Handwritten digit recognition using machine learning

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Abstract. Different people are expected to possess varying writing styles that are distinctive to their personalities. There are many aspects that make handwriting differ from person to person, which include spaces, inclination, height, basic patterns, connecting strokes, sizes and widths, markings, and ornaments, among others. However, the challenges come when the handwritten text must be converted into digital form to enhance information sharing and storage. To address this challenge, the recent past has seen the rise of reliance on machines over humans and the subsequent development of machine learning algorithms. Likewise, the recognition of handwritten text is part of the important field of research and development that appear to have a promising future. The handwritten characters recognition has gained considerable attention in the area of machine learning and pattern recognition, most recently. Several techniques have been proposed for recognizing handwritten text. In line with this, many studies have been conducted that explain techniques employed in converting textural substance from paper material to a form that is readable by a machine. Such a digital recognition system has the potential to create a paperless environment by processing existing paper documents and digitization in future. This paper presents two recent techniques based on neural networks, Convolutional Neural Networks (CNNs) and Waikato Environment for Knowledge Analysis (WEKA) and makes a comparative analysis. In this paper, we want to ensure the reliable and effective approaches to the recognition of handwritten digits. The results show that CNN is comparatively more accurate than WEKA, with an accuracy rate as high as 99.59 percent, with the lowest reported degree of accuracy standing at 88.3 percent. On the other hand, the highest report accuracy with regards to WEKA was 82.92 percent, and the lowest stood at 67.45 percent. Although there is a need for more research to be carried out, the information from the two algorithms demonstrates that the existing techniques are increasingly becoming more reliable, and CNN is leading in terms of accuracy.

Keywords: WEKA, CNN, Handwritten Digit Recognition, Machine Learning.

1. Introduction

Every human being has a distinct writing style, which is related to their personality, as even if an individual writes a group of words many times, it is possible there will be dissimilarities. There are various identifiable ways handwriting may differ, and they include height, basic patterns, sizes and width, inclination, connecting strokes, line quality, lifting pens and splitting, spaces, markings, ornaments, the pressure of the pen, prosperity and unusual letter formation [1]. Many varying techniques, both off-line and online, employ structural methods, synthetic methods, mathematical methods and neural networks. However, the major challenge these methods have to address is how to best classify the image of handwritten content that might be in the form of block, cursive or tilted writing. Such problems can be addressed with the use of an automated model that assists the user in addressing the challenge of converting to digital format from handwritten format. The biggest problem in dealing with the conventional approach is the differentiation of the recognition pattern.

In the recent past, the reliance on machines over humans has been on the rise such that almost everything today, from analyzing photos to including sound in movies, can quickly be accomplished with the help of machine learning algorithms. In a similar manner, the recognition of text written by hand is part of the important files of research and development that appear to have a promising future. According to [2], handwritten digit recognition is a subarea that is well-studied in a field that deals with learning models to differentiate handwritten digital footprints that are pre-segmented. Handwriting digital recognition is among the significant issues in data mining, pattern recognition and machine learning, along with various other areas in artificial intelligence [3].

Handwritten digit recognition can be understood as the capability of a computer to distinguish the digits written by human hand from varied sources, such as touch screens, papers, and images, among others, and categorize them into predefined classes of 10 digits, that is, 0 to 9 [4]. Such machine learning is a digit recognition task where the results are informed by prediction error, which is nothing more than the reversed classification precision. Handwriting recognition technology has gotten much attention and is widely used in many fields. The application of handwritten digit recognition includes in-form data entry, and tax treatment, among others. Optical character recognition or offline handwriting recognition is conducted after the writing is done by translating the handwritten text into digital format. Since handwritten digit recognition is not an optical character recognition, the task faces numerous challenges, mainly due to the different writing styles of people. Now, an efficient algorithm is asked to recognize handwritten digits.

The handwritten characters recognition has gained substantial acceptance in the area of machine learning and pattern recognition as it can be used in many fields. Several techniques have been proposed for recognizing handwritten text. In line with this, many studies have been conducted that explain techniques employed in converting textural substance from paper material to a form that is readable by a machine. Such a digital recognition system has the potential to create a paperless environment by digitization and processing existing paper documents in future [5]. This paper presents two recent techniques based on neural networks, Convolutional Neural Networks (CNNs) and Waikato Environment for Knowledge Analysis (WEKA) and makes a comparative analysis. In this paper, we want to ensure reliable and effective approaches to the recognition of handwritten digits.

