HANDWRITING RECOGNITION

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ABSTRACT

Humans are said to unintentionally trace handwriting sequences in their brains based on handwriting experiences when recognizing written text. The performance of handwriting recognition systems is dependent on the features extracted from the word image. A large body of features exists in the literature, but no method has yet been proposed to identify the most promising of these, other than a straightforward comparison based on the recognition rate. We examined a large set of algorithms including a deep learning method for classification of the handwriting characters. The best results were achieved using a Convolutional neural network

Keyword: - *Natural Computing, Differential evolution, Chromosomes Classification, Data Classification.*

1. INTRODUCTION

The recognition of handwritten text is a challenging task, owing to the huge variation in writing styles of individual writers [1]. Handwritten text is characterized by its diversity and unique writing style of every particular author, spaces between characters have different size or in some cases two or more characters are merged into a single character. Characters are written with different angle person by person, they can contain a noise in form of the diacritical marks or parts of nearby characters. All those factors make it challenging to make the recognition accurate [5].

Similarly, in word recognition, there are two basic strategies: analytical and holistic. In the analytical strategy, a word is first segmented into the set of its compound letters (or smaller units), and then characters are recognized. A word model is built from the concatenation of character models. On the other hand, the holistic strategy considers word images as a whole and does not attempt to segment words into characters or any other units [2].

Understanding a text image involves both recognition and comprehension. The two processes can be disjoint for machine printed text and highly constrained handwriting. When handwritten text is unconstrained, no restrictions are placed on the writing style. Therefore, a system that reads unconstrained writing must compensate for many factors that affect text appearance, e.g. variations in writing styles, size of text [3]. Hence several techniques are used previously such as CNN, NLP, ANN. Convolutional neural network design inspiration comes from the mammalian visual system structure [6].

Convolutional neural networks (CNN) are a type of neural network which are able to reduce spectral variations and model spectral correlations in signals. These networks have shown strong performance in the image recognition field and using CNN for visual document tasks is the most important practice [4].

In recent years, the optimization of Convolutional neural network is mainly concentrated in the following aspects: the design of Convolutional layer and pooling layer, the activation function, loss function, regularization and Convolutional neural network can be applied to practical problems [7]. These networks have shown strong performance in the image recognition field and using CNN for visual document tasks is the most important practice as well as getting a training data set as large as possible [8].

2. LITERATURE SURVEY

In [10], an assessment question type can be multiple choice, true-false, matching, short answer, and essay. Every type of question has its own advantages and disadvantages. For example, multiple choice question type advantages are can be used to assess broad range of content in a brief period, skill fully written items can measure higher order cognitive skills, and can be scored quickly. However, it has several disadvantages, such as difficult and time consuming to write good items and some correct answers can be guesses. These disadvantages are contradictory to assessment's purpose which is to measure students' comprehension. Another example is essay question type. This type of question can be used to measure higher order cognitive skills with relatively easy to write questions. It is also difficult to guess the correct answer for respondents. Although these advantages cover the weaknesses of multiple choice question type, new problems arise such as time consuming to administer and score, difficult
to identify reliable criteria for scoring, and the content is limited. As technologies grew, online assessment has become a thing with the usage of LMS (Learning Management System). In [9], there are three advantages of online assessment compared to written assessment:

1. No time spent revising answers.
2. Absence of human mistakes on correction (depending on the exam assembling).
3. Possibility of immediate feedback and grading.

Same research in [9] shows that the student's performance gap between written assessment and online assessment is not big in term of their averages. That research gave a conclusion
that online assessment is a solution to current problems, such as increasing number of students, limited amount of time, lack of adjusted tests, and inadequate methods relating to new paradigms. In [11], each question type has its own way to be
graded. To grade true-false and multiple-choice question type, grader must check the selected radio buttons. To grade matching question type, grader must check the matching column pairs. Lastly, to grade short answer and essay question type, grader must do it manually.

3. NATURAL LANGUAGE PROCESSING

Natural Language Processing is a theoretically motivated range of computational techniques for analyzing and representing naturally occurring texts at one or more levels of linguistic analysis for the purpose of achieving human-like language processing for a range of tasks or applications [12]. In [13], there are two categories in NLP sub-problems. They are low-level and higher-level NLP tasks. Low-level NLP tasks used in this grader development are sentence boundary detection, tokenizing, stemming, and part-of-speech assignment (POS-tagging), while for the higher-level one, the used task is spelling/grammatical error identification and recovery. There are a lot of NLP libraries which can be used, such as Stanford NLP Parser, Apache Open NLP, and INANLP.

Stanford NLP Parser [14] is capable to process a tokenizer, sentence splitter, part-of-speech, lemma, named-entities, constituency parsing, dependency parsing, sentiment analysis, mention detection, coreference, and open information extraction.

Apache OpenNLP [15] has features regarding text processing such as sentence detector, tokenizer, name finder, documents classifier, part-of-speech tagger, chunker, parser, and coreference resolution. However, it is not maintained as last update was on 2014.

INANLP [16] has a lot of features such as sentence detector, stemming, tokenizer, formalization, part-of-speech tagger, chunker, coreference resolution, semantic analyzer, and name-entity tagger. It is exclusively made for Indonesian language.

