Using Off-Line Handwriting to Predict Blood Pressure Level: A Neural-Network-Based Approach

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Abstract. We propose a novel, non-invasive, neural-network based, three-layered architecture for determining blood pressure levels of individuals solely based on their handwriting. We employ four handwriting features (baseline, lowercase letter "f", connecting strokes, writing pressure) and the result is computed as low, normal or high blood pressure. We create our own database to correlate handwriting with blood pressure levels and we show that it is important to use a predefined text for the handwritten sample used for training the system in order to have high prediction accuracy, while for further tests any random text can be used, keeping the accuracy at similar levels. We obtained over 84% accuracy in intra-subject tests and over 78% accuracy in inter-subject tests. We also show there is a link between several handwriting features and blood pressure level prediction with high accuracy which can be further exploited to improve the accuracy of the proposed approach.

Keywords: Neural networks · E-health · Bioengineering · Image processing

1 Introduction

Although used as a means of communication for millennia, only recently handwriting has been studied in relationship with psychological and medical conditions of the writer, in a rather new research area called graphology. Typically graphology is used to identify, analyze and interpret different behavior aspects of the writer as well as medical conditions he/she might have, analyzing handwriting features such as: the trajectory of the writing [1], the way letters are written (letter "t" and letter "y" [2]) or the weight of strokes. Several of these features are employed in the current work in a neural-network based approach for predicting blood pressure levels based on handwriting. Such an approach will provide a non-invasive and less costly alternative to other more invasive ways of determining blood pressure levels which are typically assessed by means of costly equipment. The proposed approach can also provide a baseline for predicting other medical or behavioral conditions (such as lying, which is often linked to an increase in blood pressure). The approach is also original as it involves building a novel three-layered architecture based on a feed-forward neural network, but also because it treats the task of predicting blood pressure from handwriting as a pattern recognition task.

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In the following chapters we will present the state-of-the-art in the area of handwriting recognition, focusing our attention on systems that use handwriting to predict different medical conditions of the writer.

2 Related Work

As mentioned before, our system aims predicting blood pressure based on off-line handwriting hence we will present the state-of-the-art in terms of predicting medical conditions by analyzing handwritten samples of an individual.

Grace et al. [3] propose a way of investigating the relationship between the grip and pinch strength in handwriting and the Autism Spectrum Disorder (ASD). They have analyzed 51 children which were divided into two groups (children with no ASD and children in the autism spectrum), each child being asked to take a test which would assess its pinch and grip strength, as well as the pencil control and writing activity independence. Their research showed that grip strength was correlated with pencil control in both analyzed groups, but with legibility only in the children without ASD which shows that grip and pinch are important features for children development tasks.

Another medical condition which was analyzed by means of handwriting is Parkinson's disease (PD), knowing the fact that PD is typically associated with micrographia. Micrographia refers to the decrease in letter size as well as increase in the movement time and decrease and frequent changes in the speed and acceleration of writing. Drotar et al. [4] propose a template to collect handwriting during different tasks which are specifically designed to determine as many aspects of micrographia as possible. Their proposed approach, tested on 75 subjects, showed an accuracy of 80% in classifying subjects suffering from PD. Similarly, in [5] several metrics are developed in order to describe micrographia, such as size-reduction, ink utilization, and pixel density. These are used to compute scores for signatures of 12 subjects in order to predict if they are suffering from PD or not. The results show significant differences in terms of pixel density between subjects suffering from PD and non-PD suffering subjects and showed promising results for developing such a system that could be used as an alternative to other dynamic sampling methods for PD diagnosis which involve specialized and costly equipment.

Bhaskoro and Supangkat [6] present a research where handwriting is analyzed with the purpose of discriminating between subjects suffering from diabetics' disease and healthy subjects. They used a term frequency – inversed document frequency method to analyze the levels of resemblance of the handwriting features in the vector space model and, tested on 56 subjects, the method offered an accuracy of 81.8%.

Neuromuscular disorders are also analyzed in [7] with the aid of handwriting movement analysis which segments the handwriting strokes in order to evaluate the motor control abilities of neuromuscular disorders and those of people who do not suffer from them. The results are promising and show that such an approach can be used to assist the diagnosis of such disorders.

