Automated handwriting analysis and personality attribute discernment using self-attention multi-resolution analysis

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ABSTRACT

Handwritten document analysis is a method used in academia that examines the patterns and strokes of a person's handwriting in order to get a deeper understanding of that person's personality and character. In spite of the fact that there are a number of models and methods that may be used in the investigation of automated graphology, there are a few challenges that need to be solved. Among these challenges is the identification of efficient classification techniques that provide the highest possible degree of accuracy. Within the scope of this study, we propose automated handwriting analysis and personality attribute discernment using self-attention multi-resolution analysis (MRA) where the data is preprocessed using histogram equalization and the spurious line segment section is attached to the genuine line segment portion in order to segment the succeeding line from the authentic picture of the document. A deep dense network is combined with self-attention MRA in order to provide a novel approach to the investigation of authentic handwritten text. Using the most recent and cutting-edge standards that are currently in use, an evaluation is performed to determine whether or not the proposed strategy is feasible. It is observed that the proposed method obtained nearly 98% accuracy with precision of 99%.

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1. INTRODUCTION

Graphology, which is another name for handwriting analysis, is a process that is useful for identifying certain personality traits that are associated with a particular individual. It is possible to think about handwriting and signatures as visual representations that are distinguished by a range of patterns. These patterns may be used for a variety of reasons, including the prediction of personality characteristics. Handwriting analysts, who are also often referred to as graphologists, are the individuals who are responsible for analyzing the handwriting of a person in order to draw conclusions about the psychological characteristics of the writer being analyzed. The study of handwriting, which is often referred to as graphology, is a subfield of psychology that seeks to decipher the personality traits, points of view, attitudes, and feelings that are conveyed via the written words of an individual. In addition, it seeks to gain an understanding of the ways in which the several components of identity interact with one another to produce the fluid structure that we know as the personality of the writer. In order to identify the traits, attributes, dispositions, emotions, or postures that are reflected in a person's writing, graphologists examine the handwriting of that individual using the concepts that are derived from mathematical graphology theory.

McNichol and Nelson [1] also make an effort to appreciate how the different components of an individual's identity might come together to form the intricate structure that we refer to as the writer's personality. These components are discussed in more detail below. One of the outcomes of the research conducted on the handwriting of patients with mental disorders [2] was the creation of a personality inventory. Specific characteristics of an individual's personality might be employed in order to identify between the various types of handwriting. In the area of identification, signatures are often used as a means of distinguishing different individuals from one another. There are a number of ways [3], [4] in which signatures may be recognized, including the existence of dots, streaks, forms, or lower lines that resemble a shell. It is possible that the graphology inspection procedure will take a significant amount of time if it is carried out manually. Additionally, the success of the handwriting analysis [5]-[7] is directly proportional to the level of expertise had by the analyst at the time. Despite the fact that it has been shown that including persons in the process of analyzing handwriting may be beneficial, it is essential to keep in mind that this approach may be both expensive and taxing on the body.

In the context of online handwriting recognition, these features include the pressure that is applied during strokes, the manner in which certain letters are created that are identified, such as the trajectory of writing. In spite of the fact that there are a number of models and approaches available in the area of automated graphology study, there are a number of problems that need to be solved. To address these problems, it is necessary to pick acceptable pre-processing approaches and image processing algorithms for the extraction of handwriting characteristics. Additionally, it is necessary to select proper classification strategies in order to achieve the highest possible level of accuracy. Furthermore, there is a connection between personality features and a variety of aspects of life, such as, but not limited to, the progress of one's career [8], [9], the provision of individualized medical treatment [10], and the presence of physical disorders accompanied by psychological symptoms [11], [12].

