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Identification of handwritten digits of database with machine learning Random Forest

By

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Abstract

Artificial intelligence research is drawn to the interesting problem of intelligent graphics and handwriting processing, which is also a crucial element of a contemporary collection of research questions. Within the discipline of handwritten number identification, the detection of presegmented handwritten numbers using learning models is a well-researched sub-field. It is among the most crucial subjects in the domains of pattern recognition, deep learning, machine learning, and data retrieval, among many others in artificial intelligence. In the past ten years, machine learning techniques have outperformed conventional manually generated artificial learning techniques in their ability to work with downstream systems that compete with human performance. In this article, we present machine learning techniques that use Python's Keras library to recognize handwritten numerals. In this study, we have given datasets that will be utilized to recognize handwritten numerals from 0 to 9 after being initially turned into photographs. An openly accessible handwritten database was used for the tests. 28,000-digit training pictures and 14,000 digit test images were recovered from the database. The precision of the findings directly relates to the accuracy of the number drawn. The findings are more accurate the more exact the drawing is. The result is 87% when drawing the number 1 with a bottom edge that is larger than the picture in the dataset, but the result increases to 88% when drawing the number 1 without a bottom edge, and it reaches 93% when drawing the number 1 more accurately.

Keywords_ Artificial intelligence; handwriting; identification; Machine learning .

Introduction

Intelligent graphics and handwriting processing is an appealing subject of artificial intelligence research, as well as a necessary component of a current set of research issues. The detection of presegmented handwritten numbers using learning models is a well-studied sub-field within the topic of identification of handwritten numbers. It is one of the most important topics in machine learning, data retrieval, deep learning, and pattern recognition, as well as many other fields in artificial intelligence [1]. Over the last decade, machine learning approaches have proven to be effective in compatibility with downstream systems that compete with human performance and outperform traditional manually created artificial learning methods [2]. Furthermore, not all parts of these unique models have been thoroughly investigated previously.

One of the most difficult problems in pattern recognition applications is recognizing handwritten numerals. The requirement to design a suitable algorithm that can recognize handwritten numbers and consumers download through smartphone Scanner and other digital devices is at the heart of the problem in many applications such as zip code, checking online bank accounts, data form entry, and so on. The major objective is to improve the accuracy and reliability of handwritten number recognition [3].

Researchers in data mining and machine learning have put forth a lot of effort to establish successful techniques to data recognition approximation [2]. In the twenty-first century, hand-written digits identification correspondence has become the standard, and it is utilized often in everyday life as a medium of discourse and collecting the details to be conveyed with others. One of the obstacles in general recognition of hand-written characters is the variability and distortion of the hand-written character collection, because various cultures will employ varied handwriting forms and control to extract the characters same patterns from their recognized language [4].

The selection of digits from which the greatest distinguishing qualities may be retrieved is one of the most important challenges in the field of digital recognition systems. Pattern recognition [2,5] use a variety of area sampling procedures to detect specific locations. The broad range of human writing styles is principally responsible for the difficulties in identifying hand-written characters [2,4]. Robust feature extraction is consequently required to improve the effectiveness of a hand-written character recognition system. Hand-written digit recognition has received a lot of interest in the field of pattern recognition device sewing to its usage in several domains.

Character recognition technology may serve as a basis for launching a paperless future in the next days by scanning and modifying current paper documents. Because crisp and precisely straight lines may not always exist, handwritten numbers datasets are ambiguous. The main goal of digit recognition is to extract features from a set of numerical attributes in order to remove uncertainty from the data and create a more powerful embodiment of the term symbol. It deals with retrieving much of the crucial information from raw image details [3].

Curves, like written characters, are not necessarily flat in comparison. Character datasets, on the other hand, can be produced in a variety of sizes and orientations, and are frequently intended to be written in an upright or straight position on a checklist. As a result, by taking these restrictions into account, a successful hand-written recognition system may be created. It's tough to memorize handwritten characters on a regular basis, especially when most individuals can't even recognize their own typed writings. As a result, a writer's ability to compose for the enjoyment of handwritten material is limited [4].

