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AI driven OCR: Resolving Handwritten Fonts Recognizability Problems

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Introduction

Handwritten script typefaces are based upon the varied and often fluid stroke created by handwriting or software. Because of their diversity, the are interesting to designers and are increasingly used. However, the problem arises with their optical readability and recognizability. Handwriting recognition is ability of a computer to receive and interpret intelligible handwritten input from different sources. An Artificial Neural Network (ANN) is commonly used for searching for dependencies between data that are not in a linear correlation, and yet can be combined into one complex input set. Generally, a network processes a set of input data in parallel, and different priorities and assigned to these values, which can be changed and processed differently according to a specific scheme during learning. The main goal of this research was to determinate AI driven OCR system effectiveness in recognizability of handwritten fonts. The results obtained from the experiment are summarized and presented with concluding remarks and recommendations for further research.

Methods

This research was carried out using artificial neural network and machine learning. For this purpose, was used the EMNIST dataset of letters. In first step specific dataset of different examples of handwriting test photos is defined. This dataset consists set of English letter characters from A to Z. It contains separated letter characters for every font type of each test group. Within the group of handwritten forms, two subgroups of fonts were created, namely independent letter characters and letter characters linked by ligatures. Furthermore, four types of font families were created in each basic cut group: bold stroke, alternating stroke, monoline stroke, and brush stroke. Finally, seven letter cuts were made for each of the four font families: thin, ultra-light, light, regular, semi-bold, bold, and ultra-bold. Thus, for testing for each group, 28 fonts were made, i.e. 56 overall. All tested fonts are made by software Fontographer 5.2. New created letter characters have been added to existing the EMNIST dataset, and using MLP BPNN architecture (Figure 1), the effectiveness of recognition of added characters in the prepared dataset was measured. All calculations were made in Statistica 13.5.0.17.

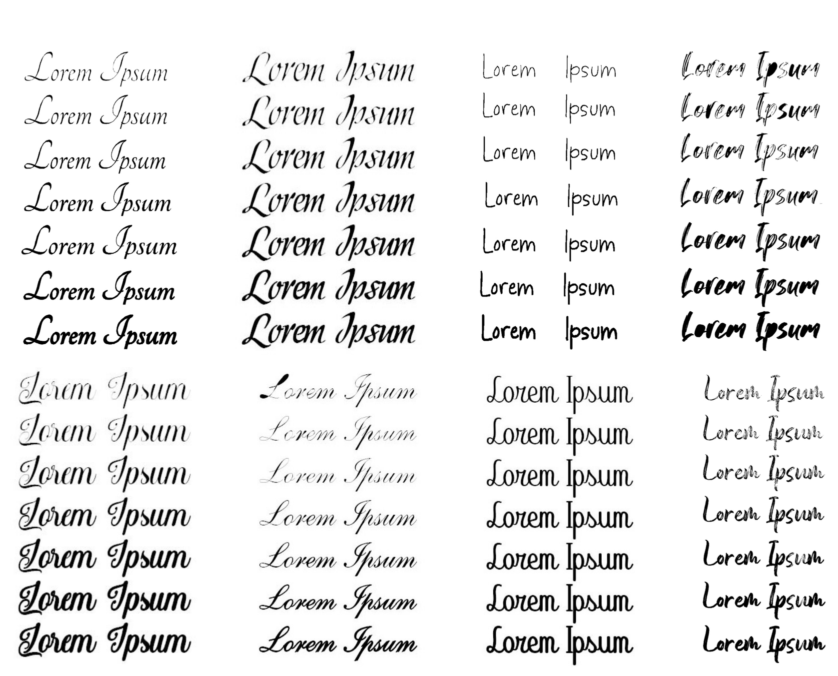

Figure 1
Sample of tested handwritten fonts

Results

The training algorithm (digital handwritten font from the EMNIST dataset) was used as a tool for training in this research. Expanded testing dataset are digital dataset of 1.456 created letter characters. Total images of Lorem Ipsum words that used in this experiment is 5.600, which mean 100 images for every single created font type. The task was to determine how the network handles the identification of handwritten letter characters in some specific order in word.

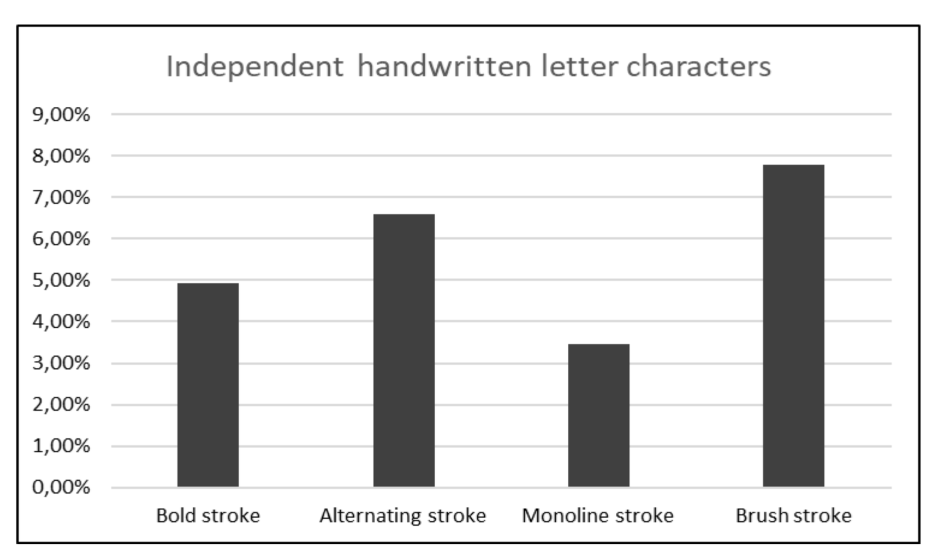

Figure 2
Average percentage increase in recognizability of independent handwritten letter characters using AI driven OCR