In light of the problems that were brought up before, our goal is to develop a system that is capable of identifying personality attributes of a person by analyzing their handwritten patterns. A method for evaluating examples of handwritten writing that have been obtained from real-world situations is presented in this study. This method makes use of the most recent technical breakthroughs. In order to identify the particular behavioral patterns that are associated with the person, the analysis is carried out on specific portions of the data. Characteristics of a person's disposition are unchanging and timeless. Although the activities those individuals engage in change depending on the circumstances in which they find themselves, there is always some underlying pattern that reveals the true nature of the individual. Person's behavior is immediately influenced by the traits that they present to the world. It is possible to define characteristics in a number of different ways. There is a widespread consensus that psychology, which is the study of the mind and human behavior, is an inconsistent scientific discipline. An individual's ability to recognize their own uniqueness is one of the few ways to get entry to this realm. The use of convolutional neural networks (CNNs) has been used by Singh *et al.* [13] in order to expedite the process of identifying essential personality characteristics via the analysis of graphology (handwriting). The use of a transformer-based (TB) technology was the basis for the unique method for personality assessment that was presented by Dhumal *et al.* [14]. The conventional methods of information extraction often include the use of a long short-term memory (LSTM)network, followed by signature-based structural representation of the textual content. However, our methodology removes both steps of the process.

The method in [15] introduced fresh methods for detecting essential personality characteristics via the use of graphological analysis. In order to accomplish this objective, they trained three visual geometry group-16 (VGG16) CNNs by making use of a database that included examples of handwritten text. The work presented in [16] aimed to establish a reliable approach for identifying personality characteristics in handwriting samples. Their efforts were focused on developing this method. Image processing and machine learning approaches that are considered to be cutting edge contribute to the achievement of this objective. Some of these techniques include filtering, thresholding, and normalization. The work in [17] used a systematic approach to extracting important features from these signals. According to the findings of their research, there is a significant connection between these characteristics and the distress-related sensations of hopelessness, anxiety, and stress. In order to classify the attribute vectors that have been created, a bidirectional-LSTM (BiLSTM) network is taken into consideration. Sati and Kumar [18] proposes a unique model for analyzing personality features and qualities based on machine learning methodologies applied to handwriting samples. The model analyses the handwriting samples of individuals. Ghosh *et al.* [19], proposed an algorithmic technique to identifying human behavior based on handwritten English letters from a to z that are lowercase. In order to formulate a hypothesis, the proposed methodology involves extracting structural elements from various regions of individual character images. The dictionary of graphological principles is used to accomplish this. The concept that emerged from this process may be used to classify the distinctive traits of a person, in addition to their positive and bad social attributes. Rahman and Halim [20] put forward the connection between a person's temperament and the attributes of his handwriting. The identification of a person's disposition classification via the use of their distinct writing style and organizational tendencies may be accomplished through the use of a method known as handwriting analysis.

The outcome of the survey implies many errors in the generated text result from the system's improper interpretation of the handwriting. This lead to nonsense, mispronounced words, or misinterpreted characters that overlap, extremely styled handwriting, or low image quality can all lead to misidentification. This occurred if the system's algorithm isn't suitable for the task, the handwriting is too illegible, or the input image is excessively distorted. For every character or phrase that is detected, several handwriting recognition programs include confidence levels that show how likely it is that the recognition is accurate. Better post-processing or human inspection is made possible as a result. This paper is organized as follows: section 2 describes the proposed method. In section 3 the results are discussed. Finally, the conclusion with future work is discussed in section 4.