In a machine vision context, hand-written digits detection is a difficult task, yet it is essential to many current technologies. Because of its practical uses in our electronic lives, the identification of hand-written digits is becoming increasingly important in the industrialized world [6].

In many areas where good classification performance is required, several recognition methods have been implemented in recent years. It enables us to take on more challenging tasks while also making our work easier. Incorporating practical applications such as the identification of zip code (postal code), an early stage hand-written digit identification has been created. In hand-written digit identification schemes [1], the postal address is widely employed in online bank account routing.

In today's environment, implementing a computerized system for some types of responsibilities is a difficult effort, as well as a sophisticated and demanding difficulty. Pattern recognition is also a key component of computer vision and an artificial intelligence framework [4].

We have introduced machine learning algorithms for identifying handwritten numbers in this research. We have provided datasets in this work, which will first be converted into photos and then used to detect handwritten numbers from 0 to 9. The testing was done using a publicly accessible handwritten database. We were able to recover 28,000 digit training photos and 14,000 digit test images from the database.

Related Works

There has been a significant amount of research and development effort that has propelled deep learning, machine learning, and artificial intelligence forward. Machines are becoming more intelligent with time, and they have made our lives more safe and controllable, from calculating basic numbers to doing retina identification.

Similarly, handwritten text recognition is an important application of deep learning and machine learning that aids in the detection of forgeries, and a wide range of research has already been done that includes a comprehensive study and implementation of various popular algorithms, such as works done by S M Shamim [7], Anuj Dutt [8], Norhidayu binti [9], and Hongkai Wang [10] to compare the different models of CNN with the fundamental machine learning algorithms on various datasets.

The Multilayer Perceptron classifier produced the most accurate results with the lowe st error rate, followed by Support Vector Machine, Random Forest Algorithm, Bayes Net, Na ve Bayes, j48, and Random Tree, respectively. [8] compared SVM, CNN, KNN, and RFC an d found that CNN (which took the most time to execute) had the highest accuracy of 98.72 pe rcent and RFC had the lowest accuracy, [9] conducted a detailed study-comparison of SVM, KNN, and MLP models to classify handwritten text, concluding that KNN and SVM correctly predict all classes of dataset with 99.26% accuracy, but the process becomes a little more complicated with MLP when it has trouble classifying number 9, for which the authors suggested using CNN with Keras to improve the classification.

On MNIST datasets, accuracy and time are compared. Between machine learning and deep learning, utilizing RFC, KNN, SVM, and Multi-layer CNN as models. Below processor measures, GPU can aid with precision, shorter preparation and testing times, parallelism, and even superior results. In CNN, the author got a decent grade [1].

A dataset of 5,000 MNIST instances was trained with a gradient descent backpropagation technique and then tested with a feed-forward approach with the number of hidden layers and iterations, and the accuracy attained was 99.32 percent. The Multilayer Perceptron (MLP) neural network was found to have 35 neurons and 250 iterations. The proposed approach delivered 99.32 percent training accuracy and 100 percent training accuracy [5].

In this article, we present machine learning techniques that use Python's Keras library to recognize handwritten numerals. In this study, we have given datasets that will be utilized to recognize handwritten numerals from 0 to 9 after being initially turned into photographs. An openly accessible handwritten database was used for the tests. 28,000 digit training pictures and 14,000 digit test images were recovered from the database. The precision of the findings directly relates to the accuracy of the number drawn.

Methodology

A system was constructed in stages to differentiate handwriting using a computer, based on a dataset that contains a set of photographs for analysis using artificial intelligence techniques in general and machine learning techniques in particular.

The proposed system approach for recognizing handwriting will be discussed in this section of the article.

