Study on determining the Myers-Briggs personality type based on individual's handwriting

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Abstract- Studies in psychology showed a close link between handwriting and personality, but this was never formally analyzed. In the context of career development there is a need to determine the personality type in a more efficient manner than the classic questionnaire. Moreover, in the fields of psychology and medicine, constant monitoring the patient's personality can provide information regarding his mental health status, if he suffers from mental disorders or show psychological symptoms for common physical diseases. We analyze the link between personality types and handwriting, by correlating the handwriting features with the personality primitives in a neural-network 3-level architecture. Results show an accuracy of 86.7% in determining the personality type, with highest accuracies for Extravert vs. Introvert and Thinking vs. Feeling personality primitives. The system computes the personality type in less than 1 minute, proving to be more efficient than a questionnaire and suitable for real-life use.

Keywords: neural networks, affective computing, personality recognition, mental health disorders, career development.

I. INTRODUCTION

Although handwriting has been used for centuries, its linkage to the behavior, emotion and personality of the writer has only recently been approached and is currently a debatable domain. Currently the method for analyzing handwriting is based on psychological analysis and is referred to as graphology. The main reason for which it is thought to be a link between handwriting and the personality of the writer is based on the neurological patterns of the brain. It is thought that the brain forms characters based on habits of the writer and each neurological brain pattern forms a radically distinctive neuromuscular movement which acts in the same way for individuals with the same type of personalities and therefore handwriting will be an accurate mirror of a person's brain [1].

Currently graphology is used for identifying, evaluating and understanding the personality of a person by studying different features of the writing, such as the weight of the strokes [2], the way certain letters are written (letter "t" and letter "y" in [3]), and other different patterns (e.g. the trajectory of writing in on-line handwriting recognition [4]). Moreover, personality is closely linked to areas such as career development [5], personalized health assistance [6], determining mental health disorders [7] as well as physical health diseases having psychological symptoms ([8],[9]). All these considered, we aim developing a system able to determine personality types based on handwriting.

II. RELATED WORK

Although there is no standard in handwriting behavior prediction and most of the graphological analysis is done subjectively by specialized graphologists, there have been various works that tried to create systems for automatic handwriting recognition and standardize the graphological analysis. Most of the applications that employ handwriting personality / behavior recognition can be divided into two categories: career development (including counseling and education) and e-health (mental health disorder detection, detecting physical diseases with psychological symptoms and personalized health assistance systems).

For the first categories, the career development has been approached from various angles. One such research is presented in [5] where handwriting is used in order to improve the performance of pupils through a system that acquires writing and test drawings and based on a probabilistic Bayesian network-based model, determines the writing strategy of the child which is analyzed by a child development psychologist and can decide on how to optimize the education of that specific pupil. Their system showed accuracy similar to those of an expert and it also proved to be robust. In terms of personality recognition application, research such as [10] showed the effects of personality types over the counterproductive work behaviors (CWBs) of employees and showed that there is a close link between psychological factors such as conscientiousness and neuroticism and CWBs. Moreover, [11] studied the personality factors of an employee in relation to the personality of other employees and showed that the mental health and stability of an employee can be estimated not only through his own personality traits, but also through the personality characteristics of his coworkers. On a similar note, [12] showed there is a close link between job satisfaction and the personality types of the employee.

