellness sharing. The fundamental thought behind this is that people in a specific specialty need to share accessible assets. The more people are located in the neighborhood of someone in particular, the more its wellness esteem is debased. In this work, authors utilized the Non-dominated Sorting Hereditary Algorithm NSGA (with elitism) proposed by Srinivas and Deb. The hybrids furthermore, change stay.

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Before the determination is performed, the populace is positioned based on an individual's non-domination. The non-dominated people present in the populace are first distinguished from the current populace. Then, at that point, this load of people is accepted to comprise the first non-dominated front in the populace also, relegated a huge faker wellness esteem. Similar wellness esteem is appointed to give an equivalent regenerative potential to every one of these non-dominated people. [12]

Postal Service project staff was in charge of securing, binarization, postal district area, and primer division (Wang and Srihari, 1988). Some of these terms imply that they will be difficult to complete. If authors could assume that a person is touching and separated from its neighbors, the division (isolating each digit from its neighbors) would be a very simple task. However, none of these assumptions holds realistically. MI-division (especially broken 5's) has resulted in several equivocal characters in the database, as seen in figure 2. A digit's size now varies but is around 40 by 60 pixels. Because a back-spread organization's contribution is of a set size, it's critical to pay attention to the details it's critical to keep the character sizes consistent. The characters were resized to fit into a 16 by 16-pixel image using a straight change. This alteration distorts the person's viewpoint proportion and is done after any unnecessary impressions in the image have been removed. Because of the linear transition, the following image isn't two-dimensional but has several dark levels, since a variable number of pixels from the original image might fall into a single pixel in the objective image. Each image's dark levels have been scaled to fit within the range - 1 to 1[13], [14].

The main layer over the information image is the convolutional layer. It is used to separate the highlights in a photograph. The information layer's input neurons are tangled with a channel, resulting in a yield of (+1) (+ 1). It uses a neural initiating approach to demonstrate non-linearity. As seen in the preceding text, the fundamental components of the convolutional layer are open field, step, widening, and cushioning. The visual cortex of animals animates CNN calculations. The visual cortex is a part of the brain that analyses information from the retina. It also measures visual data while being inconspicuous in small sub-areas of the data. A CNN which is a small district of the city, also determines an open field in the information picture that has the potential to affect a certain area of the organization it is also one of the most important plan boundaries in CNN engineering. It's about the same size as the part and functions in the same way that the natural eye's favela vision does for giving crisp focused vision. Stepping, pooling, chunk size, and CNN profundity all have an impact on the responsive field. The primary layer over the information image is the convolutional layer. It is used to extract the highlights of a photograph. [15]

Text from scanned reports or photographs has been extracted using optical character recognition (OCR) frameworks. Character discovery and acknowledgment are the two steps of this paradigm. For character recognition by their supplies, one arrangement computation is required. Neural organizations can be used to perceive the character. The multi-layer perceptron (MLP) provides acceptable character order acknowledgment exactness. Furthermore, high-accuracy character recognition is provided by the recurrent neural network (RNN), and CNN. The massive amount of computation required during the setup stage might harm MLP, RNN, and CNN. MLP is capable of coping with a wide range of issues, yet its large organizational network necessitates substantial expenditure. RNNs are good for data organization, while CNNs aren't. Appropriate for spatial data A CNN is utilized to recognize digits from the MNIST database in this part, and a report is prepared that compares the MLP, RNN, and CNN. The CNN gives greater digit recognition precision while needing the least amount of MLP and RNN framework setup. As a result of the MNIST digit dataset, when combined with geographical information, the CNN gives a superior result with 98.92 % accuracy [16].

The problem of handwritten digit recognition has become one of the most well-known in AI and computer vision applications. To deal with the problem of handwritten digit acknowledgment, many AI approaches have been used. The focus of this study is on Neural Network (NN) techniques. Deep neural network (DNN), deep belief network (DBN), and convolutional neural network are the three most well-known NN techniques (CNN). The three NN techniques are evaluated and compared in this research in terms of accuracy and execution. In any case, recognition precision rate and execution isn't the major standard in the assessment interaction, but there are several fascinating models, such as execution time. The assessments were led by an arbitrary and conventional dataset of handwritten digits the results demonstrate that DNN is the most accurate computation among the three NN techniques, with a precision rate of 98.08 %. Regardless, DNN's execution season is identical to that of the other two computations. However, because of the similarity in digit forms, every computation has a 1-2 % error rate, particularly with the digits (1, 7), (3, 5), (3, 8), (8, 5), and (9, 5). (6, 9)[17].

In this research, researchers looked at how to conduct order using an unsupervised snap–float combined with a supervised ADFUNN following up on the enactment functions. Snap–float is particularly effective at extracting specific components from confusing cursive-letter datasets. Several ages are sufficient for element disclosure. Without stowed away neurons, supervised single-layer ADFUNN resolves these indivisible element grouping challenges efficiently. According to the findings, these two techniques demonstrated greater and more computationally proficient speculation capacities than MLPs when used together within one organization (SADFUNN) [18].

In this paper, authors present another enormous Arabic Hand-written-Digits Database (AHDBase). The AHDBase is made out of 60,000 digits for preparation and 10,000 digits for testing composed of 700 people of various ages and instructive foundations. Authors likewise present an acknowledgment framework for Arabic transcribed digits with an acknowledgment pace of 99.15 % and low acknowledgment time. Our framework is made of two phases. The main stage is an Artificial Neural Network (ANN) taken care of with a short amazing component vector for quick characterization of non-uncertain cases. The first stage has an oddball choice to pass the uncertain cases to the more incredible second stage. The second stage is a slow yet incredible support Vector Machine (SVM) taken care of with an enormous component vector to group the uncertain cases dismissed from the first stage.[19]

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Because of the variety of shapes, sizes, and writing styles, handwritten digit acknowledgment has always been a serious challenge. For its instructional and monetary properties, precisely written by hand acknowledgment is proving to be more insightful to scientists. Although some work has been done on Bangla Handwritten Recognition, there is no good model developed at this time. With fewer ages and a shorter execution time, the suggested model outperforms any previously implemented technique. As a result, 99.74 % approval precision on ISI transcribed person data set, 98.93 % on BanglaLekha Isolated, and CAMTERDB 3.1.1 dataset 99.42 %, and finally, 99.43 % on a blended, CAMTERDB 3.1.1, and ISI manually written person dataset) was achieved[20].