Dataset of the proposed system

Recognition of handwritten character is a broad study subject with several implementation options, including large learning datasets, popular algorithms, feature scaling, and feature extraction approaches. The MNIST dataset (Modified National Institute of Standards and Technology database) is a subset of the NIST dataset, which is made up of two different NIST databases: Special Database 1 and Special Database 3. The digits in Special Database 1 and Special Database 3 were written by high school students and US Census Bureau personnel, respectively. MNIST comprises 70,000 anti-aliased handwritten digit pictures (60,000 in the training set and 10,000 in the test set) in a 28x28 pixel bounding box. Each of these photos has a Y value that indicates what the digit is[10].

Stages of proposed system

Based on a dataset including a series of pictures for analysis using artificial intelligence techniques in general and machine learning techniques in particular, a system was built in phases to identify handwriting using a computer.

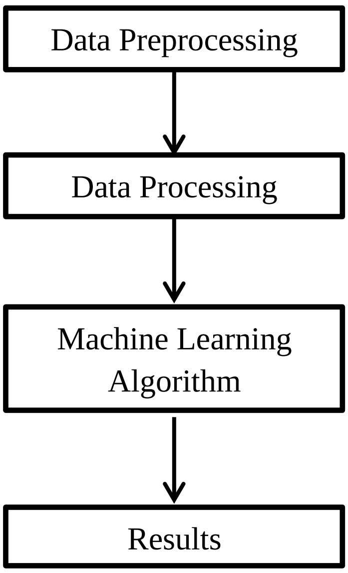

Figure 1. The proposed system process

3.2.1 Image preprocessing

The initial stage is to create the MNIST dataset, which is then split into two preprocessed datasets. The first preprocessed database is a conventional gray-scale dataset, while the second is a binary gray-scale dataset [11]. These two preparation approaches were chosen because they allow the dataset to be translated to a small figure while keeping its aspect ratio [8]. The tests will be carried out in this study work, and the MNIST dataset was prepared in two different forms. The goal of two sets of pre-processed data collections is to track the machine learning model's learning performance accuracy using various pre-processed images. As a result, scientists are thinking about how machine learning works in various pre-process picture formats. The input format values for the neural network may be affected by how the data collection is pre-processed. The data sets are pre-processed and input into the models.

3.2.2 Image processing

Segmentation is a technique for extracting individual characters from an image. There are two types of segmentation. Segmentation Implicit and Segmentation Explicit are the two types of segmentation. Without the mechanism of segmentation, the terms are remembered in tacit segmentation. Individual character extraction in specialized segmentation, on the other hand, is predicted to produce words [12].

Feature extraction is a crucial stage in every recognition technique, and the recognition algorithm starts there as well. Each character has distinct characteristics. It entails a set of laws, each of which specifies the nature of a behavior. The extraction of specific characteristics is accomplished in this stage.

3.2.3 Machine learning for identification of handwritten digit

One of the key strategies for tackling the majority of issues is machine learning. By introducing photos from the MNIST dataset into the system and analysing those images, handwriting patterns were detected in the user interface using machine learning techniques to identify handwriting.

The work was divided into two sub-stages in this system stage, the inputs and outputs are combined to train the system to recognize handwriting in the training phase, and the data is first split into training data and test data. In terms of the testing phase, the outputs are disregarded in favor of just using the inputs to determine how well the system distinguishes handwriting without the requirement for functioning outputs.

Python was used to create the system's programming. The Keras Library, which is the most significant of these libraries, is one of the reasons why the Python programming language was selected to enable machine learning techniques.

Working with machine learning techniques without this library might be quite time- and labor-intensive. This is why the Keras library was selected.

The Keras module is used to create a Multilayer perceptron model of the Sequential class and add pertinent hidden layers with different activation functions to take an image of 28x28 pixels as input for the Handwritten digits Recognition by Multilayer Perceptron [13] implementation, also known as feedforward machine learning. After building a sequential model, we added Drop out layers and a Dense layer with various parameters, as seen in the graphic below. Here, a block diagram is provided for your convenience.

