

Handwritten Digit Recognition Using Machine Learning

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ABSTRACT

Technology is getting more and more involved in our lives, and so are algorithms. These algorithms speed up work and reduce workload. Especially machine learning algorithms are improving day by day by imitating human behaviors. Handwriting recognition systems are also stand out on this field. In this study, handwriting digit recognition process has been done with algorithms having different working methods. These algorithms are Support Vector Machine (SVM), Decision Tree, Random Forest, Artificial Neural Networks (ANN), K-Nearest Neighbor (KNN) and K- Means Algorithm. The working logic of the handwriting digit recognition process was examined, and the efficiency of different algorithms on the same database was measured. A report was presented by making comparisons on the accuracy.

Keywords: handwriting digit recognition, machine learning

I. INTRODUCTION

Today, handwriting recognition systems are used in many areas. For example, there is a need for handwriting recognition systems for reading and archiving old documents, bank checks and letters. In addition to these examples, online handwriting recognition applications are also widely used. Especially in the field of education, there are educational applications that support handwriting recognition in electronic devices such as tablets. There are customized applications supported by handwriting recognition for individuals with physical or mental disabilities as well as children [2]. Some smartphone applications that we use in our daily lives also have handwriting recognition systems. Handwritten texts in the surrounding area can be quickly scanned and processed via the phone camera. The scanned texts can be translated into different languages or searches can be made over the internet. The text recognition area has a very large scope. Handwriting recognition and typewriter / computer writing recognition are subfields of the handwriting

recognition area. Computer or typewriter recognition field can produce faster and more accurate results. Unlike handwriting recognition; It is expected to see higher success rates as there are no characteristic patterns and lines in letters or digits, such as spaces between letters and words. There are many studies on handwriting recognition. EnginDagdeviren, in his handwritten number recognition studies with Modified National Institute of Standards and Technology (MNIST) data set; SVM and ANN compared to the obtained accuracy rates. In his tests on MATLAB, he reached a success rate of 99.97% in a data set of 10000 data for SVM. In the handwriting recognition system developed using ANN, he again achieved an 80.39% success in a data set of 10000 data [3]. Murat Sekerci used the correlation method for Turkish handwritten character recognition and strengthened his systems with the KNN algorithm. The data set was created with text samples taken from 172 different people. With this study, recognition rates of 93% in digits, 90.4% in lowercase letters and 91.2% in capital letters were achieved. These rates decreased by 10% in the words and digits written in combination. 100% success was achieved in text which is a mix of letters and digits. In addition, recognition system has been strengthened by using dictionary [1]. TsehayAdmassuAssegie has developed a digit recognition application with a Decision Tree algorithm on a data set consisting of 42000 rows and 720 columns. A success of 83.4% was achieved [4]. In this study, tests were performed on the MNIST handwritten digit data set with SVM, Decision Trees, Random Forests, ANN, KNN, K-Means Algorithm. The success rates of the algorithms in the field of handwriting recognition were compared. In the methods section of this article, brief information is given about handwriting recognition and compared machine learning methods. In the third section, the values obtained as a result of the study were compared. Evaluations were made on the compared machine learning algorithms.

II. METHODS

Handwriting recognition has some general steps. These are; pre-processing, segmentation, feature extraction, classification and recognition, post processing.

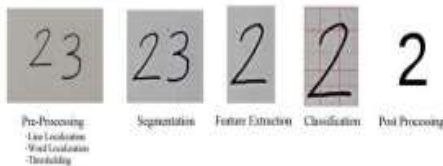


Figure 1. Handwriting digit recognition steps

In the pre-processing step, operations such as line localization, word localization, thresholding are performed [1]. In the segmentation step, words are divided into parts corresponding to letters or digits. Even this is the explanation in the literature, since the MNIST data set was used in this study, the segmentation step was not performed. In the feature extraction step, the data is processed and defined in a more limited space and prepared for the recognition step. In general, the classification and recognition step consists of only matching the character's symbolic class. There are many methods that can be used in this step. ANN, classification algorithms are some of them. 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 [5]. In post processing step, it is aimed to eliminate possible errors after recognition. Some systems use dictionaries at this stage. Thus, the recognized text after the recognition process is checked again by comparing it with possible words in the dictionary [6]. In this study, a data set that is suitable to be studied was used. Therefore, the results obtained in this study may be very different in another study. It is clear that handwriting digit recognition is affected by many situations.