2. METHOD

As a result of the fact that the approach we have shown in Figure 1 is based on the assumption that a particular handwritten document has been correctly scanned, it only takes into consideration the skew that was imposed by us. Throughout the entire pre-processing phase, a number of different image processing methods, such as a technique called histogram equalization, where one can enhance an image's brightness and contrast by redistributing the intensities of its pixels have been used. The primary objective of this is to determine the particular heights of rising segments and to count the number of ascending segments. By taking the average of the climbs that come before the threshold, the height of the threshold may be determined. Figuring out if the height of each rising component is more than or equal to the limit that has been established. It is possible to accurately extract the line from the binary document picture by making use of the rising area of the horizontal histogram, provided that the predetermined conditions are taken into consideration. It is possible that the rising area will be disregarded as a component of the line that is meaningless if the criteria that has been stated is not satisfied. These imaginary rising parts are most likely the result of the junction of two strokes or a bar existing in an uppercase character. It is possible to have both outcomes. Next, line segmentation is performed where the handwriting picture was thus divided into two distinct sections: the script region and the signature region. Both of these regions worked independently of one another. It is via the application of the predetermined writing pressure that the lines of text are retrieved from the binary document picture. We provide an improved method for horizontally projecting photographs to separate lines of text in this most recent piece of research been published. The vertical segmentation process begins by dividing an image into three distinct parts before moving on to the next step. A thorough examination and evaluation of the page margins on either side of the picture is carried out by this technique. On the other hand, an examination of the line spacing is carried out on the left side of the page. When doing horizontal segmentation, the first step is to divide an image into thirds and then the next step is to concentrate on the area that contains the middle third.

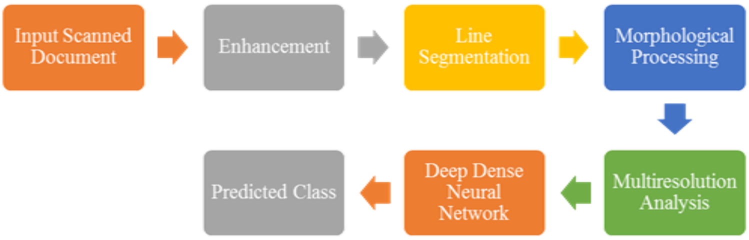

Figure 1. Architecture of intended system

The identification of line segments inside an image is made possible as a result of this. The x and y coordinates are positioned at the top left corner and bottom right corner of the box respectively. This is the first step. After determining the value of the black pixel, designated by the letter x, crop X1 will be stored. Following this, continue searching for x until there are no more black pixels that have not been found. Crop X2's y-axis has to be shifted to the point that is the furthest to the right. For CropY1 and CropY2, repeat this process, starting at the bottom and working your way up. The method described above was utilized so as to categorize an extensive range of differentiated components, such as dominance zones, baseline patterns, and inter-word gaps, amongst other things. The approach that may be considered as a succession of consecutive estimations of a given function, f(t), done at various levels of resolution is referred to as "multiresolution analysis" (MRA) in this application [21]. To put it another way, MRA may be seen as a series of consecutive estimations of a certain function. In order to explain an approximation of a function f (t) that has a resolution of 2j, the term "orthogonal projection of f (t) on a subspace Vj" is used. A successful use of the MRA approach has been used in practice. Even if the equations have not been converted into matrix equations, it is still possible to correctly handle them in real space. When used while solving integral and partial differential equations, the term MRA refers to a numerical framework that is as flexible as possible. The applications of this paradigm, in particular, have shown to be beneficial in the fields of physics and chemistry. Through the use of MRA, it is possible to construct an orthonormal framework that has adaptive resolution and the possibility for consistent improvement. As a consequence of this, the level of precision that can be accomplished via the use of this technology is not especially extensive [22].

When the detail coefficients exhibit oscillatory behavior, such as that which is induced by a density wave, it is simple to determine the significance of certain signal frequencies. This is because the oscillations occur in close proximity to the frequencies that are of interest. The oscillations are caused by the density wave, which is the reason behind this. Utilizing the highest permissible value in the detail coefficients may be of assistance in the process of transient detection. This is due to the fact that it enables route tracing across several levels of signal decomposition. It is necessary for there to be regularity in the wavelet in order to get a significant level of accurate transient identification [23]. The field of data science known as deep learning is seeing a rate of expansion that has never been seen before. Deep learning refers to a collection of algorithms that are designed to effectively analyze a broad variety of unstructured input. These algorithms are based on some kind of artificial neural network. When referring to this category of algorithms, the term "deep learning" is an appropriate term to use. As far as deep learning [24] algorithms are concerned, these data sets are well within their capabilities.