Figure 2 shows average percentage increase in recognizability of independent handwritten letter characters using AI driven OCR compared to standard OCR. The biggest increasing rate is for brush stroke font family and amounts 7.79%. The smallest increasing is noted for monoline stroke font family, 3.46%. Bold stroke font family records an increase rate of 4.94%, and alternating stroke font family of 6.59%. Average percentage for subgroup of independent handwritten characters is 5.70%. Individually speaking it is 2.35% for monoline stroke font family, regular cut, and 9.80% for brush stroke font family set, bold cut.

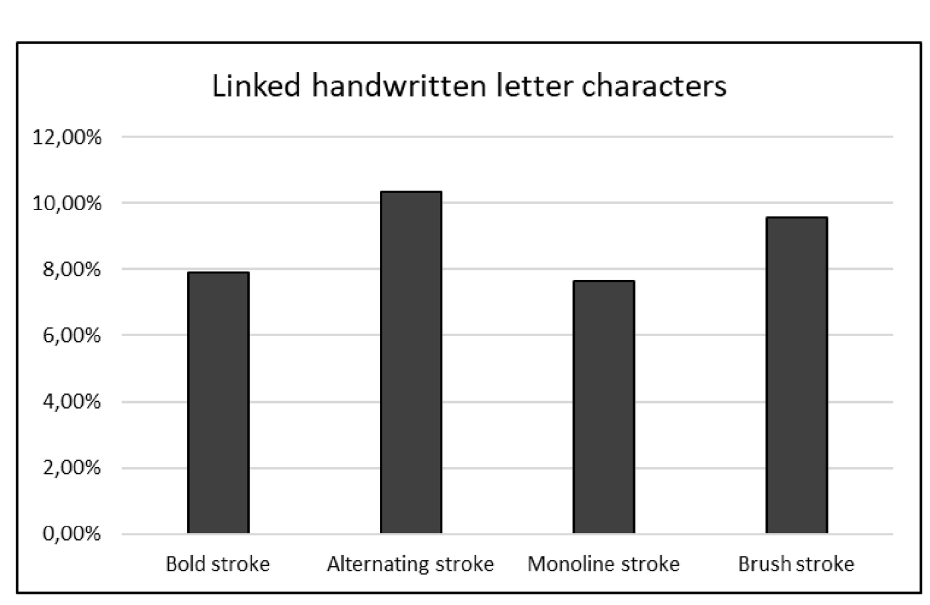

Figure 3
Average percentage increase in recognizability of linked handwritten letter characters using AI driven OCR

Figure 5 shows average percentage increase in recognizability of linked handwritten letter characters using AI driven OCR compared to standard OCR. The biggest increasing rate is for alternating stroke font family and amounts 10.36%. The smallest increasing is noted for monoline stroke font family, 7.63%. Bold stroke font family records an increase rate of 7.91%, and brush stroke font family of 9.58%. Average percentage for s ubgroup of independent handwritten characters is 8.87%. Individually speaking it is 5.26% for monoline stroke font family, thin cut, and 11.36% for brush stroke font family set, light cut.

Discussion / Conclusion

An increase in all values was observed, which means that the application of AI driven OCR increased the recognizability of the characters in the sample. The increase in recognizability using AI driven OCR was expected to bi higher in the subgroup of linked handwritten letter characters because the initial results were lower for this subgroup when using standard OCR. Analysis of the samples determined that they were deviations are the most pronounced in words with two or more ascenders (k, b, l, d, h, t) and descenders (g, j, p, q, y). If the letter characters are linked by ligatures, the ascending and descending strokes are even less recognizable to the scanners. In subgroup of independent letter characters, errors were observed in similar rounded lines such as the letter characters a, and e. In the subgroup of letter characters connected by ligatures, errors were also observed in similar rounded lines such as the letter characters a and e, m and n, but also in ascenders b and l, and descenders g and q.
Here results are based on a small number of tested samples. In future work can be extend to a larger batch pool and for other specific letter characters, and numbers as well. Because OCR is very sensitive, and any disorder can easily confuse similar letter characters it would be good to make software distortion of letter characters in order to increase the number of letter characters and different variations in the database.
Reducing the number of deviations shows that the neural network gives acceptable answers but requires creation of a larger database within about 56,000 different letter characters. Handwritten documents are increasingly being digitized. Therefore, it is important that the base of fonts and individual letter characters be as large as possible. For this purpose, it is useful to create as many digital handwriting fonts as possible. Artificial intelligence helps in the process of identification and classification within a complex database of fonts. This paper describes the application of AI driven OCR based on MLP (Multilayer Perceptron) BPNN (Back Propagation Network) algorithm. Non-linear increase of 5.70% for the subgroup of fonts with unrelated characters, and 8.87% for the subgroup of fonts with ligatures associated with characters. It is therefore indicative of the development of AI driven OCR. Also, experiment indicates that original the EMNIST dataset could be improved adding a new letter character sets which enable to neural networks for recognition to be more accurate. There are several areas for future work. The results need to be verified with extended dataset and different kind of algorithm.

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