Researchers look at how to connect many depictions of a written by hand finger to improve grouping precision without increasing the complexity of the framework or the time it takes to learn it. The information is the forceful growth of the pen tip over the strain delicate tablet in pen-based acknowledgment. There is also the picture that has been framed as a result of this evolution. Authors identify the two multi-layer perceptrons (MLP) based classifiers utilizing these representations make mistakes on various examples on a verifiable data set of transcribed digits containing over 11,000 written by hand digits, implying that an appropriate mix of the two would result in higher exactness. Casting a ballot, combining specialists, stacking, and falling are all things authors do and examine. Authors can be certain that by combining the two MLP classifiers, authors will get greater precision. Because the two classifiers/portraits fail in a variety of cases authors recommend a multi-stage falling strategy in which the second, more expensive picture-based classifier is used only in a small number of situations [21].

In the final convolutional SOM layer, the yield layer of the DCSOM network analyses the neighborhood histograms of each FII bank. Several experiments employing the MNIST written by hand digit data set and all of its variants are being conducted to test the proposed DCSOM organization's robust depiction. The display of DCSOM outperforms cutting-edge techniques for loud digits and achieves a par excellence presentation with another difficult profound learning engineering for other image types, according to test results. [22]

Another classifier blend model for Farsi written by hand digit acknowledgment is presented in this research. The model is made up of four RBF neural networks that act as experts, and another RBF network that acts as a gating network, determining how to divide the information space between the specialists. The gating network assigns a capacity coefficient to each master based on the input data, which is an 81-component vector extracted using the loci portrayal strategy. The final yield is calculated as the weighted sum of the specialists' yields. The suggested model's recognition rate is 93.5 %, which is 3.75 % higher than the rate of a combination of MLPs specialists who recently ran on a similar data set. [23]

Another element choice approach is provided in this study, with applications to write by hand digit acknowledgment. In the least squares support vector machines, this strategy relies on recursive feature elimination (RFE) (LS-SVM). One-against-all LS-SVMs are

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used for digit acknowledgment. The RFE technique is modified in two ways to accommodate multi-class grouping. The first option is to prune highlights for each paired LS-SVM classifier individually, while the second option is to prune highlights for all of the parallel classifiers collectively. The multi-class RFE is also associated to the hereditary calculations-based covering highlight selection technique. The results of the exploratory show that the combined pruning computation produces the best presentation and selects more components those are relevant to the fundamental properties of digits. [24]

Handwritten digits recognition has become an attractive area due to its applications in a some fields. Information on financial balance numbers and postal categories are just a few examples. Recognition of handwritten digits is certainly not a trivial task due to the content of the large variety recorded as an inaccessible copy style information. In order to fit this issue the two provisions and the division into categories must be competent. In this experiment, a change-based component, Discrete Cosine Transform (2D-DCT), was used. Markov hidden models (HMMs) used as a separator. The proposed figure has been edited and tested at the Mixed National Institute of Standards and Technology (MNIST) manuscript of the manuscript. The statistics provide promising results for approval in the MNIST database of handwritten digits.[25]

Two novel strategies for accomplishing handwritten digit recognition are portrayed. The primary strategy depends on neural networks that performs line diminishing and highlight extraction utilizing nearby layout coordinating. The subsequent technique is executed on an advanced sign processor and utilizes compelled programmed learning. Test results got utilizing disengaged handwritten digits taken from postal divisions, a fairly troublesome informational index, which are accounted for and talked about[26].

Even in the presence of large visual twists, people are exceptionally adept at detecting alphanumeric characters. On several typical recognition tasks, ongoing developments in the field of visual neuroscience have resulted in a robust model of recognition in visual ventral stream that competes with cutting-edge PC vision frameworks. To improve the model's presentation, all of the more naturally arousing qualities such as scarification of components, parallel impediment, and element limitation are offered. Over English and Farsi transcribed digit datasets, authors show that using highlights provided by the updated model results in greater written by hand digit recognition rates than the original model. Our findings also show that the modified model is more invariant to diverse variables[27].

The process of analyzing and converting paper archives to electronic storage includes a step called digit recognition. Using the Histogram of Oriented Gradient (HOG) highlights and SVM based classifier; this research proposes another Multiple-Cell Size (MCS) technique for successfully organizing Handwritten Digits. The HOG-based technique is affected by the cell size employed in the relevant element extraction computations. In the future, a different MCS approach will be utilized to conduct HOG inquiries and analyses of HOG highlights. The framework was evaluated on the Benchmark MNIST Digit Database of transcribed digits using an Independent Test set approach, and an arrangement exactness of 99.36 % was reached [28].

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Presents a Hidden Markov Model (HMM) based way to deal with online handwritten digit recognition utilizing stroke activities. In this methodology, a person's occurrence is addressed by an arrangement of emblematic strokes, and the portrayal is acquired by part division and stroke characterization. The part division depends on the delta lognormal model of penmanship age. The emblematic strokes are utilized for HMM different perception preparing or acknowledgment. A preparation and acknowledgment exploration has been directed utilizing the above strategies[29].

The SVM classifier tree was used to recognize handwritten digits in the presence of noise, according to the study. The conventional design of the multi-class SVM classifier was employed for the digit ID project. While the most well-known Gaussian capacity performs well, tests with numerous sections indicated that alternative possibilities, such as the Laplacian section, may perform even better. Grouping the treated informative sets is not difficult because the presentation of SVM for most parts is over 90%. When portion boundaries were chosen, the Monte Carlo method produced the best results. Other methods, such as recreated tempering [30].

TABLE 1

Summary of Literature View

Ref No.	Journal Name/Type	Pub. Year	Algorithms/ Techniques	Findings
1	IEEE,“Transactions on Pattern Analysis and Machine Intelligence”	2002	MLP	Accuracy is 94.54.
2	Arxiv.org	2010	MLP	The Best Error is 0.43.
3	GJCST, “Global Journal of Computer Science and Technology”	2018	MLP,SVM, Random Forest, Naive Bayes	Accuracy is 90.37, 87.97, 85.75, and 81.85.
4	Elsevier Neural Network	2018	CNN, SVM	Accuracy is 98.40 and 98.65.
5	ElsevierApplied Soft Computing	2012	MLP,SVM	Accuracy is 96.65 and 97.70.
6	Elsevier Pattern Recognition	2003	MLP,SVM	Best Error is 1.14 and 0.91.
7	Researchgate	2002	MLP,SVM	Best Error is 1.094 and 0.930.
8	Academia	1995	MLP	Best Error is 1.6.
9	Kybernetika	1998	Random Forest	Best Error is 5.1.
10	ElsevierHAL	2007	CNN, SVM	Accuracy is 98.45 and 98.57.
11	IEEE	2002	Genetic Algorithm	Accuracy is 99.16.
12	Elsevier NeuroComputing	2003	S Cells ,C Cells	Inhibitory Surround
13	Udel	1995	MLP	Best Error is 1.6.
14	Neurips	1989	MLP	Error Rate is 1.1.