These procedures may be used to train a machine learning in Keras after you have the training and test data.

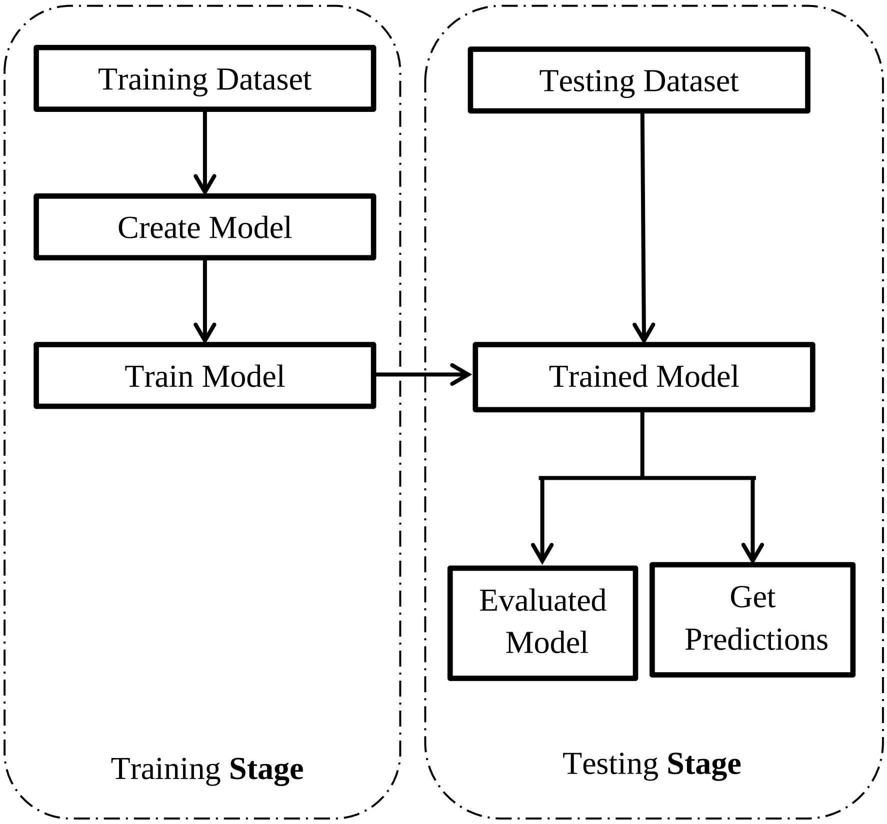

Figure 2. Identification of handwritten digits stages

The system was constructed using the serial model. We may simply stack the stages in the sequential model by sequentially adding each necessary step. We added the necessary activation function to the dense phase, also known as the completely connected phase because we are creating an autonomous system in which all phases are connected, in order to bring the necessary nonlinearity into the model. The system will be able to learn what nonlinear resolution can handle as a result.

Implementation and Results

The proposed system was developed using machine learning techniques for handwriting recognition, and after that, a graphical interface was created for the user to draw letters with their hands. This interface was connected to the proposed system as an input interface through which letters are drawn to begin the processing stages of the system by dealing with the hand-written letter.

The user interface of a typing recognition system is depicted in the following figure. Hand: Write letters using the hand in the first area of the user interface. The second area of the user interface displays the results of matching the inputs to the images stored in the system dataset by carrying out the series of operations mentioned above.