a) Loss function: the sum of two cross - entropy function H is the loss function of discriminator.

$$\begin{aligned}
&Loss(D) = H(real_{eb}, 1) + H(eb_1, 0) \\
&= \left[-1 \times \log D\,(real_{eb}) - (1-1)\log\left(1 - D(eb_{real})\right)\right] + \\
&\left[-0 \times logD\left(eb_g\right) - (1-0)\log\left(1 - D\left(eb_g\right)\right)\right] \\
&= -logD(eb_{real}) - log\,(1 - D\left(eb_g\right)
\end{aligned} \quad (1)$$

Here $eb_g \sim pdata(eb)$ i.e., eb_{real} is an image region extracted from the training dataset and $eb_g$is an image region of the testing dataset.

b) Time complexity: the amount of time spent in total by the system being recommended in studying each convolution layer.

$$(\textstyle\sum_{l=1}^{d} n_{l-1}.s_1^2 . n_1. m_1^2) \quad (2)$$

It has been determined that the convolutional layer, which is denoted by the index 1, and the total number of convolution layers that are present in the network, which is denoted by the variable d, have each been assigned values that are suitable for them. At the level l, the value n represents the total number of filters that have been applied, which is also referred to as the total number of unique input channels. For the purpose of referring to this particular value, the phrase "filtering capabilities of the layer" is often employed. One other way to express the value that was provided is to write it as the total of all of the filters that were applied to the lth layer. In spite of the fact that the filter seems to be of a size of s, the feature map that is generated as a consequence of the convolutional process has a spatial dimension of m due to the fact that it is constructed. In spite of this, it would seem that the filter has an s-length dimension. It is common for fully-linked layers and pooling layers to be accountable for a portion of the overall time cost, which typically ranges from five to ten percent of the total time spent calculating. When the previous writing was done, the consideration of the amount of time that was spent was not included. For the sake of this discussion, we will designate the first outcome generated by the module for deep neural learning as the first result Y=[y1, …,yi, … , yN]. Regarding the posterior probability at the level of frames of C classes and with a total of N frames in the data (test or training); that is Y∈ R^(C×N), similar outcome is acquired for the second subsystem. Z=[z_1,⋯,z_i,⋯,z_N]∈R^(C×N). As the details we're filtering through is a representation of medical transcripts, our sample size of N=10,000 and an assurance level of C=1,000. Linear ensemble learning is used to create the output of the integrated structure at each frame i=1, 2, 3, 4, …, Ni to be.

$$Vy_i + Wz_i \in R^C \quad (3)$$

A series, denoted by i=1, 3, 4, … N, i=1, 2, ..., N is given as input into a distinct dense model in order to create test phoneme or string of words. The two matrices, $V〚\in R〛^\wedge(C \times C)$ and $W〚\in R〛^\wedge(C \times C)$, are the variables that may be amended as per the necessity essential during training and will be discussed in detail below.

The procedure of acquiring the values of unknown parameters in a statistical model based on observed data is called parameter estimation. In order to achieve proficiency in the concepts of V and W, it is necessary to engage in the guided learning environment. The supervisory signal in this experimental configuration is the pre-allocated class of objectives that are limited to the fragment level of the data sets.

$$T = [t_1, \cdots, t_i, \cdots, t_N] \in R^{C \times N} \quad (4)$$

The training data input consists of the possibilities derived from the retrospective information obtained in Y=[y_1,⋯,y_i,⋯,y_N] and Z=[z_1,⋯,z_i,⋯,z_N]. The variable N represents the total quantity of photos used throughout the training procedure. In order to achieve this objective, the TSE loss function will be used. The training goal function is formed by including L_2 regularization.

$$E = \frac{1}{2}\sum_i \parallel Vy_i + Wz_i - t_i \parallel^2 + \lambda_1 \parallel V \parallel^2 + \lambda_2 \parallel W \parallel^2 \quad (5)$$

