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Adaptive Handwritten Digit Recognition using Machine Learning and Deep Learning Techniques

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ABSTRACT:

In the current generation, handwritten character recognition plays an important role. This also includes digit recognition which is vastly used in bank check verifications, form data entry, postal mails, etc. Since technology is more and more involved in our human life, handwritten recognition reduces human tasks and makes work easy. Handwritten digit recognition is an oppressive task where the numbers are not accurately written. Since machine learning works on a lot of real-time problems but it still would be difficult for a machine to work on handwritten patterns and digits that are not perfect and the script and style vary from person to person. Hence, handwritten digit recognition is the solution to this problem. This model enhances to build of an efficient algorithm that can identify the user-provided data through scanners and other devices that can also work as offline recognition using different machine learning techniques. The algorithms that are going to be used are Decision tree, KNN, K-mean etc.

***Keywords* - Handwriting Recognition, digit recognition, machine learning, k-nearest neighbour, classification, k-mean algorithm, cnn, random forest, feature extraction etc.**

I. INTRODUCTION

These days, handwriting recognition is being used in many sectors such as in banking for bank checks, postal mail addresses, reading old documents, etc. Especially in the educational system, we see many electronic devices that support the educational applications submitted by the students. In our day-to-day life, we use this method multiple times unknowingly through smartphones and devices. The scanners help us in scanning the handwriting and getting the information through the internet.

Digit recognition systems are used in real-world applications such as online handwriting recognition on computer tablets or systems, number plate recognition for vehicles, processing bank check amounts, processing numeric entries in forms filled out by hand, etc. to train the machine to recognize the digits from various sources such as emails, bank checks, paper, etc.

One of the major challenges faced is variating and distorting the characters and digits because various communities use diverse styles of handwriting and recognize the pattern from the script.

The main goal in digit recognition is feature extraction to remove the redundancy from the data and gain a more effective embodiment of the digit image through a set of numerical attributes.

II. LITERATURE SURVEY

In paper [1]. Rabia KARAKAYA, Serap KAZAN; (2021), Handwritten Digit Recognition Using Machine Learning . Sakarya University Journal of Science, 25(1), 65-71. In this paper, tests were run on the MNIST handwritten digit data set for this investigation. In the area of handwriting recognition, the algorithms' success rates were compared. The study's results were compared later, where the values were acquired. The comparable machine learning methods were analysed. The general steps followed here are pre-processing, segmentation, feature extraction, classification, and recognition, and post-processing for efficient and error-free digit recognition. The study made use of the Scikit Learn (v0.22.2.post1) Python module. It provides the chance to successfully implement a variety of machine learning methods. It makes it possible to quickly train and test machine learning algorithms using high-level languages. In this work, tests using Decision Trees, ANN, KNN, and K-Means Algorithm were run on the MNIST handwritten digit data set.

In paper [2]. R. Sethi and I. Kaushik, "Hand Written Digit Recognition using Machine Learning," 2020 IEEE 9th International Conference on Communication Systems and Network Technologies (CSNT), 2020, pp. 49-54, doi:10.1109/CSNT48778.2020.9115746. In this paper, the OCR(Optimal character recognition) method is used which can identify the characters by converting them into machine-encoded text in form of ASCII or Unicode. Digit recognition followed six steps to recognize the digit. They are image acquisition, pre-processing, segmentation, feature extraction, classification and recognition, and post-processing. The supervised machine learning technique is used i.e., dealing with the set of input and output pairs, the model is trained first, with labelled dataset the output can be predicted much earlier by the humans.

Involvement of Euclidean distance formula was used to determine the nearest labelled data point to the testing data point.

In paper [3]. TY - JOUR, AU - Shamim, S. M., AU - Miah, Md Badrul, AU - Sarker, Angona, AU - Rana, Masud, AU - Jobair, Abdullah, PY - 2018/03/05, SP - , T1 - Handwritten Digit Recognition Using Machine Learning Algorithms, VL - 18, DO - 10.17509/ijost.v3i1.10795, JO - Indonesian Journal of Science and Technology,ER . Multilayer Perception (MLP) is used here to classify the handwritten digits. MLP consists of three layers, input, hidden, and output layers. For learning purpose, it uses a supervised learning technique names as Back propagation algorithm. The Waikato Environment for Knowledge Analysis (WEKA) is a well-known machine learning toolkit created at the University of Waikato and written in Java. Under the terms of the GNU General Public License, it is free software. It includes a number of algorithms and visualisation tools for data analysis and predictive modelling, as well as graphical user interfaces enabling easy access to this functionality.

