Handwritten Digit Recognition using Machine Learning

Dr. V. Ramesh Babu
Professor, Dr.MGR Educational and Research Institute, rameshbabu.cse@drmgrdu.ac.in

O.Vasantha Kumari
Professor, Dr.MGR Educational and Research Institute, vasanthakumari.cse@drmgrdu.ac.in

Dr. D. Usha
Professor, Dr.MGR Educational and Research Institute, usha.cse@drmgrdu.ac.in

Pachipala Sreesree Kumar
Final Year B.Tech CSE, Dr.MGR Educational and Research Institute, psreesree1806@gmail.com

Pancheti Jayanth
Final Year B.Tech CSE, Dr.MGR Educational and Research Institute, jspjayanthsai1432@gmail.com

Ronanki Sai Krishna
Final Year B.Tech CSE, Dr.MGR Educational and Research Institute, saikrishna57921@gmail.com

Abstract

A Handwritten Digit Recognition is one of the essentially crucial drawbacks in pattern recognition applications. The applications of digit recognition consists of form data entry, processing bank checks, postal mail sorting etc. The purpose of the obligation exists within the potential to develop an effective algorithm that can recognize the hand written digits and which is submitted to the users by the way of a tablet, scanner, and other electronic devices. Handwritten digit dataset is unclear in nature because there may not always be acute and faultlessly straight lines. One of the key objectives of handwritten digit recognition is feature extraction, which aims to eliminate redundant information from the input and provide a word picture that is more effectively represented by a collection of numerical properties. It deals with the majority of the critical information extraction from the raw picture data. The best algorithm is developed via two phases: "training," in which training data are used to create an algorithm capable of discriminating between groups previously defined by the operator (e.g., patients vs. controls), and "testing," in which the algorithm is used to blindly predict the group to which a new perception belongs. Additionally, it develops ample search area for the proper classification of future data characteristics and offers a very accurate classification performance over the training records.

Keywords: *SVM, Machine Learning, UML, MNIST, SVGA, SKLEARN, Data Pre-processing.*

I. INTRODUCTION

Nowadays, handwriting recognition is quite important in the world of technology. Additionally, it is crucial for the preservation and retrieval of vital handwritten data. One of the key problems in the field of digit recognition systems is the identification of the digit from which the best discriminating characteristics may be retrieved. Different types of region sampling strategies are employed in pattern recognition to find these regions. The difficulty in reading handwritten characters is mostly brought on by the wide variety of personal writing styles. In order to enhance the performance of a handwritten character recognition system, strong feature extraction is crucial. Due to its many applications, handwritten digit recognition is currently receiving a lot of attention in the field of pattern recognition systems. Character recognition technology may one day operate as the cornerstone for the establishment of a paperless society by processing and digitizing already existent paper records. The primary use of machine learning techniques over the past ten years has shown to be effective in creating systems that compete with human performance and perform significantly better than manually created classical artificial intelligence systems used in the early days of optical character recognition. Because there might not always be precise, straight lines, handwritten digit datasets can be ambiguous.

The fundamental objective of feature extraction in digit recognition is to eliminate redundant information from the input and provide a more accurate representation of the word picture through a collection of numerical properties. It deals with retrieving the majority of the crucial data from raw picture data. In addition, unlike the written letters, the curves are not always smooth. Additionally, the characters dataset can be created in many sizes and orientations, albeit they must always be written on a guideline in either an upright or downward position. In light of these restrictions, a useful handwriting recognition system may be created.

II. LITERATURE SURVEY

[1] Grimsdale: An early notable attempt in the area of character recognition research is by Grimsdale in 1959. The origin of a great deal of research work in the early sixties was based on an approach known as analysis-by-synthesis method suggested by Eden in 1968. The great importance of Eden's work was that he formally proved that all handwritten characters are formed by a finite number of schematic features, a point that was implicitly included in previous works. This notion was later used in all methods in syntactic (structural) approaches of character recognition.

[2] K. Gaurav, Bhatia P. K.: [5] Et al, this paper deals with the various pre-processing techniques involved in the character recognition with different kind of images ranges from a simple handwritten form based documents and documents containing colored and complex background and varied intensities. In this, different pre-processing techniques like skew detection and correction, image enhancement techniques of contrast stretching, binarization, noise removal techniques, normalization and segmentation, morphological processing techniques are discussed.

It was concluded that using a single technique for pre-processing, we can’t completely process the image. However, even after applying all the said techniques might not possible to achieve the full accuracy in a pre-processing system.

[3] Salvador España-Boquera: et al [6], in this paper hybrid Hidden Markov Model (HMM) model is proposed for recognizing unconstrained offline handwritten texts. In this, the structural part of the optical model has been modelled with Markov chains, and a

Multilayer Perceptron is used to estimate the emission probabilities.