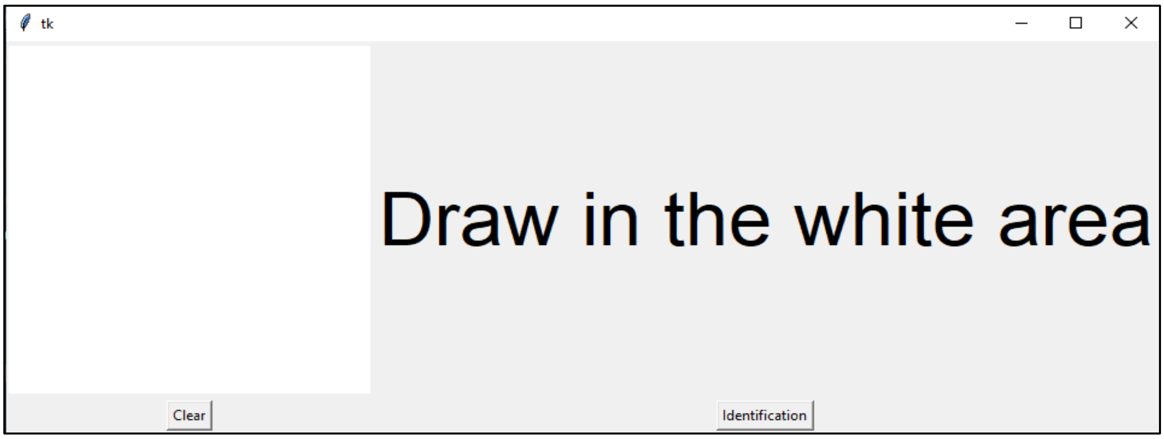

Figure 3. The proposed system user interface

The following figure displays the user's entry for the number 1. The user writes the letter using their hand on the white work area, then he presses the (Identification) button to initiate the system's necessary procedures to assess the similarity of the written letter to the images saved in the system.

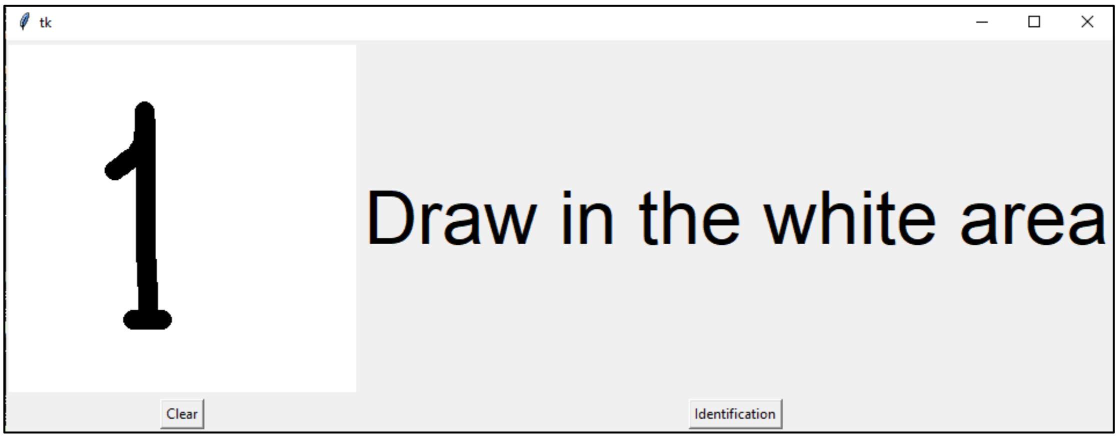

Figure 4. The user interface with drawing number 1

The result appears after matching the hand-written number with images using image processing and matching the edges of the number.