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15	MDPI Sensors	2020	CNN	Accuracy is 98.08.
16	MDPIElectronics	2021	CNN	Accuracy is 90.13.
17	IEEE	2017	Deep Neural Network	Accuracy is 98.08.
18	ElsevierInformation Sciences	2008	MLP	Accuracy is 94.25.
19	Researchgate Artificial Intelligence and Pattern	2007	Neural Network	Accuracy is 99.15.
20	Springer	2019	CNN	Accuracy is 99.55.
21	TUBITAK	2001	MLP	Accuracy is 98.76.
22	IEEE Access	2020	CNN	Best Error is 0.53.
23	IEICE	2010	MLP	Accuracy is 91.45
24	IEEE	2009	SVM	Error Rate is 4.1.
25	IEEE	2014	Hidden Markov Model	Accuracy is 94.65
26	Springer	1990	MLP	Error Rate is 1.
27	Springer Machine Vision and Application	2010	CNN	Error Rate is 1.4
28	Journal of Intelligent Learning System and Applications	2017	SVM	Accuracy is 99.36.
29	IEEE	1998	Hidden Markov Model	The Accuracy is 91.8.
30	Springer	2017	SVM	Accuracy is 95.

3 METHODOLOGY

3.1 Flow of Research Methodology

The principal objective of this research is to recognize the Hand-Written Digits by adapting MNIST Dataset using Machine learning (ML) in Jupyter Notebook (Python 3) and Deep Learning(DL) models (Matlab and python) on the MNIST image dataset. First of all, download the MNIST dataset in the form of a .csv extension and then apply the machine learning models such as Decision Tree, Naïve Bayesian, MLP, Random Forest, SVM on the MNIST dataset in Jupyter Notebook (Python 3) on I3 4^{th} Generation with the processor; Intel-R, Core i3-4010U CPU @ 1.70GHz, 1.70 GHz, RAM 4GB, System Type; 64-bit operating system and Windows 10 Professional. Secondly, download the MNIST image dataset and then extract the features fc6, fc7, and fc8 from the image MNIST dataset. Then, apply the machine learning models such as Decision Tree, Naïve Bayesian, Random Forest, and SVM on fc6,fc7, and fc8 in Matlab tool. Third of all, download the MNIST dataset. Then, apply the deep learning models MLP on MNIST dataset in Jupyter Notebook(python 3) on the said system.. Fourth of all, Compare the results of machine learning models and deep learning models in the form of tables and graphs. The fifth of all, deep learning Models produced better results than machine learning models. Fig.1 shows the complete flow of this work.

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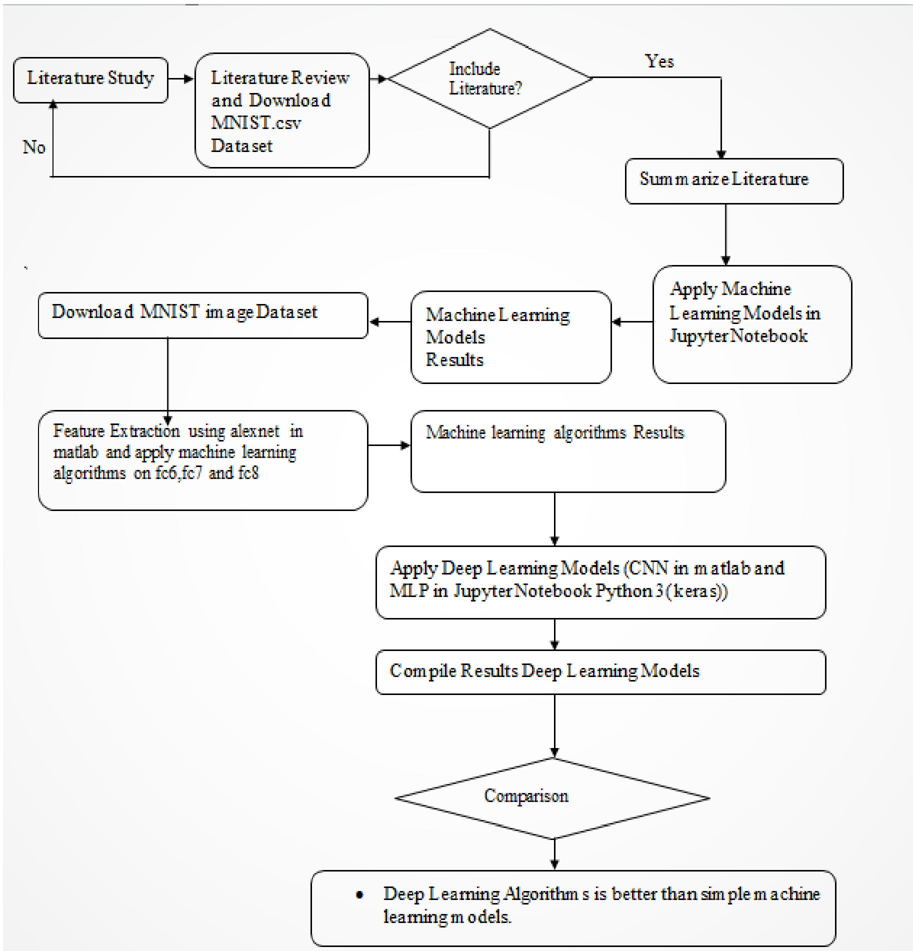

Fig.1. Flow Diagram of Research Methodology

3.2 Experiments

3.2.1 Decision Tree

This classifier is a supervised model that uses entropy and information gain to construct a tree. It shows a computation that simply keeps down prohibitive control explanations. Decision trees are normally used in assignments research, unequivocally in decision investigation, to help with perceiving a strategy most likely going to show up at a target, and yet are a notable device in AI.The accuracy score of the Decision Tree classifier on the MNIST dataset is given in Fig. 2.

