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Handwritten Recognition System Based on Machine Learning

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نظام التعرف بخط اليد على أساس التعلم الآلي

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ABSTRACT

Background:

Handwriting recognition is an important issue nowadays, where handwriting can be a image, document, etc., the ability of a computer to recognize handwritten numbers is very important in more than one application such as translation, reading and number recognition applications. The proposed project provides a system that recognizes handwritten English numbers, the input data being images downloaded from a global dataset. The proposed system consists of a number of stages. The first stage is the preprocessing, which includes resizing of the images to be one size (28 * 28), and then a step (data mapping) is applied. As for the classification stage, it relied on the use of two algorithms, the KNN algorithm and the neural network (error backpropagation). To start the process of training the selected algorithms, the data was divided into two sets, the training setand the test set. Two algorithms were used for the purpose of choosing the best of them, by evaluating their performance using a number of evaluation metrics. Accuracy and Precision were used for the purpose of evaluating the performance of the algorithms. The performance of the KNN algorithm was 0.94 and 0.942 respectively when k = 4. While the best performance reached by the neural network mechanism was 0.98673333 and 0.9698, respectively, at epoch = 15. The neural network (error backpropagation) is shows the best result in the recognation stage

Materials and Methods:

K-Nearest Neighbors (KNN) technique makes no assumptions about the basic dataset. It is recognized for its effectiveness and ease of use. It is a supervised learning algorithm. To estimate the category of the unlabeled data, a labeled training set containing data points separated into many groups is supplied.

Results:

The performance of the KNN model with various values for "K." Since the high value of model accuracy was "0.94", the "4" parameter value is the one that provides the best results and precision was "0.94".

Conclusion:

The problem of handwritten recognition needs high accuracy and precision indicators show an accurate description of the performance of the algorithms that were employed in the proposed system. The two indicators described the performance of the algorithm (KNN), which gave results (0.94 and 0.942).

Key words:

Machine Learning, K-Nearest Neighbor (KNN), MNIST

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الخلاصة

مقدمة:

يعد التعرف على خط اليد قضية مهمة في الوقت الحاضر ، حيث يمكن أن تكون الكتابة اليدوية صورة أو مستندًا وما إلى ذلك ، تعد قدرة الكمبيوتر على التعرف على الأرقام المكتوبة بخط اليد مهمة جدًا في أكثر من تطبيق مثل تطبيقات الترجمة والقراءة والتعرف على الأرقام. يوفر المشروع المقترح نظامًا يتعرف على الأرقام الإنجليزية المكتوبة بخط اليد ، ويتم تنزيل بيانات الإدخال من مجموعة بيانات عالمية. يتكون النظام المقترح من عدد من المراحل. المرحلة الأولى هي المعالجة المسبقة ، والتي تتضمن تغيير حجم الصور لتكون بحجم واحد (28 * 28) ، ثم يتم تطبيق خطوة (تعيين البيانات). أما بالنسبة لمرحلة التصنيف ، فقد اعتمدت على استخدام خوارزميتين ، خوارزمية KNN والشبكة العصبية (خطأ backpropagation). لبدء عملية تدريب الخوارزميات المختارة ، تم تقسيم البيانات إلى مجموعتين ، مجموعة التدريب ومجموعة الاختبار. تم استخدام خوارزميتين لغرض اختيار أفضلها من خلال تقييم أدائها باستخدام عدد من مقاييس التقييم. تم استخدام الدقة والدقة لغرض تقييم أداء الخوارزميات. كان أداء خوارزمية KNN 0.94 و 0.942 على التوالي عند k = 4. بينما كان أفضل أداء وصلت إليه آلية الشبكة العصبية 0.98673333 و 0.9698 على التوالي ، في العصر = 15. تظهر الشبكة العصبية (خطأ backpropagation) أفضل نتيجة في مرحلة الاعتراف.

طرق العمل:

لا تقدم تقنية (KNN) أي افتراضات حول مجموعة البيانات الأساسية. إنه معروف بفعاليته وسهولة استخدامه. إنها خوارزمية تعلم خاضعة للإشراف. لتقدير فئة البيانات غير المسماة ، يتم توفير مجموعة تدريب معنونة تحتوي على نقاط بيانات مقسمة إلى مجموعات عديدة.

الاستنتاجات:

توضح مؤشرات الدقة والدقة وصفًا دقيقًا لأداء الخوارزميات المستخدمة في النظام المقترح. وصف المؤشرين أداء الخوارزمية (KNN) والتي أعطت النتائج (0.94 و 0.942) على التوالي.