The other category is related to e-health and has many applications. [6] presents a system that studies the behavior of children of infants based on their handwriting, starting with the idea that infants are the best subjects as they are less influenced by any cultural background and their rate of cognition evolves very fast. The automatic system was aimed at detecting developmental disorders that the children might suffer from and offer accuracies of over 78%, proving as a robust tool for teachers and occupational therapist in monitoring their pupils / patients. [8] uses handwriting in researching the diabetics disease and tests conducted on 56 human handwritings showed that the handwriting can predict with 80.81% accuracy the patients suffering from diabetics. [9] uses handwriting for predicting one of the most important symptoms of Parkinson's disease (PD), micrographia, which typically manifests through a decrease in the size of letters, as well as the kinematics of the handwriting, such as velocity and accelerations. They proposed a system that would acquire handwriting information during different tasks from PD diagnosed patients and showed over 80% accuracy on 75 tested subjects. In terms of personality type detection, there have also been various researches in determining mental disorders from them. [7] uses a multi-layer perceptron (MLP) to analyze driver's behavior and the system is accurate in classifying emotions and detecting highly emotional drivers with the aim of preventing accidents. Autism Spectrum Disorder (ASD) is another mental health disorder that was intensively studied and linked to personality traits. [13] presents a human-robot interface called FACE able to express and convey emotions, as well as empathy which is used in therapy with autistic children, driving them through different social scenarios. [14] proposes a system for tracking the reactions of ASD patients in order to measure their concentration level in interaction and communication, information vital for ASD therapists. Drug addiction is another disorder that benefits from this technology, in [15] a Pervasive Environment for AffeCtive Healthcare (PEACH) being proposed in order to determine the psychological state of the subject suffering from drug addiction, detecting with over 80% accuracy mental health disorders such as depression, common to such patients. [16] shows another system using a body sensor network (BSN) in order to gather data on the affective and psychological states of the patient and to determine his depressive states, through real time psychological monitoring. This raises the motivation of the current work, as we are envisaging more non-intrusive and practical ways to determine the personality traits of the user and their evolution over time, without the use of an extensive questionnaire to be filled in everytime this information is needed which is extremely cumbersome and non-practical, as well as without the use of invasive sensors. We therefore focused ourattention over handwriting, as this is an activity common to almost everyone hence we can acquire the personality information a lot faster and more often. It is also more practical than using a questionnaire, and non-invasive compared to body sensors or electrocephalogram signals.

In the following chapters we will present the theoretical model and the architecture of our system, as well as the experimental results and conclusions drawn from them.

III. THEORETICAL MODEL

We base our research on mapping the Myer-Briggs type indicators on specific handwriting features in order to accurately determine the MBTI personality traits from handwriting. Myers-Briggs Type Indicator (MBTI) [17] is a psychometric questionnaire that is designed to measure the personality traits of an individual.

Its main applications are in career counseling and development, professional development, leadership training and executive coaching as well as team building but also offers information on the mental health of an individual, specific personality shifts being indicators of personality disorders, such as schizotypal and obsessive-compulsive disorders.

Usually these personality types are determined by means of a questionnaire specifically designed to question all four dichotomies in order to match with the best personality type.

However, this questionnaire can sometimes be faked by the subjects and is also cumbersome and non-practical to be filled in several times a month or even a year in order to determine personality shifts and hence conclude in mental disorders that affect the subject or psychological symptoms of a physical disease.

TABLE I
HANDWRITING FEATURES AND THE DETERMINED CORRESPONDING MBTI PERSONALITY TRAITS

Feature	Description	Type	Characteristics	MBTI personality traits
baseline	Line on which the writing flows	ascending	Optimistic, joy, happiness	**Extraverted, Feeling**
		descending	Pessimistic, over thinker	**Introverted, Thinking**
		leveled	Self-control, reasoning	**Thinking**
Writing pressure	Amount of pressure applied by the pen on the paper	Heavy writer	Deeply affected by emotions, "may forgive but will never forget"	**Sensing, Judging**
		Medium writer	Moderately affected by pain or traumatic experiences	**Intuition**
		Light writer	Easily getting over traumas, hardly emotionally affected by traumas	**Intuition, Perceiving**
Word slant	Inclination of the written words	Vertical slant	Persons that like to be alone and can control their emotions	**Introverted, Intuition, Feeling**
		Moderate right slant	Persons that easily exteriorize their opinions and have confidence in themselves	**Extraverted, Sensing, Feeling**
		Extreme right slant	Lack of self-control, impulsiveness, no toleration, frustration	**Extroverted, Sensing, Thinking**
		Moderate left slant	Hard to adapt, hard to express emotions	**Introverted, Intuition, Feeling**
		Extreme left slant	Defensive people afraid of the future, suffer from self-rejection, want to be in permanent control	**Introverted, Sensing, Thinking**
Connecting strokes	How the letters are connected to form a word	Non-connected	Person that can hardly adapt to change, monotonous	**Intuition, Judging**
		Connected letters	Persons who can easily adapt	**Sensing**
		Medium connectivity	Adapted to change, predilection towards changing environments	**Sensing, Perceiving**
Lowercase letter "t"	How the t-bar is written on letter "t"	Very low	Low self-esteem	**Sensing, Judging**
		Very high	High self-esteem	**Intuition, Perceiving**
Lowercase letter "f"	The way the letter "f" is written	Narrow upper loop	Narrow minded people	**Sensing, Perceiving**
		Angular loop	Strong reaction to obstacles	**Sensing, Judging**
		Angular point	Persons easily revolted	**Sensing, Judging**
		Cross-like lower case letter "f"	Increased level of concentration	**Intuition, Judging**
		balanced	leadership	**Intuition, Judging**