In paper [4]. Hui-Huang Zhao and Han Liu , “Multiple classifiers fusion and CNN feature extraction for handwritten digits recognition” , Springer , 2019. This part reviews traditional machine learning techniques and discusses prospective advancements through the use of granular computing concepts. It also gives an overview of handwritten digit recognition and a discussion of convolutional neural network applications for picture categorization. Convolutional neural networks (CNN) are a family of deep feed-forward artificial neural networks that have been effectively used in machine learning to analyse visual data. Comparatively speaking, CNN require less pre-processing than other image classification techniques. This feature design's independence from past knowledge and human effort is a significant benefit. Extraction of features from visual data appears to be advantageous for convolutional networks as well. In our method, the Convolutional Neural Network architecture is used to extract the picture properties of the handwritten digits.

In paper [5]. Patil, Pranit, Handwritten Digit Recognition Using Various Machine Learning Algorithms and Models (JULY 23, 2020). International Journal of Innovative Research in Computer Science & Technology (IJIRCST) ISSN: 2347-5552, Volume- 8, Issue- 4, July- 2020. This study used a machine learning algorithm decision tree to evaluate the standard digital dataset from Kaggle for handwritten digit recognition. Precision ranges from 0 to 9 digits.

The accuracy of the model, which was trained using the decision tree approach using a typical dataset of 42K rows and 720 columns, was 83.4%.Accuracy for 0-9 digits as follows: 0 = 83.5%, 1 = 93.7%, 2 = 83.6%, 3 = 83.1%, 4 = 83.8%, 5 = 83.6%, 6 = 83.4%, 7 = 83.8%, 8 = 84.1%, 9 = 83.7%

III. SUPERVISED MACHINE LEARNING SYSTEM

Supervised machine learning is a technique that trains the machine or system through some pre-defined input or labels from which the machine learns or gets trained such that model could identify the inputs to obtain the desired and accurate output. Since the model is trained through many pre-defined labels, output is obtained much before than humans can identify. This technique mainly develops the relationship between the input and the output and the mathematical formula is as follows:

$R(g)=1/N(\Sigma L(y,g(x)))$

The supervised machine learning algorithms are classified as regression and classification.

Regression: A statistical relationship is determined between a single dependent and multiple independent variables such as financial analysis and prediction. The best set of values of the random variables or independent variables are predicted on the foundation of dependent variables.

Classification: A supervised technique or an approach that lets the model or machine to learn from the labelled data and perform test on new input and identify them and provide an accurate result.

IV. PROPOSED WORK

The purpose of this model is to workout tasks and deduct the difficulties faced during understanding of the handwriting recognition and identifying the characters. It mainly focuses on the numerical part which have a huge impact on today’s world like in various sectors. Since the writing style and script varies form human to human it would be difficult for a person to understand the exact character. He may fail to recognize the correct character. This model helps in obtaining the accurate output to human given input by training the model.

V. FLOW CHART

Analyse the dataset: Collecting various datasets and approaching them to understand. After understanding all the datasets and analysing them and if they meet our requirements for the model.

Prepare the dataset: Among all the analysed datasets, the one which suits the model is to be chosen.

Creating the model: Through the help of dataset, the model is trained by pre-defined labelled data as inputs and acquiring for accurate output.

Compiling the model: The trained model is tested on the supervised data i.e., the labelled data that already has been learnt and made sure that it provides the result or output correctly.

Fit the model: The model need to be get used to the task it need to do based on the required concept of recognizing the handwritten digits.

Evaluate the model: After passing through so many steps, it is the main step to do by providing some various handwritten scripts of the digits in different styles.

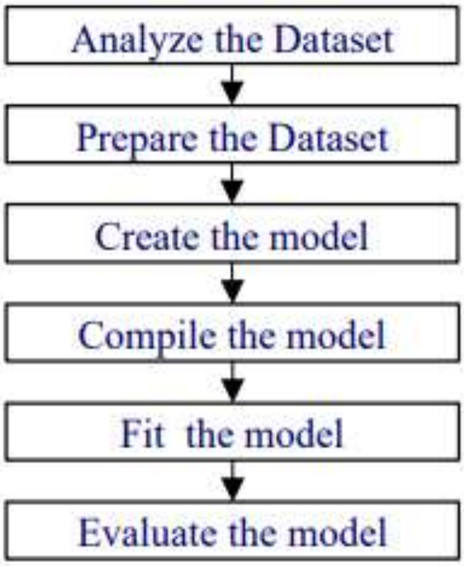

fig:5.1 flow diagram for model

Pre-processing: The technique of organizing the raw data to make it suitable for building and training machine learning models. It includes operations such as:

- Line localization
- Word localization
- Thresholding

Segmentation: The two digit numbers or more than two digit numbers are segmented since the used MNIST dataset contains single digits from 0-9. The segmentation step do not occur if the number is single digit number.