[4] Sushree Sangita Patnaik and Anup Kumar Panda: In [9], diagonal feature extraction has been proposed for offline character recognition. It is based on ANN model. Two approaches using 54 features and 69 features are chosen to Sushree Sangita Patnaik and Anup Kumar Panda May 2011 [14] et al, this paper proposes the implementation of particle swarm optimization (PSO) and bacterial foraging optimization (BFO) algorithms which are intended for optimal harmonic compensation by minimizing the undesirable losses occurring inside the APF itself. The efficiency and effectiveness of the implementation of two approaches are compared for two different conditions of supply. The total harmonic distortion (THD) in the source current which is a measure of APF performance is reduced drastically to nearly 1% by employing BFO. The results demonstrate that BFO outperforms the conventional and PSO based approaches by ensuring excellent functionality of APF and quick prevail over harmonics in the source current even under unbalanced supply.

[5] T. Som : In literature [15], T. Som have discussed fuzzy membership function based approach for HCR. Character images are normalized to 20 X 10 pixels. Average image (fused image) is formed from 10 images of each character. Bonding box around character is determined by using vertical and horizontal projection of character. After cropping image to bounding box, it is resized to 10 X 10 pixels size. After that, thing is performed and thinned image is placed in one by one raw of 100 X 100 canvas. Similarity score of test image is matched with fusion image and characters are classified.

[6] Renata F. P. Neves : In [16], Renata F. P. Neves have proposed SVM based offline handwritten digit recognition. Authors claim that SVM outperforms the Multilayer perceptron classifier. Experiment is carried out on NIST SD19 standard dataset. Advantage of MLP is that it is able to segment non-linearly separable classes. However, MLP can easily fall into a region of local minimum, where the training will stop assuming it has achieved an optimal point in the error surface. Another hindrance is defining the best network architecture to solve the problem, considering the number of layers and the number of perception in each hidden layer.

III. EXISTING SYSTEM

Currently, there is no specific method to identify the scribbled digits; human interaction is the only way to do it. It is obvious that each person has a different writing style, and that everyone has their own. A person is unable to distinguish the precise digits typed by another person, which can occasionally seriously harm the data and even change the statistics. Therefore, it is essential to create a system that correctly and error-free identifies handwritten digits. One may mistakenly think that a certain numeral is another, for example, thinking that 1 is 7 or that 7 is 1.

Disadvantages of Existing System:

- A digit may be mistaken for another.
- Replacing one digit with another might alter the outcome.
- If a single digit is off in financial matters, there will be major repercussions.

IV. PROPOSED METHOD

Since the 1980s, handwriting recognition has been a part of technology, although it has only recently become widely employed. The basic goal of handwriting technology is to allow individuals to write as they usually would before eventually digitising their handwriting. This handwriting recognition system functions in a variety of ways. An electrical gadget called handwriting recognition can tell what someone is writing. In addition to converting

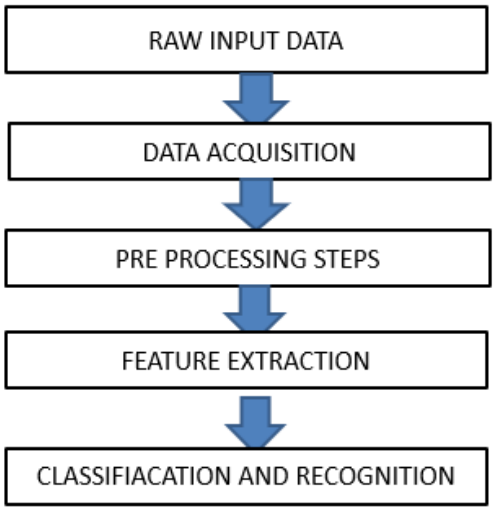
the words into conventional type on a computer, this procedure can also be carried out by having the computer display the person's handwriting.

We import the handwritten data for the digits from the MNIST database. We load the MNIST database which contains the digits as data that were handwritten. We train the dataset with the machine learning algorithms and implement convolutional neural networks that were meant mainly for digit and image processing. After training the dataset we then implement the algorithms on our actual data which then produces the accurate results.

Advantages of Proposed System:

- Data storage
- Data retrieval
- Historical preservation
- Textual studies

Fig 4.1 Digit Recognition Architecture



Importing Libraries

We import the MNIST database, together with the necessary libraries and packages, in this module. It includes the handwritten data.

Import the datasets

Add data to the MNIST database. It includes the handwritten data.

Generating SVM classifier

Generating the required SVM classifier or algorithm to carry forward the process.

Generating the accuracy of training

We should test the training set so that we can understand whether the algorithm is trained or not.

Deskew input

Deskew in the sense of cleaning up and removing unnecessary data from the input. Additionally, it alludes to muting the sounds. We then give the data to the system, which uses the supplied data to run the algorithm, predicts the result, and presents it to the user.

Predict the output

The final output will be verified and achieved.

Support Vector Machine

Support Vector Machine is the technical term. A popular supervised machine learning technique for classification and regression problems is SVM. The SVM method is frequently used in systems for intrusion detection, handwriting recognition, protein structure prediction, and spotting steganography in digital photos, among other things.

The SVM algorithm predicts the classes in step one. One of the classes has the identification number 1, while the other has the number -1.

The business problem is transformed into a mathematical equation with unknown

variables, as is done by all machine learning algorithms. The task is then transformed into an optimization problem in order to find these unknowns. In the case of the SVM classifier, a loss function known as the hinge loss function is utilized and adjusted to find the largest margin since optimization issues usually aim at maximizing or decreasing something while analysing and adjusting for the unknowns.