With all the above-mentioned research, our paper proposes building a non-invasive feed-forward neural network-based system able to determine the blood pressure level of the writer solely by analyzing his/her handwriting. This could offer a non-invasive and less costly alternative to current approaches which are more invasive and need more expensive equipment to determine the blood pressure level of a patient.

3 Proposed Architecture

3.1 Graphology Analysis and Blood Pressure Types

As mentioned previously, the area of research which studies handwriting for determining psychological, behavioral or medical conditions of the writer is called graphology. There are tens of handwriting features which can be used to analyze writing [8], but in this paper we will only use the following: baseline, lowercase letter “t”, connecting strokes, and writing pressure. We will describe each of them in the following paragraphs.

Baseline refers to the direction on which the writing flows. An ***ascending baseline*** is typically associated with easy going, happy people, ***descending baseline*** is associated with pessimistic people, while ***leveled baseline*** is associated with people with high reasoning abilities. All these psychological features can have an impact on the blood pressure hence the reason why we have chosen this handwriting feature (e.g. happiness is know to lower blood pressure).

Lowercase letter “f” refers to how the letter “f” is written. We use it because it provides clues about the precision of the writing which can convey information about blood presure as well: ***cross-like lower case letter “f”*** is related to increase levels of concentration, ***angular loop*** refers to strong reaction to obstacles, ***narrow upper loop*** refers to narrow minded people, ***angular point*** refers to persons who can get easily revolted, ***balanced lowercase letter “f”*** is typically associated with leadership abilities.

Connecting strokes refer to how letters are connected one with another to form a word. ***Strongly connected*** letters are an indicator of people who can easily adapt to change, ***medium connected*** letters refer to persons who like changing environments often, and ***not connected*** means the person has difficulties adapting to change.

Writing pressure refers to the amount of pressure that is applied by the writer on the paper and this is the most commonly used handwriting feature to assess the blood pressure level of the writer. ***A medium writer*** is a person who is moderately affected by traumas (and is typically associated with normal blood pressure), ***light writer*** is a person who easily gets over traumas (typically associated with low blood pressure), and ***heavy writer*** refers to persons who are deeply affected by traumas (and is typically associated with high blood pressure).

Analyzing these handwriting features we aim building a non-invasive system able to predict blood pressure levels. We divide the subjects analyzed into three categories, based on their blood pressure:

- Subjects with low blood pressure (Systolic: 70–90, Diastolic: 40–60)
- Subjects with normal (ideal) blood pressure (Systolic: 90–130, Diastolic: 60–85)
- Subjects with high blood pressure (Systolic: over 130, Diastolic: over 85)

In the following subchapter we will present the architecture of the proposed system and will describe in detail each of the three component layers.

3.2 Overall Architecture

As previously mentioned, we design a feed-forward neural-network based system on three layers: base layer (where the handwriting is normalized and letters are split), a middle layer (where a matrix is computed for each letter in the handwritten sample), and a top layer (where the decision regarding the blood pressure of the subject is taken). The architecture is depicted in Fig. 1.

The *base layer* has the main purpose of taking the handwritten sample in the form of a scanned image and converting it to a set of handwriting features. The contrast of the image is first increased in order to better distinguish the letters and features such as connecting strokes or writing pressure, then the area of the handwritten sample where the handwritten text is present is cropped and converted into greyscale.

Letters are then split and cropped from the image using a junction-based segmentation algorithm as used in [9] which has showed good results at segmenting characters closely linked together. The cropped character is then provided as input to a feature extraction block.

The feature extraction block implements a set of algorithms for each handwriting feature analyzed. For *baseline,* a polygonization method is used [10], a technique where a polygon is delimited around the handwritten text and its relation with the overall structure of the page is studied. For *lowercase letter "f"* the algorithm used is template matching where the letter is compared to 50 templates for letter "f" and based on the matching score the handwriting feature is determined for each letter "f" in the text. For *connecting strokes,* we analyze them using the same junction based segmentation algorithm [9] by scoring the connections between two consecutive letters in the handwritten sample. *Writing pressure* makes use of a grey level thresholding algorithm [11], which studies the thickness of the writing and determines if it is light, medium or heavy.