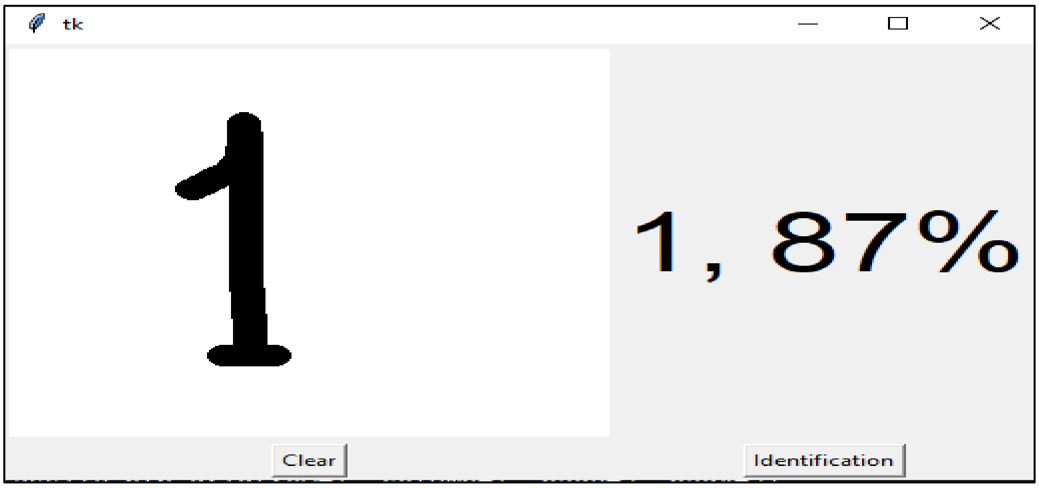

Figure 5. The user interface with drawing number 1 and bottom edge

Figure 6. The user interface with drawing number 1 and without bottom edge

We note that the result appears 87% when drawing the number 1 with an increase in the bottom edge, which is in excess of the image in the dataset, but when drawing the number 1 without the bottom edge, we notice that the result rises to 88%, and the result reaches 93% when drawing the number 1 with greater accuracy.

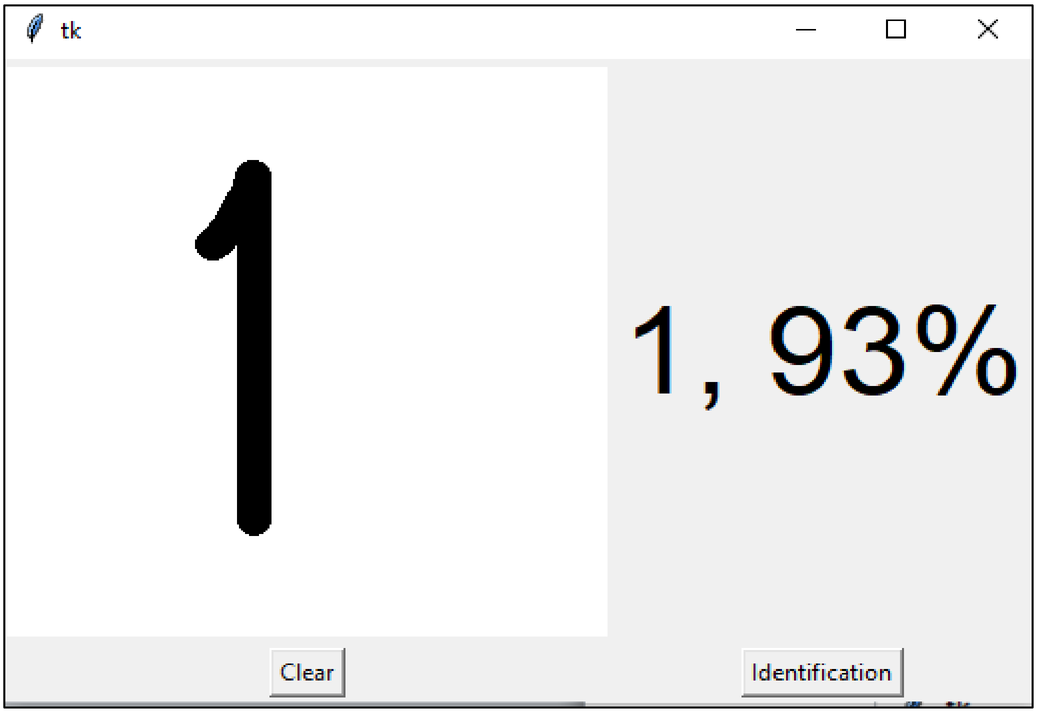

Figure 6. The user interface with drawing number 1 with high accuracy

So the accuracy of drawing the letter is directly proportional to the accuracy of the results. The higher the accuracy of the drawing, the more accurate the results.