For this we have first conducted research on 64 subjects proportionally divided according to the 16 personality types. We asked them to take the MBTI test every two weeks for a period of 2 months, as well as provide a writing sample of a predetermined text. We therefore had 8 handwriting samples from each subject as well as the corresponding results of the MBTI tests. We trained a two level feed-forward neural network to determine patterns in the handwriting samples that might be linked to personality types and we determined the links presented in Table I. If we group all these features based on the personality primitives, it will result in the following:

- **Extraverted vs. Introverted:** baseline and word slant
- **Sensing vs. Intuition:** the writing pressure, the word slant, the connecting strokes, the lower case letter "t", the lower case letter "f"
- **Thinking vs. Feeling:** the baseline, the word slant
- **Judging vs. Perceiving:** the writing pressure, the connecting strokes, the lower case letter "t", the lower case letter "f"

We will study all these handwriting features grouped by the information they provide on the personality primitives and then correlate them with a final personality type.

IV. Proposed Architecture

The system is designed on three levels, with a base layer where the handwriting characteristics are acquired, an intermediary level where a neural network for each personality characteristic is employed in order to determine its presence or absence as well as the intensity and the last layer that combines the intensity of the personality primitives provided by the intermediate level in order to determine the actual personality type (this level is specifically used for decisions when the intermediary level provides non-decisive results, e.g. 48% Extroverted and 52 % Introverted).

A. Base layer

The base layer is the level where the handwriting features are determined. As detailed in Fig. 1, this layer typically contains three blocks: the normalization block, the letter splitting block, and the feature extraction block.

The Normalization block contains algorithms related to preprocessing the handwritten sample, and does the following: increase the contrast in order to make characters more visible, remove the noise, isolate the regions where the handwritten text is present and converts the image to greyscale for normalizing it with the templates on which the classifiers are trained.

The Splitting block is specifically designed to detect all the characters in the handwritten text. All the characters are cropped from the entire image by means of a junction-based segmentation algorithm, as detailed in [18], as this algorithm has proven efficient in segmenting characters when they are closely connected one with another. The detected cropped character is then fetched to the feature extraction block.

The Feature Extraction block is responsible for determining the features of the handwriting via specific algorithms that are detailed in the following paragraphs.

For determining the baseline characteristics of the writing, we use a polygonization technique [19]. This technique is broadly used for determining the baseline of the writing and typically delimits a polygon around the scanned handwritten sample and studies the coordinates of the polygon versus the overall structure of the page. The same polygonization method is also used for word slants by studying the slant of a set of letters and comparing it with the polygon surrounding the text as well as with its position in the entire page.

Writing pressure is another feature that is determined using the grey level thresholding algorithm detailed in [20] and which has as main purpose to study the thickness of writing.

Connecting strokes was analyzed with a personalized algorithm that studies the entire text, delimits each letter with the junction based segmentation algorithm [18] and determine the amount of connection between each two letters in a word. The amount of connection is correlated with the average amount of connection calculated from all the letters in the handwritten sample.

For the lower case letter "t" and lower case letter "f" we used template matching, after the entire text was split into letters. Each letter was compared to a set of predefined templates corresponding to combinations of personality primitives. The letters were detected, cropped and then matched with predefined templates using the hamming distance algorithm [21].