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```
In [110…  from sklearn.metrics import accuracy_score
          accuracy_score(y_pred,y_test)

Out[110…  0.8662
```

Fig. 2. Accuracy Score of Decision Tree

3.2.2 Naïve Bayesian Classifier (NBC)

This classifier contributes a probabilistic technique, addressing and learning the probabilistic data or information with clear semantics. It depends on two significant rearranging accepts that prescient characteristics are restrictively confident given the class, and it thinks that no secret credits impact the forecasting strategy. It is one of the most mind-blowing fundamental text characterizations approaches with various applications in close to home email arranging, email spam identification, physically unequivocal substance discovery, report classification, opinion location, and language recognition. Albeit the guileless plan and misrepresented presumptions that this methodology utilizes, NB achieves comprehensive in many jumbled genuine issues.[3]

The accuracy score of the Naïve Bayesian Classifier on the MNIST dataset is given in Fig.3

```
In [127…  from sklearn.metrics import accuracy_score
          accuracy_score(y_pred,y_test)

Out[127…  0.5658
```

Fig. 3.Accuracy Score of Naïve Bayesian

3.2.3 Random Forest Tree

The random forest just like order trees, activated from bootstrap tests of the preparation information, takes on arbitrary element determination in the tree impersonation measure. The conjecture is made by collecting the forecasts of the gathering by prevalence deciding in favor of order. It returns a speculation blunder rate and is more intense to the commotion. RF may likewise experience the ill effects of the scourge of gaining from a seriously imbalanced preparing informational collection. Since it is developed to relieve the general mistake rate, it will in general zero in additional on the expected effectiveness of the greater part class, which over and again brings about helpless precision for the minority class.[3]

The accuracy score of the Random Forest Classifier on the MNIST dataset is given in Fig. 4.

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```
In [161… from sklearn.metrics import accuracy_score
        accuracy_score(y_pred,y_test)

Out[161… 0.9471
```

Fig. 4. Accuracy Score of Random Forest

3.2.4Multilayer Perceptron

Neural based classifier, called Multilayer perceptron (MLP), is utilized to arrange the written by hand digits. The MLP comprises three unique layers, one is input layer, second is hidden layer, and third is the output layers. In MLP, the association amongthe two layers neurons comprises of weight. Through preparation measures, it fundamentally learns the precise weight change which is related to every association. For the learning reason, it utilizes a regulated learning procedure named Back spread calculation.[3]

The accuracy score of MLP Classifier in machine learning on MNIST dataset is given in Fig. 5.

```
In [178… from sklearn.metrics import accuracy_score
        accuracy_score(y_pred,y_test)

Out[178… 0.96
```

Fig. 5. Accuracy Score of Multilayer Perceptron

3.2.5 Support Vector Machine (SVM)

The SVMis a particular kind of supervised ML technique that purposes to arrange the information focuses by advancing the edge amongst the classes in the high dimensional space. The SVM is a rendering models as focused in space, planned because the instances of the different classes are isolated by a reasonable hole that is pretty much as broad as could be expected. The ideal calculation is created through a "preparation" stage in which preparing information is taken on to foster a calculation competent to separate between bunches prior characterized by the administrator (for example patients versus controls), and the "testing" stage in which the calculation is taken on to dazzle anticipate the gathering to which another discernment has a place.[3]

The accuracy score of the SVM Classifier in machine learning on the MNIST dataset is given in Fig. 6.

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```
In [195… from sklearn.metrics import accuracy_score
          accuracy_score(y_pred,y_test)

Out[195… 0.97595
```

Fig. 6. Accuracy Score of Support Vector Machine

3.2.6FC6 (Feature extraction using AlexNet)

Decision Tree (DT) Classification and Decision Tree (DT) diagram of FC6 is shown in the Fig.7 and Fig.8.

```
Decision tree for classification
 1  if x175<-20.5697 then node 2 elseif x175>=-20.5697 then node 3 else 5
 2  class = 5
 3  if x47<-13.7449 then node 4 elseif x47>=-13.7449 then node 5 else 1
 4  if x70<-13.3584 then node 6 elseif x70>=-13.3584 then node 7 else 3
 5  class = 1
 6  if x34<0.812771 then node 8 elseif x34>=0.812771 then node 9 else 0
 7  class = 3
 8  if x37<5.50089 then node 10 elseif x37>=5.50089 then node 11 else 6
 9  class = 0
10  if x8<-14.2496 then node 12 elseif x8>=-14.2496 then node 13 else 6
11  class = 9
12  if x2<-16.6434 then node 14 elseif x2>=-16.6434 then node 15 else 4
13  class = 6
14  if x12<6.56056 then node 16 elseif x12>=6.56056 then node 17 else 7
15  class = 4
16  if x6<-13.4518 then node 18 elseif x6>=-13.4518 then node 19 else 2
17  class = 7
18  class = 8
19  class = 2
```

Fig. 7. Decision Tree for Classification

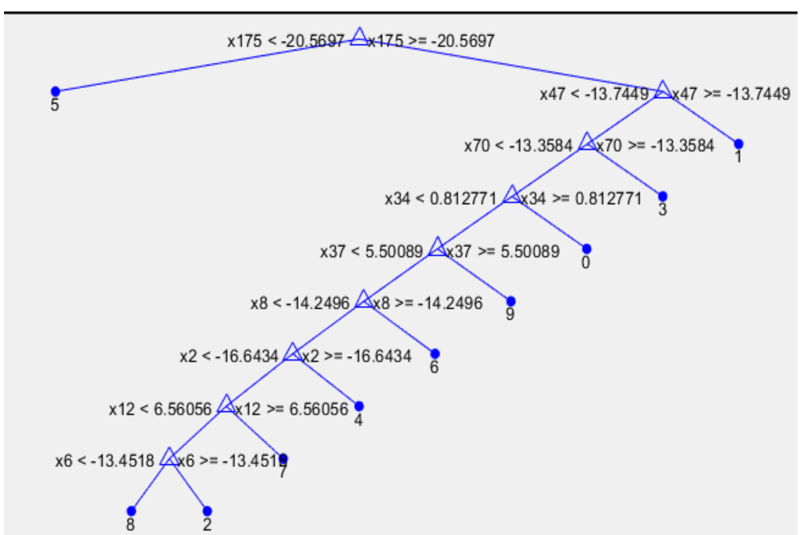

Fig. 8. Decision Tree Diagram

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The accuracy score of Random Forest, Decision Tree, SVM, and NBC on feature extraction fc6 using AlexNet are 100, 97.83,100, and 100 respectively as shown in Fig. 9.

Workspace

Name	Value
accuracycnb	100
accuracyrf	97.8313
accuracysvm	100
accuracytree	100
ans	25x1 Layer
ctree	1x1 ClassificationTree
featuresTrain	199x4096 single
featureTest	83x4096 single
imds	1x1 ImageDatastore
imdsTrain	1x1 ImageDatastore
imdsValidation	1x1 ImageDatastore
layer	'fc6'
Md2	1x1 ClassificationNai...
Md3	1x1 ClassificationEns...
mdl	1x1 ClassificationECOC
net	1x1 SeriesNetwork
YPred	83x1 categorical
YTest	83x1 categorical
YTrain	199x1 categorical

Fig. 9.FC6, AlexNet Accuracy Score

3.2.7 FC7 Feature extraction using AlexNet

The Decision Tree (DT) classification is shown in Fig. 10