Each of these features collected for each letter in the handwritten sample are sent to the middle layer where each result is binary coded. Hence, for *baseline* we will have the following possible values: 100 – Ascending, 010 – Descending, 001 – Leveled, for *lowercase letter "f"* we will have as possible values: 10000 – Cross-like, 01000 – Angular Loop, 000100 – Balanced, 00010 – Angular Point, 00001 – Narrow Upper Loop, 00000 – not a lowercase letter f, for *connecting strokes* we have 100 – Not Connected, 010 – Medium connectivity, 001 – Strongly connected, and for *writing pressure* the binary codes will be: 100 – Light Writer, 010 – Medium Writer, 001 – Heavy Writer. Hence, for each letter in the handwritten sample, we will have a row in the Letters matrix; for example a row like [100][10000][010][100] will mean ascending baseline – 100, cross-like letter "f" – 10000, medium connectivity – 010, light writer – 100. This matrix is fetched to the top layer which will analyze it in a pattern recognition task using a neural network in order to determine the blood pressure level of the writer (low, normal or high).

In the top layer we will have a neural network that is trained in order to determine the blood pressure level of the writer by only analyzing the previously mentioned features. Being a pattern recognition task in a bottom-up architecture with no feedback

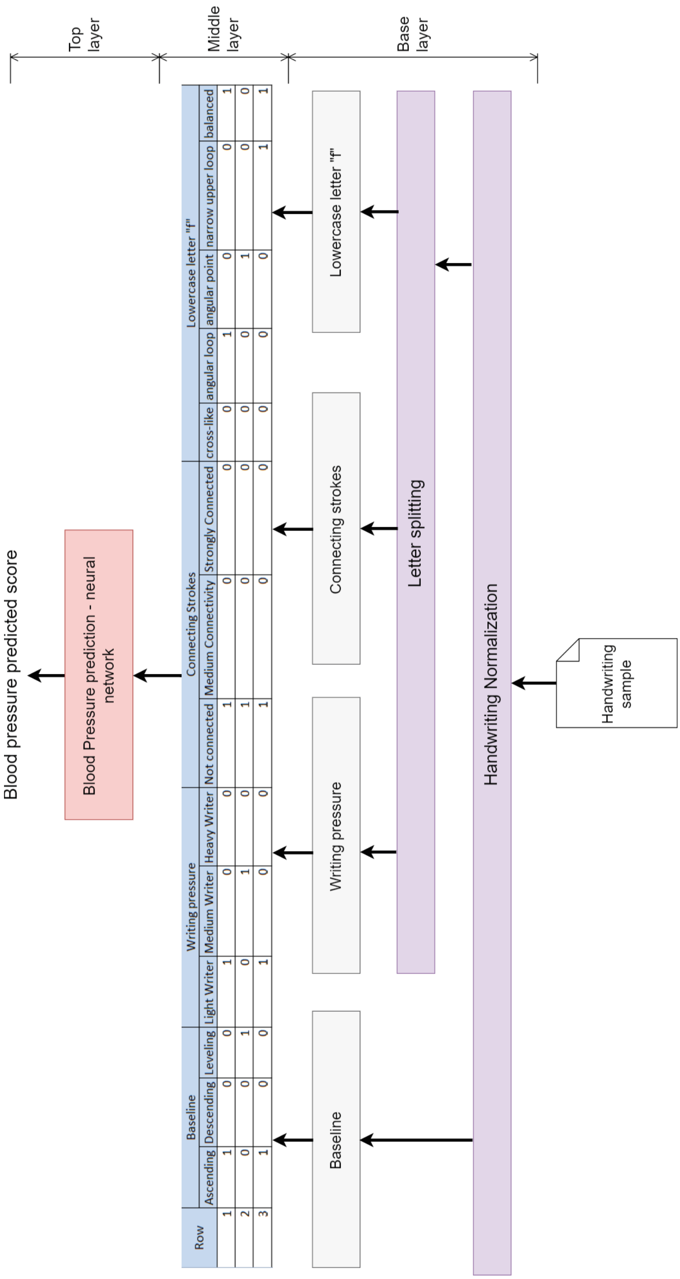

Fig. 1. Overall architecture.