Rahul Kala in [17] used genetic algorithm for offline handwriting recognition. Algorithm was applied on English capital letters (26 categories). In this case 69 characters were used for 978-1-5090-3982-1/17/$31.00 ©2017 IEEE TSP 2017 775 training and 385 for testing. Efficiency of this approach was 98.44 %.

Yafang Xue in [18] achieved 83.3 % accuracy using HOG features (pixels have an orientation and magnitude) and support vector machines algorithm. The training dataset has 10 categories and consists of 1020 synthetic and handwritten images and the training set consists of 120 images.

Authors of [19] used support vector machines with RBF kernel for classification CEDAR database consisting of 52 categories of the English handwritten characters. 85.11 % accuracy was recorded on all 52 categories and keeping separately uppercase and lowercase characters (26 categories in particular), 95.90 % and 93.50 % accuracy was achieved.

N. Sankaran and C.V. Jawahar in [20] got 5.65% character error rate (CER) on good quality images data set and 15.11 % CER on poor quality images. Their data set had 685 categories with 90k training and 67k testing images and Recurrent Neural Network, known as Bidirectional Long Short-Term Memory (BLSTM) was used as a classifier. Comenia script is a novel font recently introduced in Czech elementary schools and there are no classifiers related to these methods.

3. NEURAL NETWORK

The features extracted from the handwriting samples are given as input to the network (in the same order). The desired output pattern consists of four Os and a 1. As mentioned earlier each individual was tagged to a particular node. The desired output of that person's node is awarded a value 1 from who's handwriting the sample features were extracted. Rest of the nodes are assigned a desired output of value 0. Therefore, the concept of pattern interleaving is employed so that each feature vector contributes equally to the training. Approximately 150 epochs were used for the training. The method of training for both the experiments was the same.

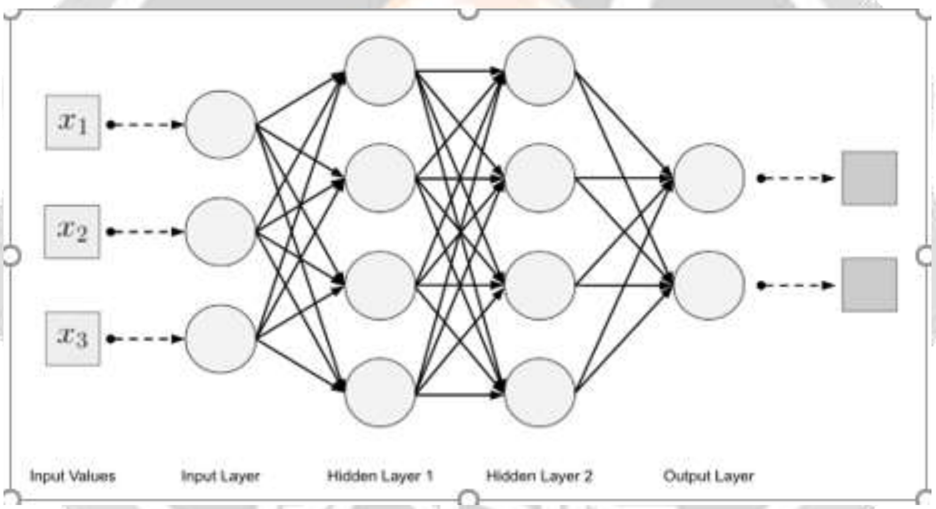

Figure 1:Neural Network

4. CONCLUSIONS

We have begun our discussion from different facts of natural computing and further pointed out three desirable properties of discovered knowledge. These are prediction accuracy, comprehensibility, and interestingness. We believe a promising research direction as to design nature-inspired algorithms which aim at discovering truly interesting classification rules. Clearly, this is much easier said than done. This task is not as easy as seems to be. Indeed, the interestingness is a complex concept and intertwined with objective as well as subjective aspects. In majority of nature-inspired algorithms implemented for knowledge discovery task, the emphasis is generally given on objective aspects of rule quality, and more precisely they are concentrated on predictive accuracy. Very often rules comprehensibility was also taken into account.

However, mere picking these two factors, i.e., accuracy, and comprehensibility cannot ensure interestingness of the classification rules. Uninterestingness might creep in a highly accurate, comprehensible classification rules, particularly in that segment of knowledge which has previously been known to the user. Concerning data mining tasks, which correspond to kinds of problem to be solved by data mining algorithms in this survey focus has been given only on the classification task.

However, many of the ideas and concepts discussed in this paper are also relevant to other data mining tasks such as prediction and dependence modeling.

We believe that the development of novel nature-inspired algorithms is important to augment the domain of evolutionary computation in the purview of data mining and knowledge discovery.

The proposed view of concurrency of knowledge, nature, and computations envisaged the body as basic cognitive element required for knowledge generation.

It is important to mention that information and its processing are two essential structural and dynamical characteristics of nature and it creates pivotal role of knowledge and computation in present day computational paradigm.

In conclusion, we would like to sum up the convergence of knowledge, nature, and computations with the following insight related to biological systems.

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