```
Decision tree for classification
 1  if x925<0.663283 then node 2 elseif x925>=0.663283 then node 3 else 5
 2  if x53<-1.79334 then node 4 elseif x53>=-1.79334 then node 5 else 1
 3  class = 5
 4  if x150<-5.82382 then node 6 elseif x150>=-5.82382 then node 7 else 3
 5  class = 1
 6  if x116<-4.47123 then node 8 elseif x116>=-4.47123 then node 9 else 0
 7  class = 3
 8  class = 0
 9  if x49<-2.9789 then node 10 elseif x49>=-2.9789 then node 11 else 6
10  class = 6
11  if x133<-4.68915 then node 12 elseif x133>=-4.68915 then node 13 else 9
12  if x22<-4.24362 then node 14 elseif x22>=-4.24362 then node 15 else 4
13  class = 9
14  if x4<-4.49125 then node 16 elseif x4>=-4.49125 then node 17 else 4
15  class = 7
16  if x1<-1.46826 then node 18 elseif x1>=-1.46826 then node 19 else 2
17  class = 4
18  class = 8
19  class = 2
```

Fig. 10. FC7, Decision Tree for Classification

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The Decision Tree Diagram for FC7 is shown in Fig. 11.

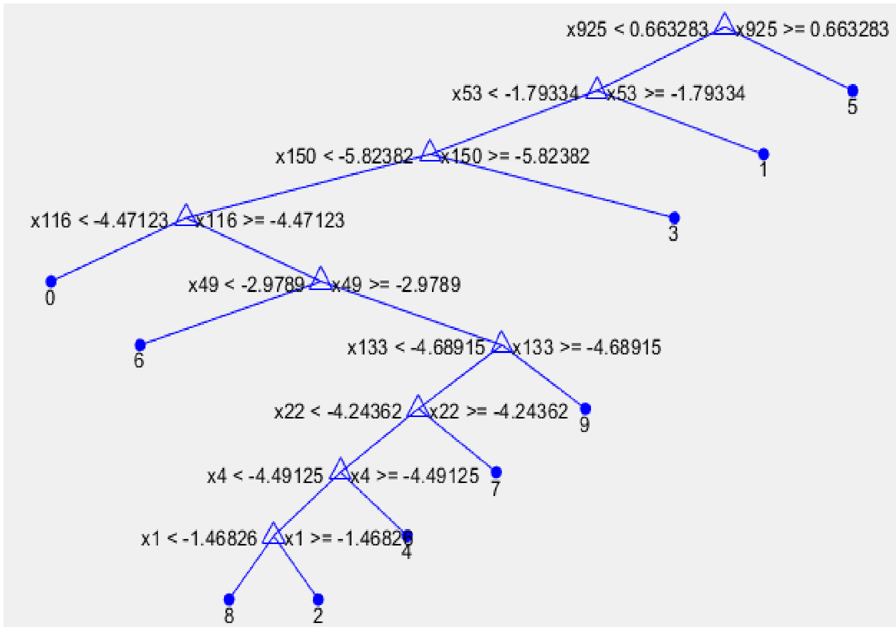

Fig. 11. Decision Tree Diagram for FC7, AlexNet.

The accuracy score of Random Forest, Decision Tree, SVM, and NBC on feature extraction fc7 using AlexNet are 100, 97.83,100, and 100 respectively shown in Fig. 12.

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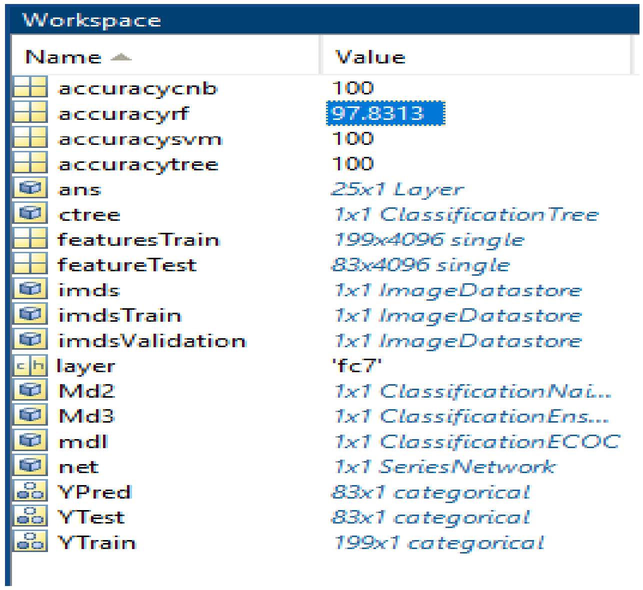


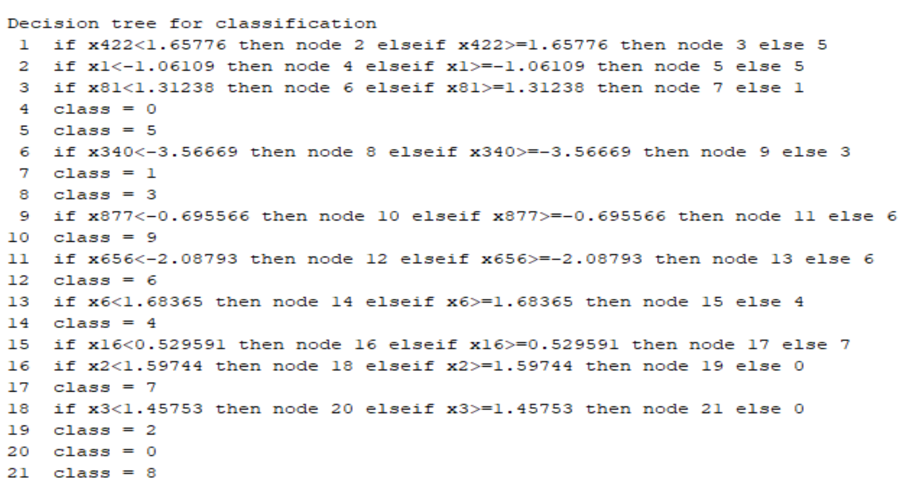
Workspace

Name	Value
accuracycnb	100
accuracyrf	97.8313
accuracysvm	100
accuracytree	100
ans	25x1 Layer
ctree	1x1 ClassificationTree
featuresTrain	199x4096 single
featureTest	83x4096 single
imds	1x1 ImageDatastore
imdsTrain	1x1 ImageDatastore
imdsValidation	1x1 ImageDatastore
layer	'fc7'
Md2	1x1 ClassificationNai...
Md3	1x1 ClassificationEns...
mdl	1x1 ClassificationECOC
net	1x1 SeriesNetwork
YPred	83x1 categorical
YTest	83x1 categorical
YTrain	199x1 categorical

Fig. 12. Accuracy score of Layer FC 7 AlexNet

3.2.8 FC8 Feature extraction using AlexNet

Decision Tree Classification and Decision Tree Diagram on FC8, *the Decision Tree for Classification is shown in Fig. 13*