CNN is a deep learning algorithm that has the capacity to take an image as an input, assign learnable biases and weights as a matter of importance to various objects or aspects related to the image and be intelligent enough to distinguish one from the other [6]. In fact, the architecture of CNN imitates the communication form of the neurons of the human brain, enhanced by the arrangement of the visual cortex. As [7] affirms, CNN can take the spatial dependencies within an image to correlate with the substance of the image for recognition reasons, as the design offers a robust fitting of the source image to find the distinctive attributes. The biases, weights and parameters associated with transforming to feature vector from the original image to understand well the nature of the image are found during the training. And the Figure 1 shows a typical structure of the CNN to recognize the hand-written number.

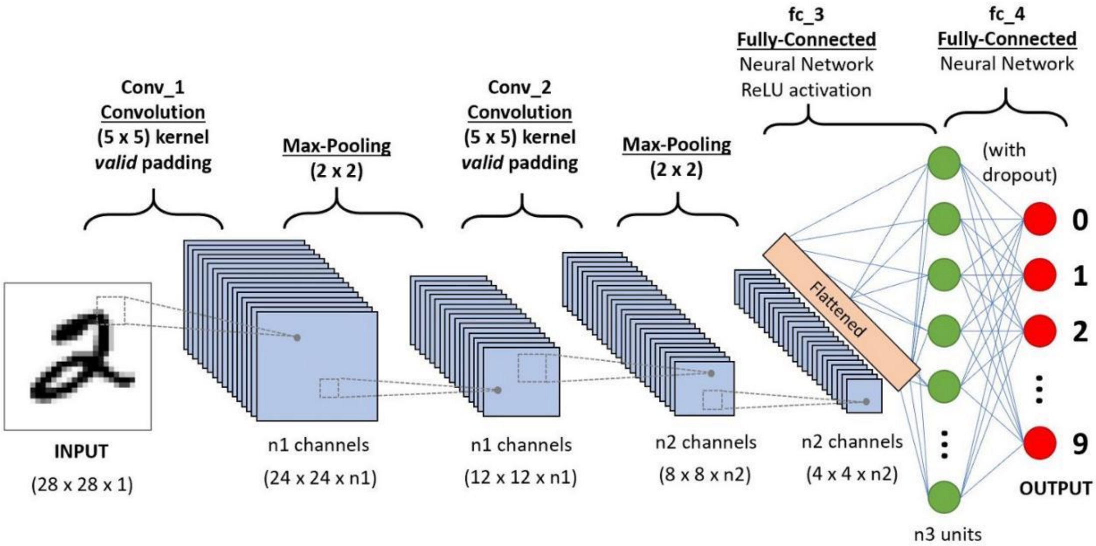

Figure 1. A Convolutional Neural Network (CNN) sequence for classifying handwritten digits [8].

According to the paper [9], WEKA, or the Waikato Environment for Knowledge Analysis, is a workbench created to help in the use of machine learning techniques for actual data sets. The processing workflow of WEKA is shown in Figure 2. This learning workbench has evolved from the urge to apply machine learning to actual datasets in a manner that promotes an exploratory approach or a 'what if?'.