Feature Extraction: the data is processed and defined in a more limited space and prepared for the recognition step.

Classification: classification may be a supervised learning concept which basically categorizes a set of data into classes. The data set to be used at this step is so important. The diversity and richness of the data set in which the algorithm is trained will increase the success rate

Post-processing: In post processing step, it is aimed to eliminate possible errors after recognition. Some systems use dictionaries at this stage. Thus, the recognized numbers after the recognition process is checked again by comparing it with possible numbers in the dataset.

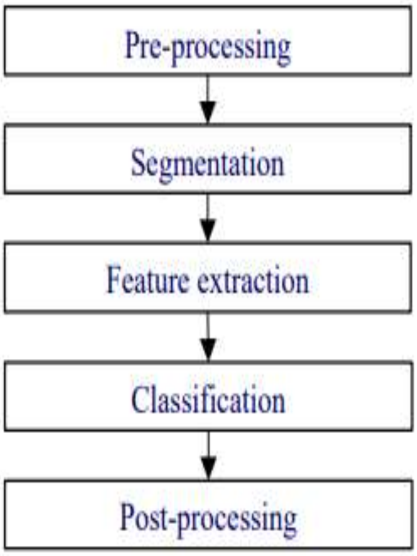

fig:5.2 handwritten digit recognition steps

VI. METHODOLOGY

During our method, we use CNN LeNet-5 to obtain more diverse features from each handwritten digit image. The LeNet architecture is considered as the first architecture for Convolutional Neural Network. It is an excellent architecture for handwritten digit recognition. It consists of two parts: (i)Feature extraction (ii)Classification

It have many feature maps generated in each layer. During the process, initially we don't use much classification but progress in the feature extraction. Feature Extraction is done through some input devices like scanners and cameras or using the upload image option etc., for letting the handwritten digit as an input. From the images obtained through the devices, the features are extracted. During the classification, we use the proposed ensemble learning framework instead of a neural network that consists of fully connected layers as shown in fig:6.1.

CNN Feature Extraction-

Initially, the image taken as an input is considered as a pixel of 32×32×1 which passes through the first layers and gets deducted to 28×28×6.

The pixels gets deducted as passing through the convolutional layer and the subsampling occurs that reduces the data size by selecting the subset of the sample.

Since the pixels get deducted passing every layer, from 28×28×6, it reduces to 14×14×6 by taking the average stride of the pooling width 2. Pooling helps in reducing the size of the feature map. Another convolution layer is also employed, this time with sixteen 5×5 filter rows, creating an output matrix of 10×10×6. The final output matrix is a 5×5×6 matrix and involves a second pooling layer. This leads to the extraction of sixteen 5×5 feature maps from each picture, and the treatment of each 5×5 feature map as a column vector (25×1). LeNet-5 has two convolutional layers, two subsampling layers, and two fully linked layers altogether.