```
Decision tree for classification
 1  if x422<1.65776 then node 2 elseif x422>=1.65776 then node 3 else 5
 2  if x1<-1.06109 then node 4 elseif x1>=-1.06109 then node 5 else 5
 3  if x81<1.31238 then node 6 elseif x81>=1.31238 then node 7 else 1
 4  class = 0
 5  class = 5
 6  if x340<-3.56669 then node 8 elseif x340>=-3.56669 then node 9 else 3
 7  class = 1
 8  class = 3
 9  if x877<-0.695566 then node 10 elseif x877>=-0.695566 then node 11 else 6
10  class = 9
11  if x656<-2.08793 then node 12 elseif x656>=-2.08793 then node 13 else 6
12  class = 6
13  if x6<1.68365 then node 14 elseif x6>=1.68365 then node 15 else 4
14  class = 4
15  if x16<0.529591 then node 16 elseif x16>=0.529591 then node 17 else 7
16  if x2<1.59744 then node 18 elseif x2>=1.59744 then node 19 else 0
17  class = 7
18  if x3<1.45753 then node 20 elseif x3>=1.45753 then node 21 else 0
19  class = 2
20  class = 0
21  class = 8
```

Fig. 13. Decision Tree for Classification

The Decision Tree Diagram (DTG) is shown in Fig. 14.

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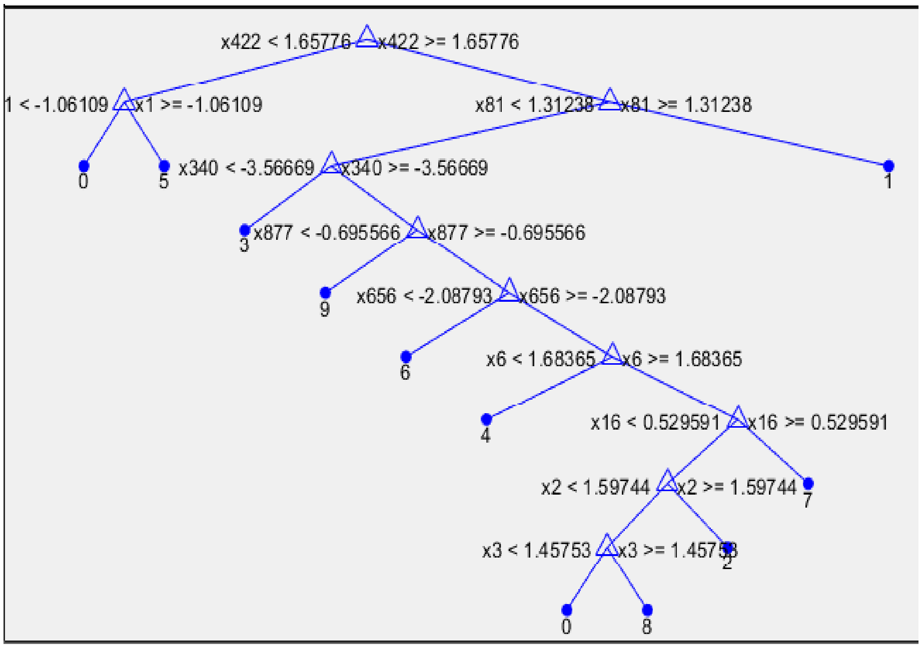

Fig. 14. Decision Tree for Classification

The accuracy score of Decision Tree, SVM, Random Forest (RF), , and NBC on feature extraction fc6 using AlexNet are 100, 97.83,100, and 100 respectively shown in Fig. 15.

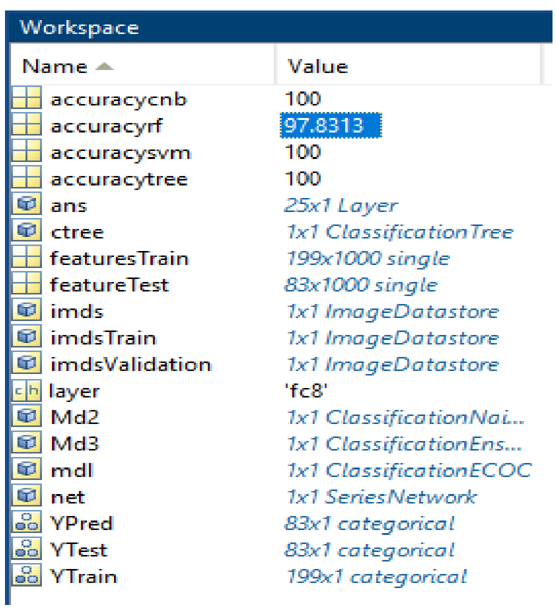

Fig. 15. Accuracy Score of Layer FC 8 AlexNet

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3.2.9Deep Learning Models

Convolutional Neural Network

This convolutional-based neural network uses the Kernel size matrix normally a 3*3 matrix with the help of stride to convert the reduced-sized matrix and then applies max polling to convert the matrix into the more reduced matrix. They have various applications regarding picture and video acknowledgment, and recommender frameworks, picture arrangement, picture division, and clinical picture examination, normal language preparation, mind PC interfaces, and otherfinancial time series.

Figure 16 shows the validation accuracy is 99.68%. The elapsed time for 4 epochs is 1 min 27 sec. The total no of iterations is 232 and 58 iterations per epoch.

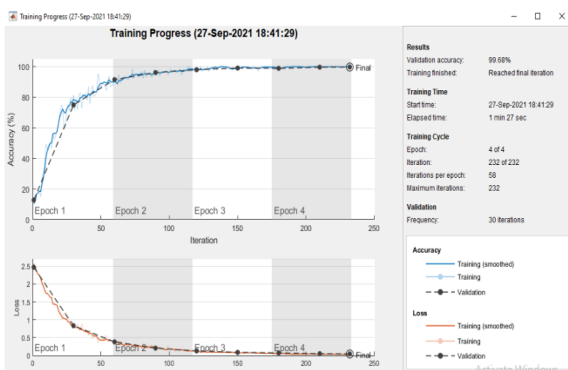

Fig.26. Validation Accuracy

The Figure 17 shows input, conv_1, BN_1, Relu_1, MaxPool_1, conv_2, BN_2, Relu_2, MaxPool_2, conv_3, BN_3, Relu_3, MaxPool_3, conv_4, BN_4, Relu_4, FC, SoftMax and Output Classification.

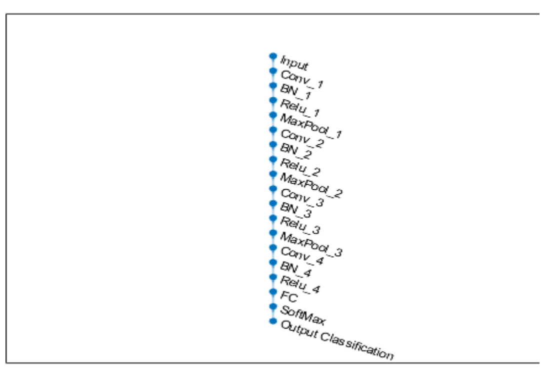

Fig. 17. Convolutional Neural Network

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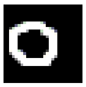
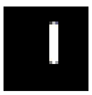
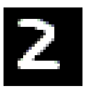
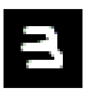
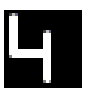
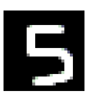
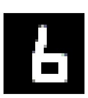
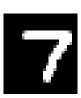
TABLE 2

Test Image of Convolutional Neural Network

Input Image	Recognized Image	Accuracy
		accuracy 0.9976 digitimages 1x1 ImageDatastore filename '0.bmp' filewithpath 'C:\Users\osama\Des...