الكلمات المفتاحية:

التعلم الآلي، خوارزمية اقرب جار , قاعدة بيانات المعهد الوطني للمعايير والتكنولوجيا المعدلة.

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INTRODUCTION

A handwriting recognition system (HTR) refers to the capability of a computer or other device to accept as input handwriting from a source such as printed physical documents, images, or other devices [1].

Text written by hand may be found in several images, including but not limited to handwritten notes, memoranda, whiteboards, medical records, historical documents, and stylus-entered text. As a result, a comprehensive OCR system has to have the capability of identifying handwritten text contained inside photographs [2], [3]. Many offline handwritten text recognition systems have moved their attention to line-level recognition methodologies in recent years. For feature extraction, these algorithms use a mix of convolutional neural networks (CNN) and Long Short-Term Memory (LSTM), recurrent neural networks [1].These networks are educated using Connection Temporal Classification .The characters in an image may be identified by this method, which can turn them into text. Afterwards, the text may be transformed into the language of the reader's choosing [4],[5] .

Handwriting has been affected by every advancement in computer and communication technology, including word processors, fax machines, and e-mail. The role of handwriting and handwritten texts has been adjusted and reinterpreted as a result of these in-variations. Despite these technological marvels, a pen and paper are considerably more practical than a computer or mouse. Handwriting-processing computers will need to be able to read messages written in various writing styles and languages and cope with arbitrary user-defined alphabets [6- 10].

Materials and Methods

- **k-Nearest Neighbor**

k-NN, algorithm is considered to be one of the more straightforward approaches to machine learning. Despite its apparent simplicity, it has shown to be highly useful in resolving numerous classification and regression issues, including those in the fields of image analysis and character recognition [11].

The (Modified National Institute of Standards and Technology database) MNIST dataset is a sizable collection of handwritten numbers that is frequently employed in the development of image processing systems as well as other applications for training, learning, and testing in learning robots. One of the most well-liked data sets in the machine deep learning areas is called MNIST [11].

Methods

The proposed system is illustrated in Figure (1) in which the work steps are shown, where first the images are obtained from the data set, and then the preprocessing, in which the images are placed in the appropriate size for the work, data mapping put the pixel in a specific range, KNN classifier Finally, the system is evaluated by a set of metrics.