When all these features are extracted, they are fetched to the neural networks in order to analyze the patterns and determine the personality type of the individual.

B. Two-layer neural network

For determining the amount of each of the personality primitives under which the writer stands, we used two layers of neural networks. In the first layer each personality primitives is determined, while in the second layer the final personality type is computed taking into consideration the correlations between the personality primitives. In the first layer, the following neural networks were implemented:

- *E/I Neural Network* – feed-forward neural network trained with backpropagation to determine if the subject is an extrovert or an introvert based on the baseline and word slant handwriting features.
- *S/N Neural Network* – feed-forward neural network trained with backpropagation to determine if the subject is more inclined towards Sensing or Intuition, based on writing pressure, connecting strokes, lower case letter "t", lower case letter "f" and word slant handwriting features.
- *T/F Neural Network* – feed-forward neural network trained to determine if the subject is more inclined towards Thinking or Feeling based on the baseline and word slant handwriting features.
- *J/P Neural Network* – feed-forward neural network trained to determine if the subject is more inclined towards Judging or Perceiving based on the writing pressure, connecting strokes, lower case letter "t" and lower case letter "f" handwriting features.

The features determined by these four NN blocks will contain information on how much the subject stands under a certain personality primitive. Typically it will provide a set of percentages from each of the handwriting features as well as their combinations. All these will be fetched to the final neural network in order to take the final decision on the personality type of the subject, by combining the separate results from the four neural networks lying on the lower level.