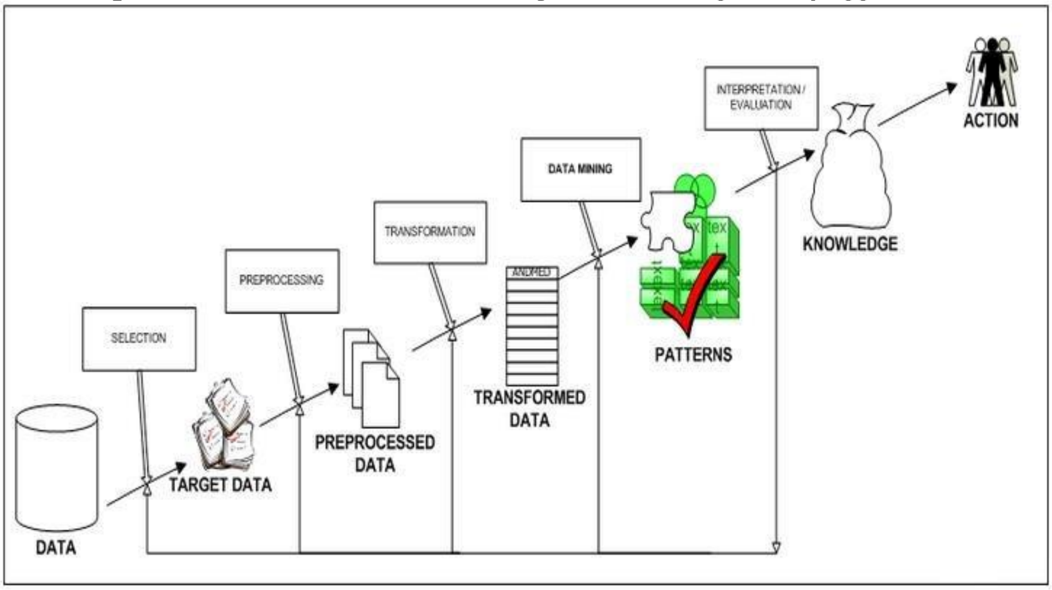

Figure 2. Processes essential for data mining in WEKA [10].

2. Algorithms

2.1. Features of CNN

The most established developed and most tested algorithm among the models of deep learning is CNN. CNN is a model that is employed in the processing of data presented has a grid pattern, as exemplified by images, and it was inspired by the arrangement of the animal visual cortex and devised to adaptively and automatically learn spatial orders of attributes from low-level to high-level patterns [11]. As a mathematical construct, CNN is characteristically constituted of three building blocks or layers: pooling,

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convolution and fully connected layers. The pooling layer and the convolution layer carry out extraction, while the layer which is fully connected translates into the ultimate output from the extracted features. The convolution block comprises a stack of mathematical functions, playing a critical role. A convolution is a specialized form of linear operation employed as a feature extractor that is usually comprised of a blend of linear and non-linear functions, that is, activation operations and convolution functions.

2.2. Features of WEKA

WEKA is a set of machine learning software written in java that was devised at New Zealand's University of Waikato [12]. It is a kind of data mining application that utilizes a set of algorithms of machine learning and is a collection of regression, association, clustering, data pre-processing, data classification and data visualization tools. These algorithms can either be called from a Java code or used directly on the data. According to the paper [13], it came about through the supposed need for an integrated platform that has the capacity to allow users to access modern methods in machine learning. The platform tends to provide a robust collection of data processing tools and machine learning algorithms to both practitioners and researchers, giving them the chance to check out and compare various machine learning datasets.

WEKA has a number of graphical user interfaces that allows the users to access the inherent functionality with ease, and the main interface is Explorer, and the feature of the WEKA is shown in Figure 3. The algorithm to investigate and gauge the performance of algorithms or methods includes but is not limited to a random forest, j48 Decision tree, Naïve Bayes, Bayes Net, Random Tree, Multilayer, Perception, and Support Vector Machine [2]. All the dataset in WEKA is taken as features, and instances in the data are also referred to as attributes.