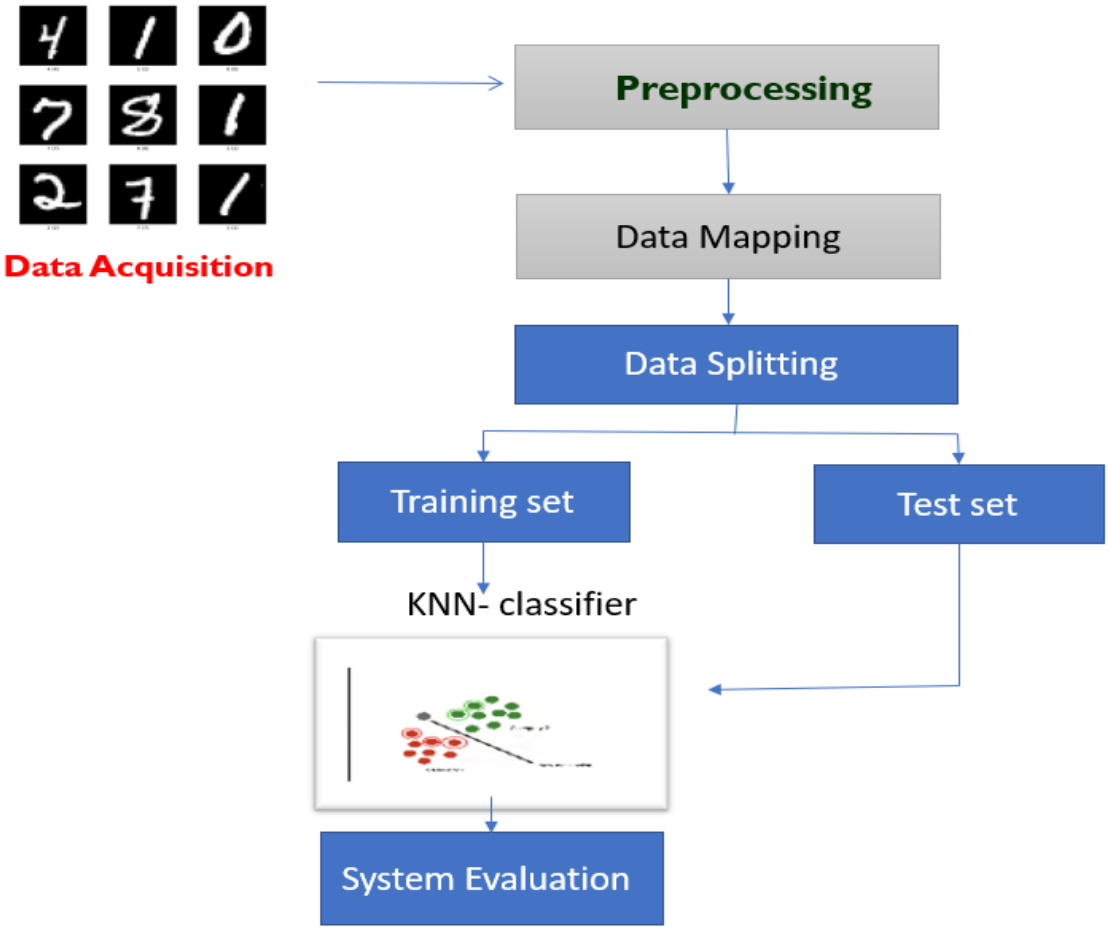

Figure (1) the proposed system

preprocessing

The preprocessing is very necessary on the data set to prepare it for the main processing, which is the classification process. The pre processing is done on handwriting images by normalized the dataset pixel.

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Data Mapping

The MNIST dataset contains grayscale images, and the range of values for each pixel in those images is between 0 and 255, including both boundary values. To convert the pixel values to a scale from 0.0 to 1.0, we multiply them by 0.99 / 255 and then multiply 0.01. Because of this, the 0 values don't get counted as inputs, which means they don't have the potential to prohibit weight updates using the procedure below.

Algorithm: Data Mapping

Input: Input Image from MINST dataset .

Output: Mapping Image form MINST dataset .

1. **Begin**
   i. Step1:read input image that is grayscale and its pixels are (0- 255).
      Step 2: applying the Formula
   ii. Map.value = (X*(0.99/255)*0.01)
2. **End**

End Data mapping

- k-Nearest Neighbor Classifier

K-Nearest Neighbor

It is considered to be one of the more straightforward approaches to machine learning. Despite its apparent simplicity, it has shown to be highly useful in resolving numerous classification and regression issues, including those in the fields of image analysis and character recognition.

The key idea behind the nearest neighbor classification approach is identifying a subset regard training samples which consider most similar to a modern instance which been classed. This is symbol for the number. These adjacent samples will be used to establish the label for the newly generated sample. The number of neighbors to be discovered in KNN classifiers is a user-defined parameter that is kept constant. Another kind is the method for discovering neighbors based on a radius. These methods take into account all samples within a certain radius; therefore, the number of neighbors varies depending on the local density of points. The distance may be measured in any metric system; however, the traditional Euclidean distance is the one most often employed. Since they simply "remember" all of their training data, techniques based on neighbors are known as non-generalizing methods in machine learning. Neighbors of the mystery sample may vote on how to categorize it, and the winner is chosen by majority vote.

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Algorithm K-Nearest Neighbor

Algorithm: K-Nearest Neighbor

1. Input k equal zero.

2. Set counter begin from 1 and finished when arrived the total training data number points to get the predicted classes.

3. Find out how much space should be left between the rows of data that be training in addition to rows data to be test. The Euclidean distance is measurement that is employed the majority of the time; thus, it will be applied here.

4. Based on distance values, order the distances computed in order of increasing.

5. Take a first k of rows of the saved array.

6. Identify the dominant class in the row.

7. Provide the anticipated class.

End K-Nearest Neighbor

- **system evaluation**

The performance of the two algorithms will be evaluated using different metrics to compare their performance. Three types of metrics will be used for evaluation:

Accuracy: The level of accuracy indicates how much we can rely on the forecast made by our model. This measure is incapable of distinguishing between various error classes and types.

Precision or Positive Predictive Value (PPV): It is the proportion of True Positives to every positive result the model had predicted. It is helpful for the dataset that is uneven and biased. The precision decreases as the model predicts more false positives.

Confusion Matrix: An error matrix or confusion matrix is a table that displays the kind of errors being made as well as the number of correct and incorrect predictions made by the model in relation to the actual classifications in the test set. This matrix shows how well a classification model performs when tested on test data with known true values. There are n classes, hence it is a n*n matrix. After using the test data to make predictions, this matrix can be created.

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Results and Discussion

The K neighbors Classifier bases its classification on a sample's k closest neighbors. The user-specified integer value 'k' is the number. Of the two algorithms, this is the classifier that is used the most. The rule of "trial and error" will be used to apply the model with a set of trials and compare the accuracy that is obtained after applying it in order to get the best or optimal value of "K." KNN models with different "K" values. By plotting the precision with the number of K values in the graph, it is possible to find out the differences and choose the best value for K Figure (2) shows the performance of the KNN model with different value for “K”, where the optimal value for is “4” since the high value of model accuracy was “0.94”.