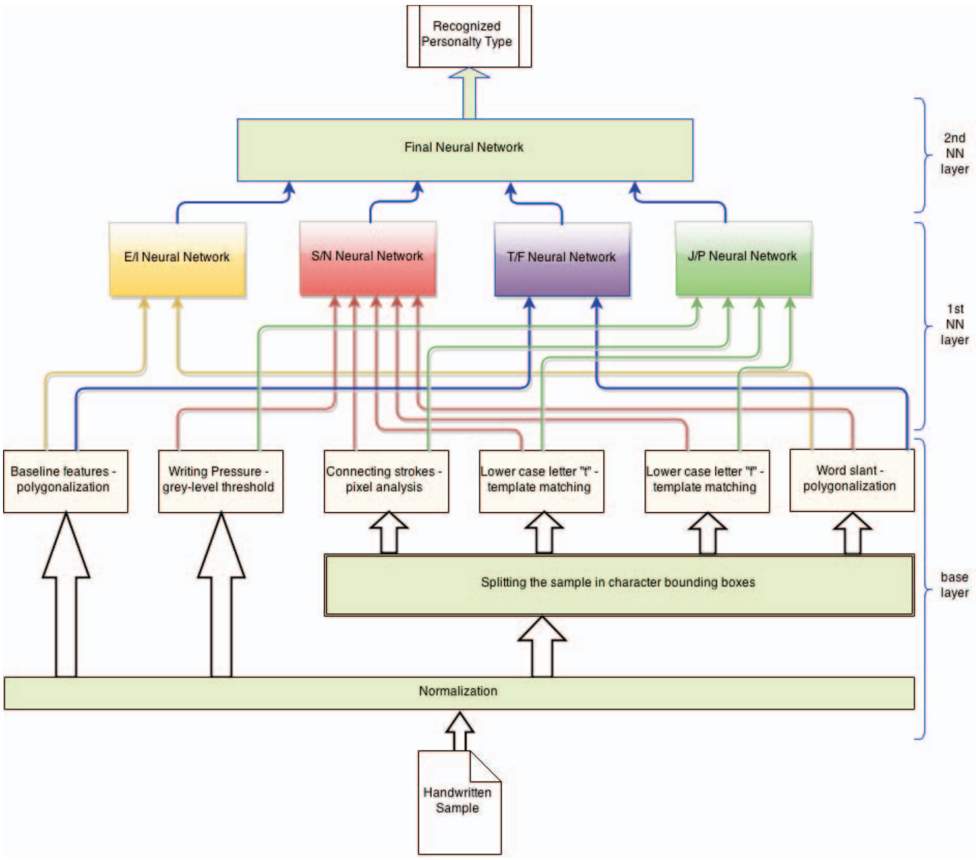

Fig. 1. Proposed Architecture – Overview

The number of nodes in the input layer for each of the neural networks in the first layer depends on the number of features that are used for class representation, so it depends on the number of blocks from the base layer that provide useful features for determining the nature of the personality primitive. We made use of a Feed Forward Neural Network because it is an artificial neural network where the connections between the units do not have any directed cycle and the information moves only in one direction. Moreover, the feed-forward neural network is often used successfully in pattern recognition tasks. The number of inputs is not that high and we made use of a large number of hidden units in order to assure the refinement of the neural network.

As mentioned, the learning algorithm that was used is backpropagation. Input vectors and corresponding target vectors are used to train the entire network until the sigmoid functions are approximated in each neural networks to appropriate results expected from training data. Backpropagation is done in cascade, first for the four neural networks in the first layer, then for the last neural network.

C. Training database and handwriting text samples

As a ***training database*** we asked 64 subjects to take the MBTI questionnaire every 2 weeks for 2 months as well as provide a sample of 300 words containing all the information we need for training our database. The 64 subjects were chosen in order to fulfil the global statistics related to MBTI personality types as follows: ISTJ - 11.6% - 7 subjects, ISFJ 13.8% - 8 subjects, INFJ 1.5% - 2 subjects, INTJ - 2.1% - 2 subjects, ISTP - 5.4% - 3 subjects, ISFP - 8.8% - 5 subjects, INFP - 4.4% - 3 subjects, INTP - 3.3% - 3 subjects, ESTP - 4.3% - 3 subjects, ESFP - 8.5% - 5 subjects, ENFP - 8.1% - 5 subjects, ENTP - 3.2% - 3 subjects, ESTJ - 8.7% - 5 subjects, ESFJ - 12.3 – 7 subjects, ENFJ - 2.8% - 2 subjects, ENTJ - 1.8% - 2 subjects.

The **handwriting samples** contain 3 letters of 100 words each written in Romanian language that are specifically designed in order to properly determine the features used for behavior analysis. Fig. 2 shows one of the three handwriting sample texts written by one of the subjects.

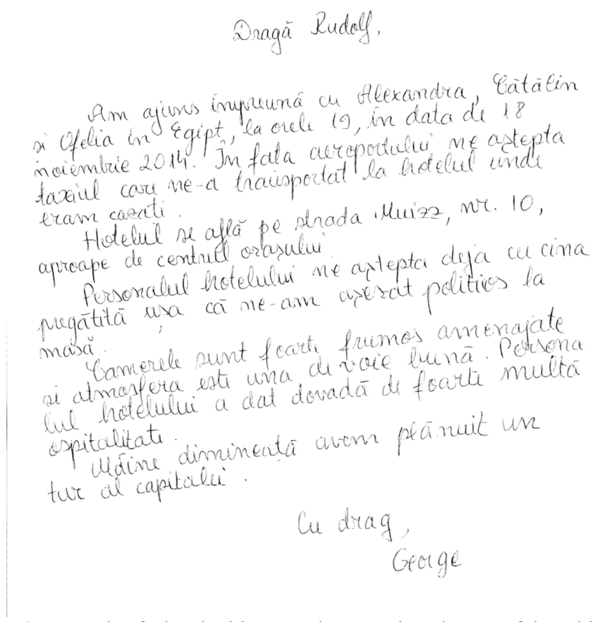

Fig. 2. Example of a handwriting sample text written by one of the subjects

The handwriting sample texts were inspired from *The London letter*, a standard request exemplar used by graphologists in handwriting analysis [22]. In conceiving the handwriting text samples we took into consideration the following points:

- **letter "t"** position in words: beginning (e.g. "**t**ransportat", "**t**axiul"), middle (e.g. "s**t**rada", "aş**t**epta"), end (e.g. "plănui**t**", "transporta**t**")
- **letter "f"** position in words: beginning (e.g. "**f**oarte", "**f**rumos"), middle (e.g. "atmos**f**era", "a**f**lă"), end (e.g. "Rudol**f**")
- **for connecting strokes** we made sure the sample tests the following cases that usually add difficulties in connecting letters when writing a word: words starting with uppercase (e.g. "**A**lexandra", "**E**gipt"), intercalating numbers (e.g. "în data de **18** noiembrie **2014**"), intercalating numbers and punctuation (e.g. "strada Muizz**,** nr**. 10**"), group of long words (e.g. "personalul hotelului", "multă ospitalitate"), use of letters that need an additional stroke - such as x, z, i or j - (e.g. "ta**xi**ul", "ca**z**a**ț**i", "a**j**uns"), words containing doubled letters (e.g. "Mui**zz**").

In terms of the platform used, we used C++ programming with a code complexity of about 10.000 code lines. The handwriting sample is analyzed in parallel in six feature extraction blocks, then, for each neural network, a delay is added in order to wait for all blocks to finish. Each neural network runs on a separate thread, and the last decisional feed-forward neural network thread also has a delay block to wait all the layer 1 NN threads to finish so it can process the result.

V. Experimental results

As mentioned in previous chapter, because of the lack of any database containing the personality types associated with handwriting samples, we created a new database of handwritings collected from 64 subjects, keeping the proportions of the global distribution of personality types. Results are detailed in Table II.

As it can be observed, we performed two tests. First we trained the system on 32 subjects and then tested it on the remaining 32. In this case the personality type recognition rates were lower (67.1% when using a single NN layer and 69.4% when using both NN layers). In the second test we trained the system on 48 subjects and tested it on the remaining 16. In this case the accuracy increased to 83.3% after the first NN layer and 86.7% after the last decisional neural network layer. We can therefore see that using only the first layer, the overall personality type recognition is 15% less accurate. This clearly indicates that the final decisional neural network ads accuracy to the system, either because the other four neural networks do not perfectly combine the handwriting features, or because some of the personality types are interdependent in specific cases. Moreover, the difference of only 3% between the two tests conducted when both NN layers were employed proves the system is a robust one, even when trained on a small database. Needless to say, the personality trait is computed in less than 1 minute on our testbed, hence the system is extremely suitable to replace the MBTI questionnaire.

TABLE II
RECOGNITION RESULTS ON DIFFERENT TYPES OF TESTS [%]

Type of test	Trained = 32 subjects, Tested = 32 subjects	Trained on 48 subjects, tested on 16 subjects
One layer of NN	67.1	69.4
Two layers of NN	83.3	86.7

We also analyzed the false positive and false negative rates for all the personality primitives and the results are shown in Table III. As it can be observed, the highest error rates are seen for Intuition vs. Sensing, followed by Judging vs. Perceiving. This is an indication that for these personality primitives other handwriting features should be approached in order to improve their prediction. Moreover, the highest false positive and false negative rates are for Intuition, which could be explained by the fact that we developed a training database with 64 subjects that imitate the global statistics; hence we only had 21 subjects for Intuition, compared to 43 subjects for Sensing. Increasing the number of subjects involved in training and therefore increasing the training database should increase the prediction accuracy for Intuition. For Extraverted vs. Introverted and Thinking vs. Feeling, the error rates are really small, proving that our system can indeed determine with good accuracy the psychological characteristics related to these four primitives.

TABLE III
FALSE POSITIVE AND FALSE NEGATIVE RATES

Primitive	False positive rate (%)	False negative rate (%)
Extraverted	2.2%	2.4%
Introverted	2.2%	2.6%
Sensing	4.7%	4.5%
Intuition	8.3%	8.8%
Thinking	3.8%	3.7%
Feeling	2.9%	3.2%
Judging	3.7%	3.4%
Perceiving	3.5%	3.4%

In order to verify the degree of generalization of our system, we tested the system trained on all 64 subjects it in two more scenarios that are depicted in Table IV.