loops, the neural network employed is feed-forward and the training method used is backpropagation which is known to offer good results and fast convergence in such tasks. The neural network has three layers: an input layer, one hidden layer, and the output layer. The Letters matrix formed in the middle layer is provided as input to the neural network every 70 letters in order to avoid overfitting the neural network (we are also considering we don't have more than 70 letters on a row; if more than 70 letters are present on a row, only the first 70 letters will be taken into account). As for each letter we will have 14 binary numbers, the input layer will therefore have 980 nodes. The output layer will have only one node which will provide a score on a scale from 1 to 3 (1 – Low Blood Pressure, 2 – Normal Blood Pressure, 3 – High Blood Pressure). In the training phase the Average Absolute Relative Error (AARE) is computed as the difference between what is expected and what is determined and the neural network's weights are tuned to accommodate better results. Through trial and error it was determined that the optimal number of hidden nodes is 1120 with an AARE of 0.005. For learning the weights and biases of the neural network, gradient descent algorithm is employed while for the initialization of weights in the input node Nguyen-Widrow weights initialization method was used. The optimal learning rate is 0.01, the optimal momentum 0.03 and the number of training epochs needed 50000.

In the following chapter we will present the experimental results obtained when testing the previously described system.

4 Experimental Results

In order to test the proposed architecture, due to lack of any publicly available database to use, we have created our own datasets by asking 18 subjects (9 males and 9 females with ages between 18 and 45, participating in accordance with Helsinki Ethical Declaration) to provide each three handwritten samples at three different times as well as acquired their blood pressure each time they provided these samples. Out of the three handwriting samples, one of them contained a pre-defined text from *The London Letter* (a standard request exemplar used by graphologists in handwriting analysis [8] because the text is designed in such manner as to provide relevant information for all the handwriting features we analyze), while the other two handwriting samples contained texts which were freely chosen by subjects, but needed to contain at least 200 words. We have used this database for both testing and training the system proposed. We therefore divided the two handwritings into two different datasets which we tested in both intra-subject and inter-subject methodologies: controlled dataset (pre-defined text is used – *The London Letter*), random dataset (text freely chosen by the writer containing minimum 200 words).

4.1 Intra-subject Methodology

For intra-subject methodology we trained and tested the system on handwriting samples attributed to the same subject, by alternating the type of the dataset used (controlled, random or controlled and random). Results can be found in Table 1.

Table 1. Blood pressure prediction accuracy and average number of rows in intra-subject tests.

Type of training samples	Type of test samples	Number of training samples/number of test samples	Accuracy (%)	Specificity (%)	Sensitivity (%)	Avg. no. of handwritten rows analysed
Controlled	Controlled	2/1	86.4	82.2	87.4	4
Controlled	Random	3/6	84.4	78.2	85.2	5
Random	Controlled	3/3	74	70.2	79.5	10
Random	Controlled	3/6	74.5	71.3	79.2	10
Controlled + Random	Random	8/1	80.4	77.5	84	7

As it can be observed, the highest prediction accuracy as well as results in terms of specificity and sensitivity are obtained when the controlled dataset is used for both training and testing the system, reaching over 86% accuracy. However, the results are kept considerably high when the controlled dataset is used in training while the system is tested on random dataset, the decrease being of only 2% in terms of accuracy. This shows that the most important thing is to have a well-chosen pre-defined text used for training purposes, while for testing purposes any text can be used and the accuracy is still high. This is important as in a real application the subject will only have to write a pre-defined text when he first uses the application, while for all other subsequent measures he can freely write any text he wants. This is also sustained by the fact that when random dataset was used for training, the results were 10% lower than when using the controlled dataset.

The average time taken to compute the results in the case where the controlled dataset is used for training purposes is 15 s (the average number of rows to analyze is 5 and analyzing a row takes on average 3 s) which makes such an application suitable for real time implementation as it is very fast.

4.2 Inter-subject Methodology

The same tests were conducted in an inter-subject methodology, which means that we trained the proposed system on handwriting samples coming from a set of writers and we tested it on handwriting samples coming from a different writer not involved in training. The results are similar, the highest accuracy, specificity and sensitivity being obtained when the controlled dataset is used for training, up to 7% higher accuracy than when random dataset is used in the training stage. This shows consistency for the proposed system, the accuracy provided in this methodology being 78.3%. The remaining 21.7% typically refers to blood pressure levels which were mistaken with their neighbor values (such that low blood pressure is mistaken with normal blood pressure, normal blood pressure with high blood pressure and vice versa) for which better algorithms for level discrimination should be proposed. Results can be observed in Table 2.