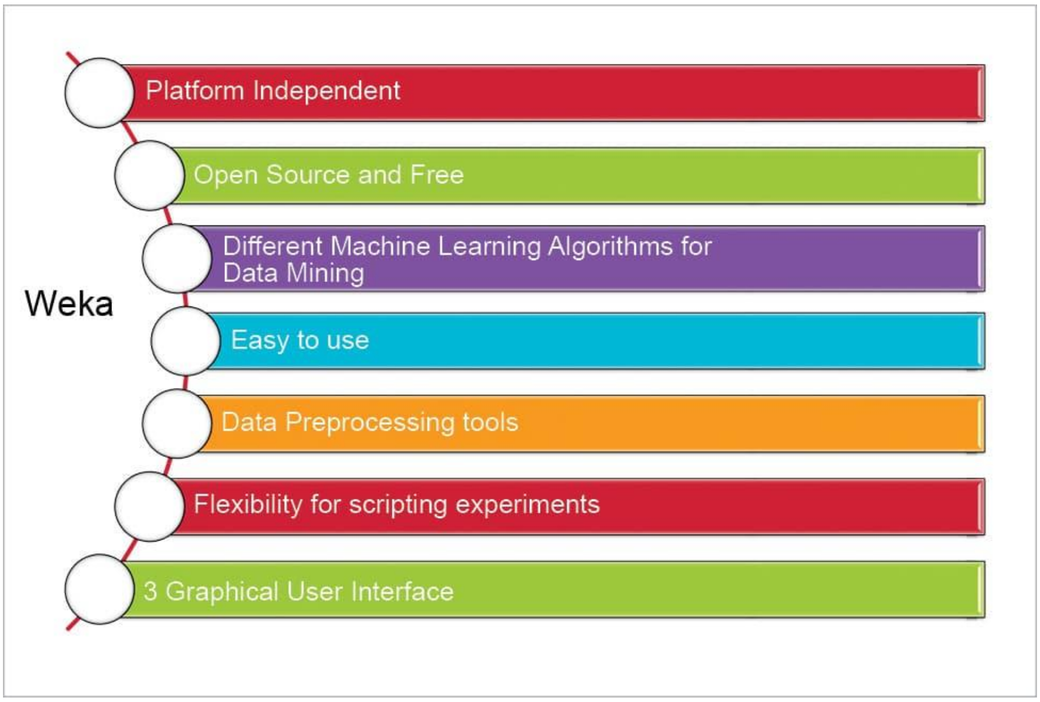

Figure 3. Features of WEKA [14].

3. Comparative Analysis

The paper [15] Presented an experimental assessment research study on how effective some of the WEKA-based classifiers are using off-line handwritten Gurmukhi character recognition. They opted for two robust feature extraction methods: power curve-fitting-based features and parabola curve-fitting-based features. They used a total of 18 different kinds of classifiers and employed 3,500 collected

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samples from different off-line handwritten Gurmukhi characters sourced from at least 100 writers. A total of 60 percent of the data were taken as training data, whereas the remaining 40 percent were taken as testing data. The researchers managed to attain a maximum accuracy of 82.92 percent and 82.86 percent for power curve-fitting-based features and parabola curve-fitting-based features, respectively, while using the multilayer perception model classifier. Table 1 below shows the experimental results for both the parabola curve fitting-based features and power curve fitting-based features.

Table 1. Experimental output of both power curve fitting-based features and parabola curve fitting based features with multiplayer perceptron model classifier [15].

Method	Accuracy (%)	Root mean squared	Weighted average precision (%)	False rate (%)	Rejection rate (%)	Weighted F-measure average (%)
Parabola curve	82.92	8.88	83.40	0.50	16.60	82.90
Power curve	82.86	8.80	83.50	0.50	16.60	82.60

The paper [16] explored the likely classification rate of the rate of handwritten symbols as they check the performance against the output retrieved by a number of classifications, clustering, and regression, among other machine learning algorithms. They then carried out a comparative analysis and the data employed at the experimental stage involving selective handwritten math symbols and after which they reported the accuracy rate of all the tested algorithms. Table 2 below shows the experimental outcomes of various algorithms indicating the accuracy and model time. The experiment shows that the Decision gave the highest accuracy rate of 72.93 percent, followed by Bayesnet, Kstar, Naïve Bayes, Random tree, J48, and PART, respectively. The rest of the algorithms had accuracy less than 70 percent.

CNN has been perceived to be quite effective by some researchers with regard to how good it is while determining the structure of handwritten texts [17]. proposed and tested a new CNN model on handwritten character datasets with training feedback, that is, the classification feedback and reconstruction feedback used simultaneously. In this case, the standard character images are employed as the basic truth for the reconstruction feedback. More precise information can be retrieved from the reconstruction feedback as compared to classification feedback, which includes the varying strokes relationships and the shape of the character. The authors noted that the model proposed outclassed other modified CNN models, and the speed of processing was relatively higher than other models.