This loss function may alternatively be seen as a cost function, whose cost is zero when no class is predicted wrongly. Error/loss is then assessed if this is not the case. The issue with the current situation is that there is a conflict between maximising margin and the loss that results from doing so to an extreme degree. The addition of a regularisation parameter theoretically grounds these ideas.

Weights are optimised by computing the gradients using advanced calculus ideas, namely partial derivatives, as is the case with the majority of optimization issues.

When there is no classification mistake, the gradients are just updated using the regularisation parameter. when misclassification occurs, the loss function is also employed.

Updating the gradients when there is no misclassification or misclassification.

When there is no classification mistake, just the regularisation parameter is utilised to update the gradients; when misclassification occurs, the loss function is also applied.

V. IMPLEMENTATION

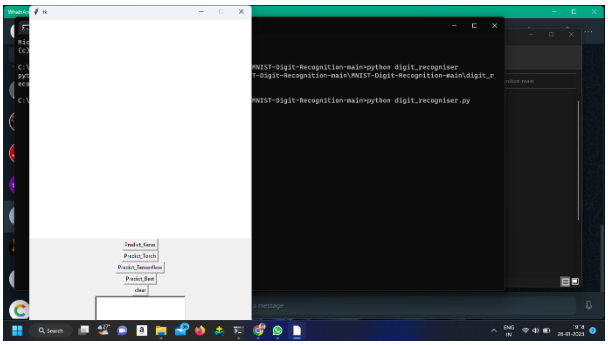
The project's implementation phase is when the conceptual design is transformed into a functional system. As a result, it may be said to be the stage that will determine if a new system is a success and whether its users have faith in its ability to function well.

The implementation step entails meticulous planning, investigation of the current system and its implementation barriers, creation of transitional techniques, and assessment of transitional methods.

The technique is designed to properly detect handwritten digits.

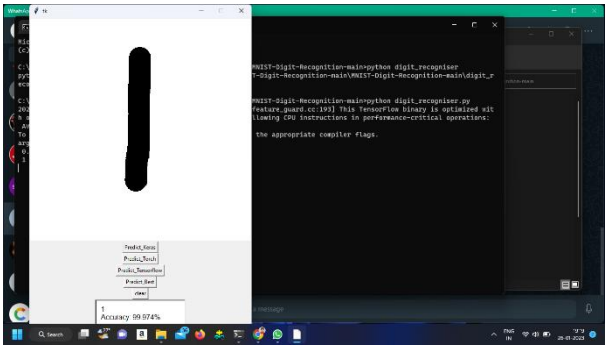
Each writer has their own unique writing style. Here, the issue emerges because it is unable to determine the written digit with accuracy, rendering the system confusing. We train the dataset first, then give the system the real data; the system then shows the digit that was typed.

1.Import the packages: To begin, we had to import the packages from the libraries that contain OpenCV, Numpy, and Sklearn.



2.Read the dataset: Check out the dataset. The MNIST database is employed. It comprises entirely handwritten data in the form of digits.

3.Train the dataset: Using machine learning methods, we train the data in the database. We may then provide the actual data after using the dataset to train the algorithms.

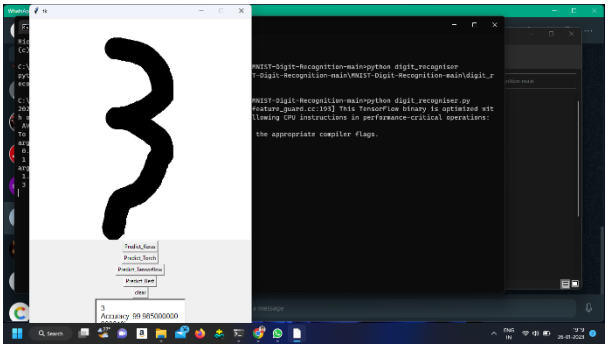


4.Give input: After using the test dataset to train the algorithms, we now provide the input

to the system so it can identify the written digit.

5.Deskew the output: After gaining access to the input, we deskew the data and clean it if there is any noise or extraneous information present. The data is then processed by applying the algorithms to the input data.

6.Predict the output: The result is predicted by the algorithm once it has processed the input data, and the output is then shown on the screen.



VI. CONCLUSION

To reliably recognise the written digits, we have created a handwritten digit recognition system. Particularly when the material is totally handwritten, it aids in accurately estimating the digit without any misunderstanding. Python programming is used to implement the entire system. It accurately anticipates the digits. In the future, the accuracy rate can be raised. Due to the absence of standardised benchmarking datasets, we have limited our investigation to isolated numeral recognition and isolated character recognition. The following are the next directions for Devanagari Character Recognition study, based on the data we have so far. Since it is assumed that the pictures are of high quality, sophisticated normalization, skew removal, and slant removal processes are not carried out because the job specifically relates to isolated Devanagari letters. If these processes are used as well, accuracy can be improved. The created model may be enhanced to support a more comprehensive method of word recognition.

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