TABLE IV
RECOGNITION RESULTS ON DIFFERENT HANDWRITING SAMPLES AND SUBJECTS

Handwriting sample	Type of subject	Recognition Results (%)
New / 100 words	Subject used in training	70.4%
New / 200 words	Subject used in training	73.5%
New / 300 words	Subject used in training	78.5%
New / 100 words	New subject	54.6%
New / 200 words	New subject	57.9%
New / 300 words	New subject	60.1%

First we used subjects that were involved in the initial training and we tested them on a brand new handwriting sample. We obtained up to 78.8% accuracy when we used a random handwriting sample of 300 words length, which is 8% smaller than the results obtained when we employed the samples used in training, while when we reduced the number of words in the handwriting sample, the accuracy decreased to 73.5% for 200 words and 70.4% for 100 words. The second test conducted involved testing the system in uncontrolled conditions (random subject and random handwriting sample). In this case the results were less satisfactory, obtaining 54.6% for 100 words sample and 60.1% for a 300 words handwriting sample, proving we need a more consistent training data to improve the recognition results in random scenarios.

VI. Conclusions

With the idea in mind that we need to envisage new ways of determining the personality types of individuals in contrast to the cumbersome and non-practical questionnaire, we study the possibility of using handwriting as an input for such a system. We used handwriting because it is a common and practical activity and has applications in the domain of career counseling and development, increasing performance and learning, as well as determining mental health disorders.

We have built a three layer system that studies the most common handwriting features and determines a link between them and the MBTI personality traits. The system offered close to 87% accuracy when tested on predefined handwriting sample texts and 78.8% accuracy when tested on random handwriting texts (using the subjects involved in training), proving that handwriting can be indeed used to determine the personality type. Moreover the difference between the recognition rates obtained when the system was trained with 32 subjects compared to 48 subjects was only of 3%, proving also the robustness of the system.

We observed a difference in recognition rate of 15% between using only one layer with the four feed-forward neural networks and using an additional decisional neural network which is a sign that some of the handwriting features are not inputs of the right primitives, hence additional research needs to be conducted to identify the misconnections. Moreover, we saw the error rates are higher for Intuition vs. Sensing and Judging vs. Perceiving, indicating the misconnection can come from these blocks. The highest errors were identified for Intuition and are considered to be due to only having 21 subjects with such a personality trait in our training database (compared to 43 for Sensing). A more complete training database can therefore improve this aspect, as well as the recognition rate of only 60% obtained in uncontrolled conditions (random subject, random sample text).

The system offers however a good accuracy of 87% in controlled scenarios, computing the results in less than 1 minute, making the system practical for determining the MBTI personality types through handwriting and could be successfully implemented in career counseling and development applications, as well as for personalized health assistance or monitoring patients suffering from mental diseases when looking for personality related symptoms.

REFERENCES

[1] Plamondon, R., "Neuromuscular Studies of Handwriting Generation and Representation", *2010 Internation Conference on Frontiers in Handwriting Recognition (ICFHR)*, pp. 261, Kolkata, November 2010

[2] Youbao Tang, Xiangqian Wu, Wei Bu, "Offline text-independent writer identification using stroke fragment and contour based features", *2013 IEEE International Conference on Biometrics (ICB)*, pp. 1-6, June 2013

[3] Champa, H. N., Anandakumar, K. R., "Automated Human Behavior Prediction through Handwriting Analysis", *2010 First International Conference on Integrated Intelligent Computing (ICIIC),* pp. 160-165, August 2010

[4] Naghibolhosseini, M., Bahrami, F., "A behavioral model of writing", International Conference on Er 2008lectrical and Computer engineering (ICECE), pp. 970-973, December 2008

[5] Zaarour, I., Heutte, L., Leray, Ph., Labiche, J., Eter, B., Mellier, D., "Clustering and Bayesian Network Approaches for Discovering Handwriting Strategies of Primary School Children, *International Journal of Pattern Recognition and Artificial Intelligence*, Vol. 18, No. 07, pp. 1233-1251, 2004

[6] Sudirman, R., Tabatabaey-Mashadi, N., Ariffin, I., "Aspects of a Standardized Automated System for screening children's handwriting", *First international conference on Informatics and Computational Intelligence (ICI)*, 48-54, December 2011