Conclusion

Intelligent graphics and handwriting processing is a fascinating issue that artificial intelligence research is drawn to and is also a key component of a current collection of research issues. The detection of pre segmented handwritten numbers using learning models is a well-studied sub-topic in the subject of handwritten number identification. It is one of the most important topics in the artificial intelligence fields of pattern recognition, deep learning, machine learning, and data retrieval, among many others. Machine learning approaches have improved over traditional manually produced artificial learning techniques in the last 10 years in terms of their capacity to integrate with downstream systems that rival human performance. The precision of the findings directly relates to the accuracy of the number drawn. The findings are more accurate the more exact the drawing is. The result is 87% when drawing the number 1 with a bottom edge that is larger than the picture in the dataset, but the result increases to 88% when drawing the number 1 without a bottom edge, and it reaches 93% when drawing the number 1 more accurately.

References

M. Z. Alom, P. Sidike, T. M. Taha, and V. K. Asari, “Handwritten Bangla Digit Recognition Using Deep Learning,” vol. 6, no. 7, pp. 990–997, 2017.

S. Majumder, “Handwritten Digit Recognition by Elastic Matching,” J. Comput., vol. 4, no. 04, pp. 1067–1074, 2018.

G. Cheedella, “Critique of Various Algorithms for Handwritten Digit Recognition Using Azure ML Studio,” Glob. J. Comput. Sci. Technol., vol. 20, no. 1, pp. 1–5, 2020.

S. M. Shamim, M. B. A. Miah, A. Sarker, M. Rana, and A. Al Jobair, “Handwritten digit recognition using machine learning algorithms,” Indones. J. Sci. Technol., vol. 3, no. 1, pp. 29–39, 2018.

Y. Lecun, L. Bottou, Y. Bengio, and P. Ha, “LeNet,” Proc. IEEE, no. November, pp. 1–46, 1998.

I. Ali, I. Ali, A. Khan, S. A. Raza, B. Hassan, and P. Bhatti, “Sindhi Handwritten-Digits Recognition Using Machine Learning Techniques Sindhi Handwritten-Digits Recognition Using Machine Learning Techniques,” Int. J. Comput. Sci. Netw. Secur., vol. 19, no. 5, pp. 195–202, 2019.

Handwritten Digit Recognition using Machine Learning Algorithms”, S M Shamim, Mohammad Badrul Alam Miah, Angona Sarker, Masud Rana & Abdullah Al Jobair.

” Handwritten Digit Recognition Using Deep Learning”, Anuj Dutt and Aashi Dutt.

Handwritten recognition using SVM, KNN, and Neural networks”, Norhidayu binti Abdul Hamid, Nilam Nur Binti Amir Sharif

Comparison of machine learning methods for classifying mediastinal lymph node metastasis of non-small cell lung cancer from 18 FFDG PET/CT images” by Hongkai Wang, Zongwei Zhou, Yingci Li, Zhonghua Chen, Peiou Lu, Wenzhi Wang, Wanyu Liu, and Lijuan Yu.

Al-Behadili, Hayder. Classification Algorithms for Determining Handwritten Digit. Iraqi Journal for Electrical and Electronic Engineering. 12. 96-102. 10.37917/ijeee.12.1.10, 2016.

M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, “The WEKA Data Mining Software: An Update,” ACM SIGKDD Explor., vol. 11, no. 1, pp. 10–18, 2009.

L. Bottou, C. Cortes, J. S. Denker, H. Drucker, I. Guyon, L. D. Jackel, Y. A. LeCun, U. A. Mü,ller, E. Sä,ckinger, P. Y. Simard, and V. N. Vapnik, "Comparison of classifier methods: A case study in hand written digit recognition", Proc. 12th Int. Conf. Pattern Recognition and Neural Networks, Jerusalem, pp. 77-87, 1994.