The model was tested in two sets of character databases: the uppercase letters of CASIA-HWDB and the MNIST. The CASIA-HWDB comprises a mixture of English letters and Chinese characters that have been written by hand, whereas the MNIST database consists of handwritten digits databases with at least 60,000 and 10,000 training samples and test samples, respectively. On the MNIST databases, the author reported an error rate of 0.41 percent (accuracy of 99.59 percent), a slight improvement from the baseline error rate of 0.53 percent (accuracy of 99.47 percent). On the CASIA-HWDB database, the error rate was about 1.53 percent for the proposed model against an error rate of 1.91 percent for the original CNN. The model was compared against other models such as Network in Network, Maxout, and Stochastic pooling, which also indicated that they were efficient for improving the character recognition of CNN. Table 3 shows the accuracy of handwritten text for CNN against other modified versions.

Table 2. Experimental results show accuracy and time taken to build the model using WEKA [16].

Algorithms	Accuracy (%)	Time taken to build the model (s)
J48	72.36	1
Hoeffding tree	67.45	6.71
Decision stump	67.45	0.16
Random tree	72.68	0.84
REPTree	67.45	0.09
Bayesnet	72.76	0.44
Naïve Bayes	72.68	0.09
Multinomial Naive Bayes	67.45	0.01
Decision table	72.93	15.05
Jrip	68.90	8.39
One R	68.69	0.08
PART	71.80	3.08
Zero R	67.45	0
Input map classifier	67.45	0.01
Kstar	72.76	18.93

Table 3. Accuracy of handwritten recognition for original CNN against other modified models [17].

Model	MNIST	CASI-HWDB
CNN	99.47	98.09
Stochastic pooling	99.53	98.36
Network in Network	99.53	98.38
Maxout	99.55	98.44
Proposed model	99.59	98.47

The paper [18] proposed a workflow, and a machine learning model observing that CNN is a robust feature extraction technique, and that Support Vector Machines (SVM) is an excellent classifier. The method they proposed was found to be more effective than amending the CNN with a complicated design. The authors tested the accuracy of the model by using data from the 192nd edition of the National Institute of Standards and Technology (NIST) Special Database, which is housed under the US Department of Commerce. And the accuracy comparison is as Table 4 shows. The proposed method achieved a recognition rate of 98.85 percent with regard to numerical characters, 93.05 percent with regard to upper case characters, 86.21 percent for lower case characters, and 91.37 percent on the combined lower case, upper case, and numerical characters. They compared their model against the conventional CNN, whose accuracy on numerical characters stood at 98.30 percent, the upper case at 92.33 percent, lowercase at 83.54 percent, whereas the combined uppercase and numerical stood at 88.32 percent.

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Table 4. Accuracy of handwritten recognition for CNN and CNN + SVM [18].

Method	CNN	CNN+SVM
Numeral	98.30	98.85
Uppercase	92.33	93.05
Lowercase	83.54	86.21
Numeral + Uppercase	88.32	91.37

4. Conclusion

In this study, a comparative analysis of the performance of two algorithms for handwritten character recognition was conducted. Handwritten text recognition can be described as the capacity of the computer to admit and interpret perceivable handwritten information from photographs, paper documents, and touchscreen, among others. The algorithms compared in this study include the WEKA technique, which is a set of machine learning algorithms employed in mining data, and the CNN technique, which is a class of artificial neural networks that are frequently applied in the analysis of visual images. WEKA is a workbench created to help in the use of machine learning techniques for actual data sets. This learning workbench has evolved from the urge to apply machine learning to actual datasets in a manner that promotes an exploratory approach.

CNN is a deep learning algorithm. It has the capacity to take an image as an input, assign learnable biases and weights as a matter of importance to various objects or aspects related to the image and be intelligent enough to distinguish one from the other. In fact, the architecture of CNN imitates the communication form of the neurons of the human brain, enhanced by the arrangement of the visual cortex. The results show that CNN is comparatively more accurate than WEKA, with an accuracy rate as high as 99.59 percent, with the lowest reported degree of accuracy standing at 88.3 percent. On the other hand, the highest report accuracy with regards to WEKA was 82.92 percent, and the lowest stood at 67.45 percent. Although there is a need for more research to be carried out, the information from the two algorithms demonstrates that the existing techniques are increasingly becoming more reliable, and CNN is leading in terms of accuracy.

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