		accuracy 0.9940 digitimages 1x1 ImageDatastore filename '1.bmp' filewithpath 'C:\Users\osama\Des...
		filewithpath 'C:\Users\osama\Des... filename '2.bmp' digitimages 1x1 ImageDatastore accuracy 0.9960
		filewithpath 'C:\Users\osama\Des... filename '3.bmp' digitimages 1x1 ImageDatastore accuracy 0.9960
		filewithpath 'C:\Users\osama\Des... filename '4.bmp' digitimages 1x1 ImageDatastore accuracy 0.9960
		filewithpath 'C:\Users\osama\Des... filename '5.bmp' digitimages 1x1 ImageDatastore accuracy 0.9960
		filewithpath 'C:\Users\osama\Des... filename '6.bmp' digitimages 1x1 ImageDatastore accuracy 0.9960
		filewithpath 'C:\Users\osama\Des... filename '7.bmp' digitimages 1x1 ImageDatastore accuracy 0.9960
		filewithpath 'C:\Users\osama\Des... filename '8.bmp' digitimages 1x1 ImageDatastore accuracy 0.9960

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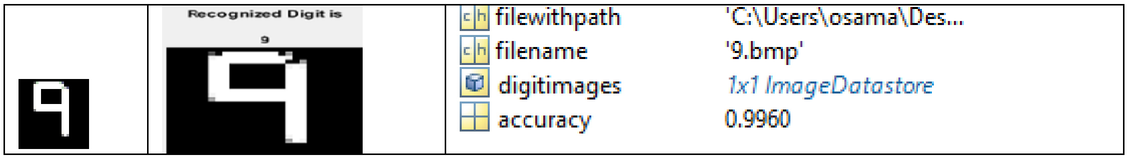

3.2.10 Multilayer Perceptron in Deep Learning in Jupyter Notebook Python Keras

Fig. 18 shows the accuracy score of MLP in deep learning.

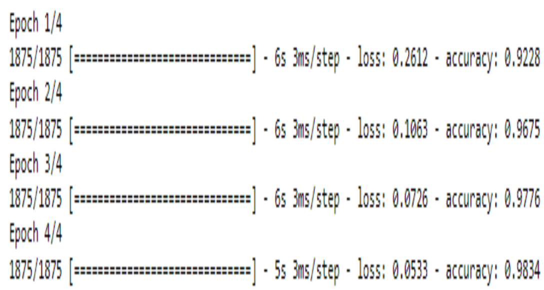

Fig.18. Multilayer Perceptron

4 RESULT AND DSCUSSION

Table 3 shows the accuracy score of a Decision Tree, Bayesian learning, MLP, SVM, and Random Forestsuch as 86.62, 56.58, 96, 97.59, and 94.71 respectively. SVM is the highest accuracy score in machine learning models on MNIST Dataset.

TABLE 3

Machine Learning (ML)

Accuracy Score in % using MNIST Dataset in Machine Learning	
Decision Tree	86.62
Bayesian Learning	56.58
MLP	96
SVM	97.59
Random Forest	94.71

Fig.19 shows the accuracy score of a Decision tree, Bayesian learning, Multilayer Perceptron, Support Vector Machine, and random forest in a blue bar such as 86.62, 56.58,

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96, 97.59, and 94.71 respectively. SVM Blue Bar is the highest accuracy score in machine learning models on MNIST Dataset in the given graph.

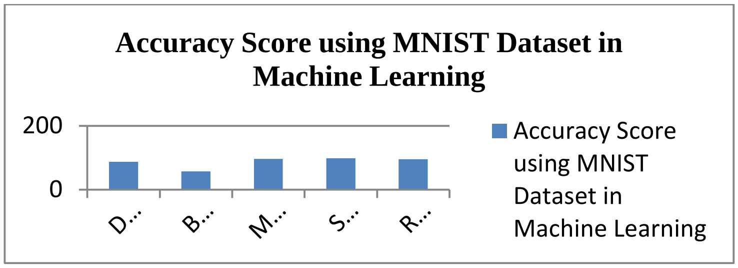

Fig. 19: Accuracy Score

Table 4 shows the accuracy score of the Decision Tree, Bayesian learning, Support Vector Machine, and Random Forest such as 100, 100,100, and 16.86 respectively. Random Forest is the lowest accuracy score in the deep learning model “AlexNet” on MNIST image Dataset.

TABLE 4

Feature Extraction Using AlexNet and applying Machine learning algorithms

Feature Extraction Using AlexNet and applying Machine learning algorithms to get an Accuracy Score	
Decision Tree	100
Bayesian Learning	100
SVM	100
Random Forest	97.83

Fig 20 shows the accuracy score of Decision Tree, Bayesian learning, Support Vector Machine (SVM), and Random Forest in Blue Bar such as 100, 100,100, and 97.83 respectively. Random Forest is the lowest accuracy score in the deep learning model “AlexNet” on MNIST image Dataset.

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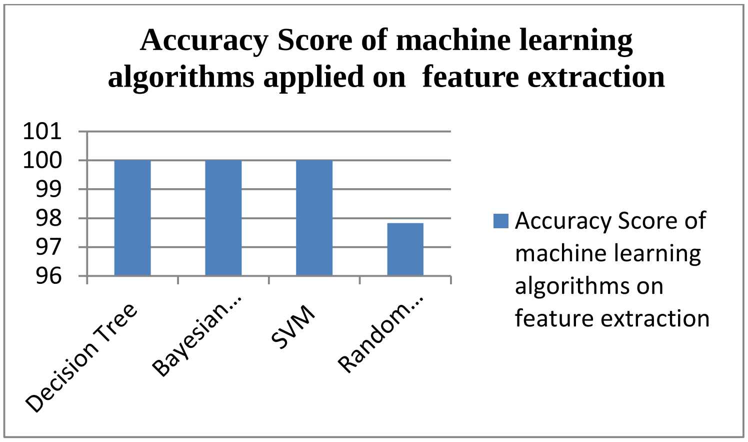

Fig.20 Accuracy Score