[7] Nor, N.M., Wahab, A., Kamaruddin, N., Majid, H., "Post accident analysis of driver affection", *2011 IEEE 15th International Symposium on Consumer Electronics (ISCE)*, Pages 278-283, June 2011

[8] Bhaskoro, s.B., Supangkat, S. H., "An extraction of medical information based on human handwritings", *2014 International Conference on Information Technology Systems and Innovation (ICITSI)*, pp. 253-258, November 2014

[9] Drotar, P., Mekyska, J., Smekal, Z., Rektorova, I., "Predicition potential of different handwriting tasks for diagnosis of Parkinson's", *2013 E-Health and Bioengieering Conference*, Pages 1-4, November 2013

[10] Liu, Yuxin, Zhang, Lihong, Huawei zhang, Liangliang Ma, "The big five personality and counterproductive work behavior (CWB): The moderating role of Perceived Organizational Support", *2011 International Conference on Computer Science and Service System (CSSS),* pp. 2680-2683, June 2011

[11] Pujol, R. S., Umemuro, H., Murata, K., Yano, K., "Mental health assessment based on personality of individual and associated workers in workplace", *2011 International Conference on Business, Engineering and indistrial applications (ICBEIA)*, pp. 16-19, June 2011

[12] Husin, L.I.B.A., Zaidi, N. A., "The correlation effects between big five personality traits and job satisfaction among support staff in an organization", *2014 IEEE Colloquium on Humanities, Science and Engineering (CHUSER)*, pp 883-887, December 2011

[13] Mazzei, D., Lazzeri, N., Bileci, L., Igliozzi, R., "Development and evaluation of a social robot platform for therapy in autism", *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Pages: 4514-4518, August 2011

[14] Ismail, L., Shamsuddin, S., Yussof, H., Hashim, H., "Face detection technique of Humanoid Robot NAO for application in robotic assistive therapy", *2011 IEEE International Conference on Control System, Computing and Engineering (ICCSCE)*, Pages 517-521, November 2011

[15] Taleb, T., Bottazi, D., Nasser, N., "A novel middleware solution to improve ubiquitous healthcare systems aided by affective information", *IEEE Transactions on Information Technology in Biomedicine*, Volume 14, Issue 2, pp. 335-349, March 2010

[16] Massey, T., Marfia, G., Potkonjak, M., Sarrafzadeh, M., "Experimental analysis of a mobile health system for mood disorders", *IEEE Transactions on Information Technology in Biomedicine*, Volume 14, Issue 2, pp. 241-247, March 2010

[17] Myers, I. B., "Gifts Differing: Understanding Personality Type", *Davies-Black Publishing*, Reprint edition, 1 May 1995, ISBN 0-89106-074-X

[18] Jayarathna, U.K.S.; Bandara, G.E.M.D.C., "A Junction Based Segmentation Algorithm for Offline Handwritten Connected Character Segmentation," *in Computational Intelligence for Modelling, Control and Automation, 2006 and International Conference on Intelligent Agents, Web Technologies and Internet Commerce*, vol., no., pp.147-147, Nov. 28 2006-Dec. 1 2006

[19] Djamal, E. C., Ramdlan, S. N., Saputra, J., "Recognition of Handwriting Based on Signature and Digit of Character Using Multiple of Artificial Neural Networks in Personality Identification", *Information Systems International Conference (ISICO)*, 2-4 December 2013

[20] Coll, R., Fornes, A., Llados, J., "Graphological Analysis of Handwritten Text Documents for Human Resources Recruitment", *12th International Conference on Document Analysis and Recognition*, pp. 1081-1085, July 2009

[21] Tian, H. Shen, H., "Hamming Distance and Hop Count Based Classification for Multicast Network Topology Inference", *Proceedings of the 19th International Conference on Advanced Information Networking and Applications (AINA)*, pp. 267-273, 2015

[22] Ron N. Morris, "Forensic Handwriting Identification: Fundamental Concepts and Principles", 2000