Table 2. Blood pressure prediction accuracies and average number of rows in inter-subject tests.

Type of training samples	Type of test samples	Number of subjects involved in training/number of test subjects	Accuracy (%)	Specificity (%)	Sensitivity (%)	Avg. no. of handwritten rows analysed
Controlled	Controlled	9/9	76.2	73	76.2	10
Controlled	Controlled	12/6	78	75.2	79.3	8
Controlled	Controlled	17/1	78.9	76	82.2	7
Random	Random	9/9	71	67.4	73.2	13
Random	Random	12/6	72.1	68	74	14
Random	Random	17/1	72.5	69.2	74.2	16
Controlled	Random	17/1	78.3	75.4	81	7
Random	Controlled	17/1	70.4	68.4	73.2	15
Controlled + Random	Controlled + Random	17/1	77.8	74.3	80.2	9

The average time needed to converge to a result when the controlled dataset is used in training stage is 30 s, which also shows that such an application is fast and can be an attractive alternative to other more expensive ways and equipment used for assessing the blood pressure of an individual.

4.3 Links Between Handwriting Features and the Blood Pressure Levels

In order to determine the links between the handwriting features we are studying and the blood pressure levels, we have created a residual application which counts the number of appearances for each handwriting feature when a specific level is detected with over 90% accuracy. Table 3 depicts these relationships which can be further used to tune the system and increase its accuracy even more.

Table 3. Correlation between handwriting features and the blood pressure levels.

Blood pressure levels	Most present handwriting features in the letters matrix
Low blood pressure	Writing pressure – light writer
	Ascending baseline
Normal blood pressure	Writing pressure – medium writer
	Connecting strokes – strongly connected
	Lowercase letter “f” – cross like
High blood pressure	Writing pressure – heavy writer
	Descending baseline
	Connecting strokes – not connected
	Lowercase letter “f” – angular point

5 Conclusions

We propose a novel, non-invasive, neural-network based system with an architecture on three layers with the purpose of determining the blood pressure of a subject solely based on his/her handwriting. The architecture contains a base layer where the scanned handwriting is normalized, the handwritten text is split into letters and for each letter four handwriting features are determined (baseline, writing pressure, lowercase letter “f”, and connecting strokes), a middle layer where a binary matrix is computed containing rows for each line in the handwriting sample and depicting the handwriting features for each letter using a combination of binary codes, and a top layer containing a feed-forward neural network trained via backpropagation to determine the blood pressure level by studying the patterns in the binary matrix computed in the middle layer.

We have created our own database containing handwriting samples collected from 18 subjects as well as their corresponding blood pressure. The database is divided into controlled dataset (the written text is pre-defined) and random dataset (the written text is freely chosen by the writer). We have shown that in both intra-subject and inter-subject methodologies, the controlled dataset ads more value in the training stage, offering up to 10% better accuracy for intra-subject tests and 7% for inter-subject tests compared to when the random dataset is used for training. This is an important observation as for such an application the subject will only have to write a pre-defined text at the beginning in order to train the system, and after that he can write any text, hence it will involve less effort from their side, while the accuracy is kept at similar levels. We obtained over 84% accuracy, over 78% specificity and over 85% sensitivity for intra-subject tests and over 78% accuracy, over 75% specificity and over 81% sensitivity for inter-subject tests. The time needed to converge to a result was no more than 30 s, making such approach more attractive comparted to other more expensive ways of assessing the blood pressure.

We have also showed there is a link between several handwriting features and prediction with high accuracies of each of the three blood pressure levels which can be further exploited to tune the system and reach better accuracies. Also the fact that the non-accurate results are typically mistaken with neighbor levels (low blood pressure is typically mistaken with normal blood pressure, normal blood pressure is typically mistaken with high blood pressure and vice-versa) shows the need for other algorithms to be integrated in this approach to better discriminate between blood pressure levels which will be the direction of our future research.

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