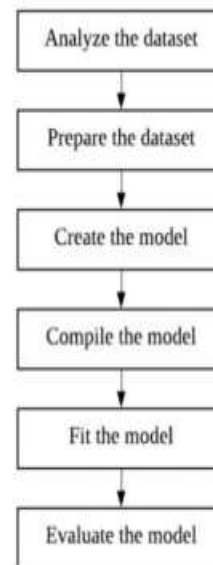


Figure 2. Handwriting recognition processing steps

In this study, MNIST data set was used for the training and tests of the system. MNIST database is widely used internationally. It consists of handwritten numbers. The MNIST database contains 60,000 training data and 10,000 test data. The black and white images from MNIST were normalized to fit into a 28x28 pixel bounding box and anti-aliased, which introduced grayscale levels [12]. All tests within the scope of this study were performed on the PyCharm (v2020.1 community edition), which is an integrated development environment used in programming, specially for the Python language.



Figure 3. Sample images of MNIST data [13]

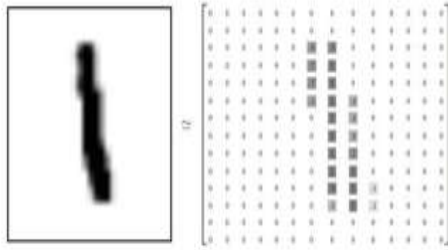


Figure 4. Representation of the digit 1 on matrix form in MNIST [14]

A Python library called Scikit Learn (v0.22.2.post1) was used in the study. It offers the opportunity to effectively implement many machine learning algorithms. It enables the rapid training and testing of machine learning algorithms with high level languages. The definitions of the values in the reports provided by the ScikitLearn's Metrics module are as follows: Precision: $TP / (TP + FP)$ It is the accuracy rate of positive predictions. Recall: $TP / (TP + FN)$ is the sensitivity or true positive rate (TPR). F1 Score: This value is the harmonic mean of precision and recall values. Accuracy: This value, which can also be called accuracy, shows the accuracy rate. It is calculated by the ratio of correct predictions to all predictions made. While determining the algorithms to be compared within the scope of the study, algorithms belonging to different sub-branches of machine learning were chosen.

1.1. Support Vector Machine

SVM, a supervised classification method, starts with a previously created training set. During the training, SVM learns the relationship of each data and tag in the existing training set. Creates SVM with these relationships [3]. SVM is successful in solving classification problems compared to many other techniques. This is one of the reasons why this technique is chosen as one of the algorithms to be tested in this study. Kernel function selection is an important step in the process of SVM to solve a problem [7]. Polynomial kernel function was used in the tests performed on the MNIST data set on Scikit Learn. In tests performed on other kernel functions, the highest accuracy was obtained in this function. The test results are given on Table 1.

Table 1. SVM tests for choosing kernel function

Kernel Function	Training Time (s)	Test Time (s)	Accuracy (%)
Polynomial	0.7	6.3	90
RBF	0.8	7.7	89
Linear	0.4	5.8	87
Sigmoid	0.6	7.8	84

1.2. Decision Tree

Decision trees form a classification model as a tree structure for the solution of a problem. The tree structure and rules are easy to understand. This simplifies the implementation of the algorithm. Decision trees method consists of simple sequential decision making operations [8]. One of the most important steps in creating the tree structure is choosing the attribute value for which the branching in the tree will be determined [8]. The division criterion for decision trees in the Scikit Learn library is the Gini Index. The decision tree method provided by the Scikit Learn library was used in the tests. Scikit Learn library uses CART algorithm that creates binary trees. In this algorithm, each node has only two sub-nodes or end leaves. Tree structures with more subnodes can be created using different algorithms such as ID3 [9].

1.3. Random Forest

Random forest algorithm can be used in both classification and regression problems like decision trees. The logic of work is to create more than one decision tree and produce average results with the help of these trees. The reason why this algorithm is called randomly is that it offers extra randomness during the creation of the tree structure. When splitting a node, instead of looking for the best attribute directly, it looks for the best attribute in a subset of random attributes. This situation creates more diverse trees [9]. In this test, the Gini index was used as the branching factor like the decision trees. The number of trees is determined as 150.

1.4. Artificial Neural Network

ANN model is modeled on the transmission model of human nervous system and parallel computing ability of human brain instead of computer architecture. Neurons, which are the basic units in the human nervous system, take certain data and produce a binary output. Similar logic is also valid for ANNs [3]. When designing a handwritten character recognition application with ANN, the first step is to create a matrix of a

character in the text expected to be recognized in accordance with the input for the neural network. In this way, artificial neural network can be trained. Outputs are created for each character's matrix. In the learning process, the excess number of neurons in the hidden layers causes the training process to take too much time and increases the remembering ability of the network at the same rate. After learning, verification is done. This process can be done in many ways. One of these methods is to use databases that contain combinations of two or three letters. Thus, the letter sequence will not contain impossible combinations. (eg 'fdr') Another way is to use a word dictionary. Thus, it can be understood whether the string is a real word [1]. MLPClassifier stands for Multi Layer Perceptron. Unlike other classification algorithms such as SVM machines or Naive Bayes, MLPClassifier has a neural network to perform its classification task. After the MLPClassifier model was created, it was trained with MNIST data and then tested. While creating the MLPClassifier, the 'batch_size' value was set to 200 as default. And the 'learning_rate' value is constant. It was set to '0.001'. Lastly as the activation function 'relu' was chosen.