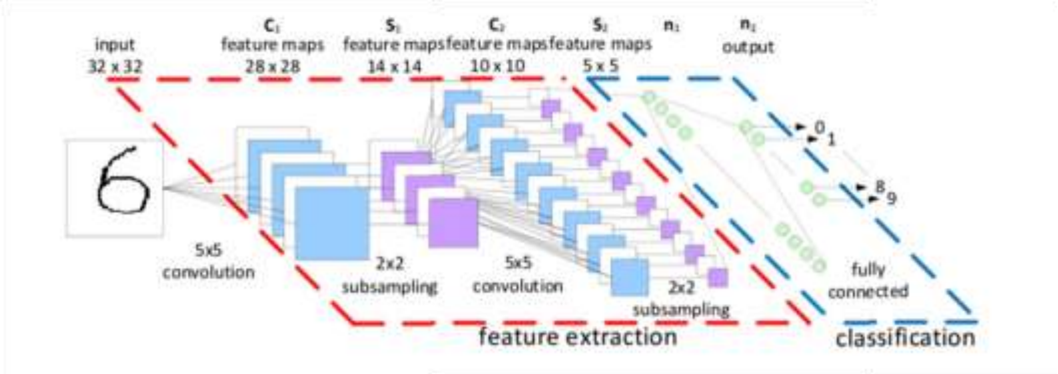

Fig:6.1 CNN feature extraction for handwritten digit image

Multi-level fusion of Classifiers-

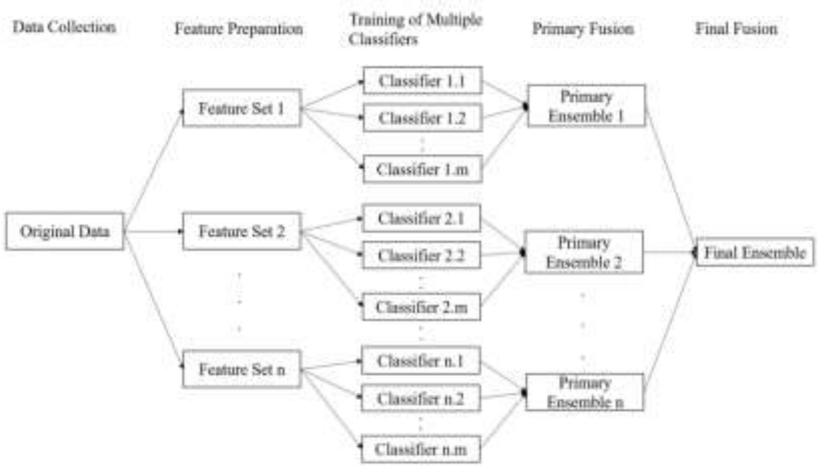

Fig:6.2 Proposed framework of ensemble learning

As demonstrated in the primary fusion layer, a primary ensemble Ei is generated on each of the n feature sets in the third layer of fig:6.1, which is about training multiple classifiers. This is done by using m learning algorithms to train base classifiers on each feature set Fi. In order to produce the final ensemble, which produces a final classification as seen in the final fusion layer, the n primary ensembles formed on the n feature sets are fused further. A primary ensemble made up of some basic classifiers that have been trained on a given feature set can then be coupled with the other base classifiers to form a secondary ensemble. In this situation, a secondary ensemble may be built on each feature set, and some or all of the secondary ensembles may then be combined to form a final ensemble or even a higher level ensemble. In the classifiers training and fusion stage, we adopt KNN and RF for training base classifiers and first ensembles, respectively, on the two feature sets. On each feature set, a secondary ensemble is obtained through combining the bottom classifier (trained using KNN) and therefore the primary ensemble of decision trees (created using RF).the two primary ensembles created on the 2 feature sets are combined further to make up a larger ensemble for final fusion. In terms of parameters setting, the K value for KNN is about to 3 and the trained random forest consists of 100 decision trees.

VII. RESULTS AND DISCUSSION

Here, feature set is extracted using CNN. the full procedure involved feature extraction, training, feature selection and fusion classifiers. Each digit is taken as input.

After browsing all of the layers, the recognized digit gets verified among the dataset and therefore the one pattern that gets within the limited patterns will be the output. In this section, we report an experimental study conducted on the MNIST dataset, which is actually a 10-class (0–9) classification task in the setting of machine learning. For the aim of training various image processing algorithms, a sizeable database of handwritten numbers called the MNIST database (Modified National Institute of Standards and Technology database) is usually employed. 60,000 training photos structure the database, whereas 10,000 test images structure the database.

The entire process in this experimental investigation entails feature extraction, feature selection, training, and classifier fusion. We fed each digit picture into the LeNet-5 during the CNN feature extraction and generated its feature maps within the third layer (16×10×10).

The *Training time* for this model is *106.12s*.

The *Test time* taken is *1.645s.*

The *Accuracy* of this model is *98.07%.*

Method	***Full set of features***	***Selected set of features***
KNN (Zhang 1992)	0.972	0.958
RF (Breiman 2001)	0.965	0.957
Fusion (KNN+RF)(Zhao and Liu 2018)	0.975	0.965
Final fusion (proposed)	0.981	---

Table:7.1 classification accuracy

VIII. CONCLUSION

In this paper, we've proposed a framework that involves CNN based feature extraction and multi-level fusion of diverse classifiers.

By creating various feature sets and employing various learning techniques for training classifiers, we've specifically intended to improve the diversity among them. The experimental results demonstrate that our suggested ensemble approach, when applied to the MNIST dataset, are able to do a classification accuracy of around 98%. The results also show that ensemble learning, which aims to coach a variety of classifiers, may be a very useful strategy for improving classifier performance as a whole.

Future research will specialise in finding the best feature subsets to select in order to further improve performance (Chen and Chung 2006; Chen and Chien 2011; Chen and Kao 2013; Tsai et al. 2008, 2012). it's also important to investigate the effectiveness of the suggested framework in the context of fuzzy ensemble learning (Nakai et al. 2003), where base classifiers are trained as members of an ensemble using fuzzy set theory-related techniques (Zadeh 1965; Wang and Chen 2008; Chen (Liu and Chen 2018).In the context of multi-attribute decision-making, it's also important to assess how effective the suggested framework for ensemble learning is.

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