Table 5 shows the comparison between the accuracy score of Machine Learning Algorithms and feature extraction fc6, fc7, fc8 using AlexNet, then applied machine learning algorithms. AlexNet is a Convolutional Neural Network in deep learning. AlexNet shows the highest accuracy score of Decision Tree, Bayesian learning, and SVM in the form of 100,100 and 100 respectively.Machine learning algorithm Random Forest is the highest accuracy score than random forest in AlexNet.

TABLE 5

Machine learning versus fc6, fc7, and fc8 using AlexNet

	Accuracy Score Using MNIST dataset applied machine learning algorithms on fc6, fc7, and fc8	**Accuracy Score using MNIST Dataset in Machine Learning**
Decision Tree	100	86.62
Bayesian Learning	100	56.58
SVM	100	97.59
Random Forest	97.83	94.71

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Fig. 21 shows the comparison between the accuracy score of Machine Learning algorithms and feature extraction fc6, fc7, fc8 using AlexNet, then applied machine learning algorithms. AlexNet is a Convolutional Neural Network in deep learning. AlexNet shows the highest accuracy score of the Decision tree, Bayesian learning, SVM, and Random Forest in the form of 100,100,100, and 97.83 respectively than machine learning algorithms.

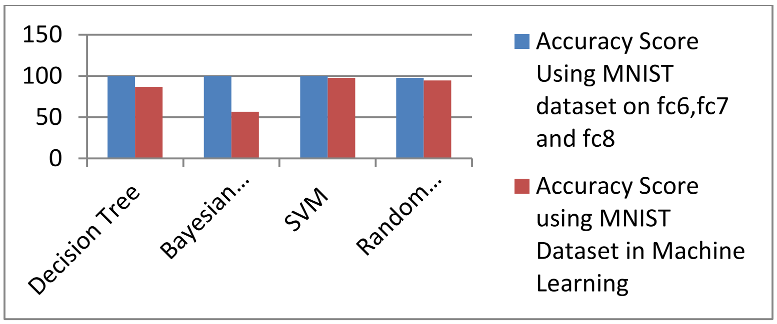

Fig.21: Accuracy Score:

Table 6 shows the accuracy score of deep Learning algorithms such as CNN and MLP.CNN stands for Convolutional Neural Network in deep learning. MLP stands for multilayer perceptron in deep learning. CNN shows the highest accuracy score than MLP in the form of 99.68 and 98.34 respectively.The deep learning algorithm CNN is the highest accuracy score than the deep learning algorithm MLP.

TABLE 6

Shows the accuracy score of Deep Learning algorithms

Accuracy Score using MNIST Dataset in Deep Learning	
CNN	99.68
MLP	98.34

Fig.22 shows the accuracy score of deep learning algorithms such as CNN and MLP.CNN Blue Bar shows the highest accuracy score than MLP in the form of 99.68 and 98.34 respectively.The deep learning algorithm CNN is the highest accuracy score than the deep learning algorithm MLP.

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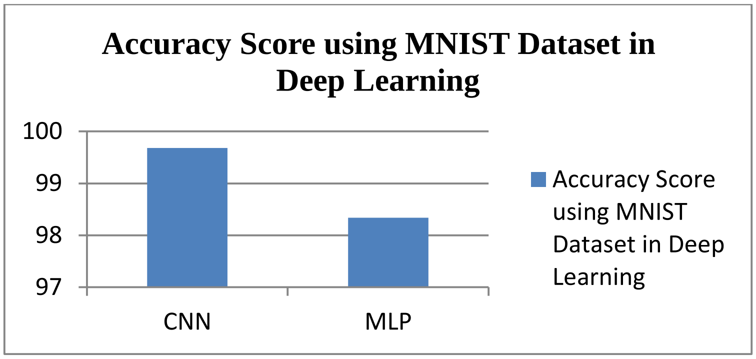

Fig. 22: Accuracy Score of Deep Learning Models

5 CONCLUSION

The outcomes describe that Deep-Learning Models (DLM) produce better results than Machine-Learning Models (MLM) on the MNIST dataset. The deep learning models produce accuracy scores of CNN and MLP in the form of 99.68 and 98.34, while machine learning models produced accuracy scores of the Decision Tree, Bayesian, SVM, and Random forest in the form of 86.62, 56.58, 97.59, and 94.71 respectively.

The results show that getting feature extraction using AlexNet and then applying machine learning models on fc6, fc7 and fc8 produce better results than simple MLM and DLM models except for the Random Forest classifier.

6 FUTURE WORK

In this research, test and training ratio 3/7 are used to get the results of Hand- Written Digits Recognition in the form of accuracy. The Changing in training and test ratio may cause variation in the results. The furthermore new features extraction of the dataset may also improve the results in term of Accuracy.

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