1.5. K-Nearest Neighbor

KNN is one of the classification methods. The KNN algorithm is used to determine which class a new observation to be included in the sample from the observation values in a sample set with certain classes [10]. In this method, first of all, the similarity of the test data to be classified with the education data is calculated. Classification is made according to the threshold value determined with the average of the k data that appears to be the closest. The performance of the method is influenced by the closest neighbor number, threshold value, similarity measurement and sufficient number of normal behaviors in the learning cluster [11]. It was trained with MNIST data and then tested. While creating the KNN classifier with Scikit Learn, the number of neighbor was set to 5. And all points in each neighborhood are weighted equally as 'weight' parameter was set to 'uniform'.

1.6. K-Means Algorithm

This algorithm is one of the most preferred unsupervised learning algorithms. Clusters are created by looking at the similarity rates of the data. The number of clusters to be created in the algorithm is determined in advance. The number of clusters is expressed by "k". Among the algorithms compared within the scope of the study, the only algorithm that is an unsupervised learning algorithm is the K-means algorithm. While

creating K-Means clustering with Scikit Learn, the number of clusters was set to 10. In the tests performed with Scikit Learn on the MNIST data set, it was observed that the accuracy of the clusters was high. Accuracy scores are given in table 3.

III. RESULTS AND DISCUSSION

In this study, handwriting digit recognition was made with six different machine learning algorithms. MNIST handwritten digits dataset was used in all tests.

Table 2 lists the values obtained from the algorithms tested. The definitions of the listed values are defined in the methods title. All values are average.

Table 2. Report values of compared algorithms

Algorithm	Precision	Recall	F1-Score
Support Vector Machine	0.97	0.98	0.97
Decision Tree	0.85	0.90	0.86
Random Forest	0.97	0.97	0.96
Artificial Neural Network	0.98	0.98	0.97
K-Nearest Neighbor	0.96	0.98	0.96

The accuracies of the compared algorithms are given in Table 3. The goal of this study and the table; to guide the people who will work in the field of handwriting digit recognition in the field in which they will advance and in the method of machine learning they choose.

Table 3. Accuracies of compared algorithms

Algorithm	Accuracy	Training Time	Test Time
Support Vector Machine	%90	372.294 s	97.769 s
Decision Tree	%87	21.142 s	0.645 s
Random Forest	%97	63.055 s	1.106 s
Artificial Neural Network	%97	178.390 s	1.014 s
K-Nearest Neighbor	%98	36.396 s	865.93 s
K-Means Algorithm	%98	8.350 s	0.569 s

The use of SVM in the field of handwriting digit recognition is quite common. SVM based on statistical learning method have some advantages when compared with other classification algorithms. They can also work strongly and efficiently in situations where educational data are small. The ability to produce and generalize better classifiers is also high. Within the scope of this study, it has been observed that the SVM is widely used in the field of handwriting digit recognition and are suitable for use in the field of handwriting digit recognition, as evidenced by its values such as speed and efficiency. Decision trees and random forest algorithms are actually built on the same basis. Random forest algorithms consist of trained decision trees algorithms. These two algorithms are well suited for use in handwriting digit recognition. Decision trees make inferences from the existing data set and form the tree structure. A little more prediction and randomness predominate in random forests. As can be seen in random forests, random forests provide higher accuracies, although they are trained much slower. Despite the low accuracy, a fast training period is in the decision trees. ANN are used in many fields other than handwriting digit recognition today, and they are getting more and more popular. It is among the algorithms that give the best results with its high accuracy. It gives good results in problems aimed at imitating more people's decision-making mechanism, such as handwriting digit recognition. KNN algorithm is one of the most preferred classification algorithms. Although it has a simple structure, it worked fast and gave high-accuracy results. The only algorithm that is unattended among the algorithms compared in the study is the K-Means algorithm. It provided

a very high efficiency in the tests and made very little mistakes in clustering. In this thesis study, only one data set was studied. The working conditions of the algorithms can be examined by performing tests on different data sets. In this way, studies can be expanded and clearer results can be obtained.

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