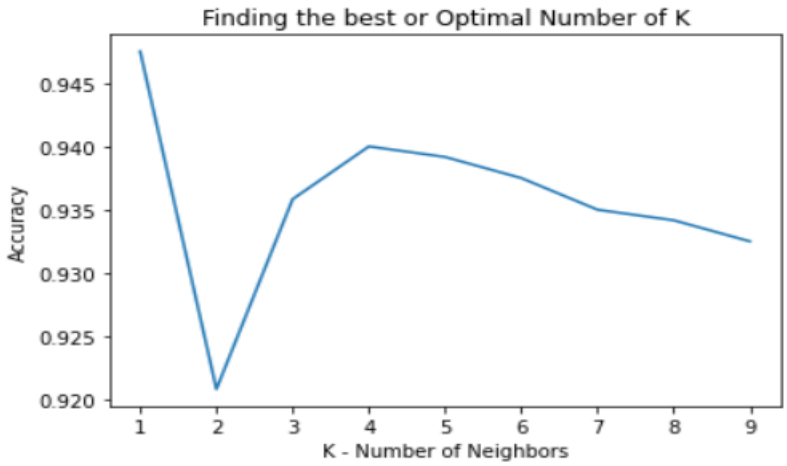

Figure (2) the K value and accuracy of model

The following table represents a comparison between the values of precision and accuracy with the change in the values of the number of neighbors (K), where the best value for accuracy and accuracy appears when the value of (k) is 4.

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Table (1) the values of K, accuracy and precision

K	Accuracy	Precision
1	0.9475	0.948
2	0.9208333	0.925
3	0.9358333	0.938
4	**0.94**	**0.942**
5	0.9391666	0.942
6	0.9375	0.940
7	0.935	0.938
8	0.9341666	0.937
9	0.9325	0.936

Confusion is a matrix that is represented in the following form. It represents the testing phase of the model and its final results when the accuracy is (94) in the training phase, but in the testing phase it is (96). The confusion matrix represents the performance of the final model. Figure (2) shows the confusion matrix.

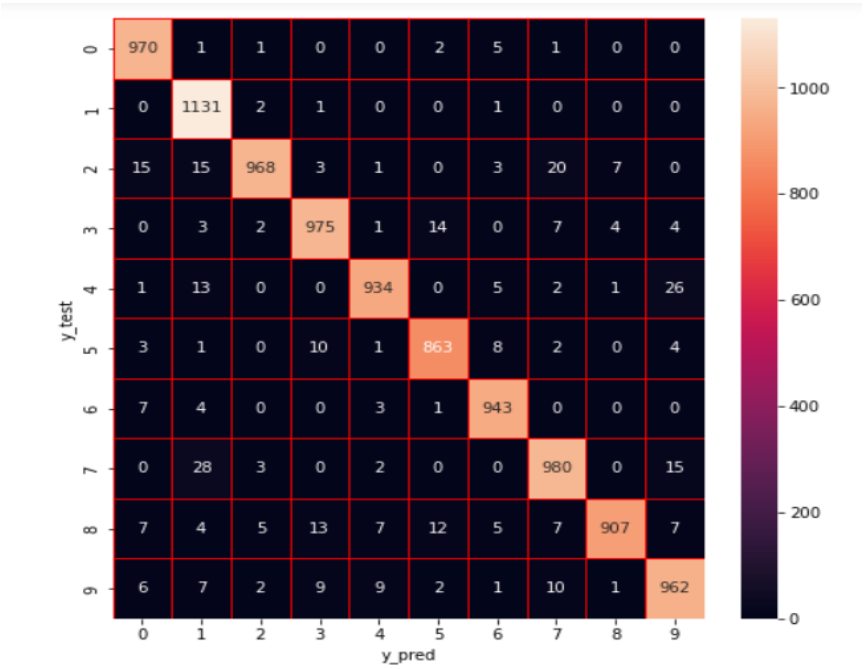

Figure (2) the confusion matrix

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Conclusion

The model used in the proposed system, which is (KNN), contains a sensitive parameter that affects the accuracy obtained by the model, which is the number of neighbours. The optimum number of neighbours was determined by the rule of trial and error. The optimal number was (4) and the accuracy was (94). The proposed system has given very good results in terms of accuracy and precision, and it is reliable in recognizing the image of handwriting completely, and it can be applied to numbers and letters as well.

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Conflict of interests.

There are non-conflicts of interest.

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