The hyper-parameters, λ1 and λ2 are experimental Lagrange multipliers, adapted using both trained and verified data. Making few adjustments to (2) enhances its quality.

$$\partial E/\partial V=0 \text{ and } \partial E/\partial W=0 \quad (6)$$

The process of acquisition is undertaken.

$$\sum_i (Vy_i + Wz_i - t_i)y_i^T + \lambda_1 V = 0 \quad (7)$$

$$\sum_i (Vy_i + Wz_i - t_i)z_i^T + \lambda_2 W = 0 \quad (8)$$

The equations within this collection have the potential to be simplified to a more concise form.

$$V(YY^T + \lambda_1 I) + W(ZY^T) = TY^T \quad (9)$$

$$V(YZ^T) + W(ZZ^T + \lambda_2 I) = TZ^T \quad (10)$$

The resolution to the quandary of learning using an analytical approach:

$$[V, W] = [TY^T, TZ^T]\begin{bmatrix} YY^T + \lambda_1 I & ZY^T \\ YZ^T & ZZ^T + \lambda_2 I \end{bmatrix}^{-1} \quad (11)$$

3. RESULTS AND DISCUSSION

Image samples of people’s handwriting and signatures need to be acquired from a variety of sources in order to complete the image preprocessing and collect the data that is necessary for this project. Digital methods are used in order to acquire the samples, such as scanning the handwritten scripts of 1,000 samples for the purpose of training data and 20samples for the purpose of testing data.

3.1. Performance parameters

For classification models to be evaluated, accuracy is an important metric. As a binary classification technique, accuracy can also be calculated by counting the positives and negatives as follows: we evaluated the dependability of the proposed system using the following criteria based on well-known state-of-the-art methodologies. On the same dataset, the same training and testing procedure is used to implement and evaluate the well-known state of the art method.

$$Accuracy = (True\ Positive\ Images + True\ Nagative\ Images)\ /\ (Positive\ Images + Negative\ Images) \quad (12)$$

$$Precision\ =\ (True\ Positive\ Images)/\ (True\ Positive\ Images + False\ Positive\ Images) \quad (13)$$

The accuracy of different classes is shown in Figure 2. The x, y axis represents disposition attributes and the level of correctness in terms of accuracy respectively. The proposed technique has an average accuracy of 0.98, surpassing the performance of the classic VGG-based approach.

Precision is calculated by knowing the number of true positives, false positives, and true negatives. The precision of different classes is shown in Figure 3. The x, y axis represents disposition attributes and the level of correctness in terms of precision respectively. The proposed technique has an average precision of 0.99, surpassing the performance of the classic VGG-based approach.

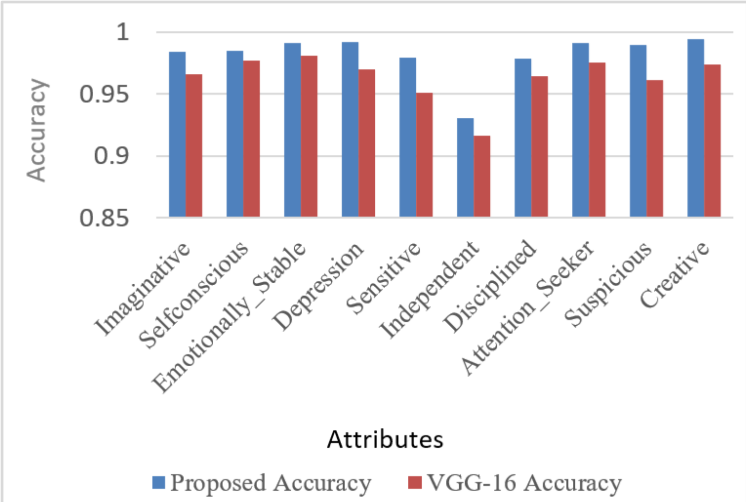

Figure 2. Comparison of accuracy

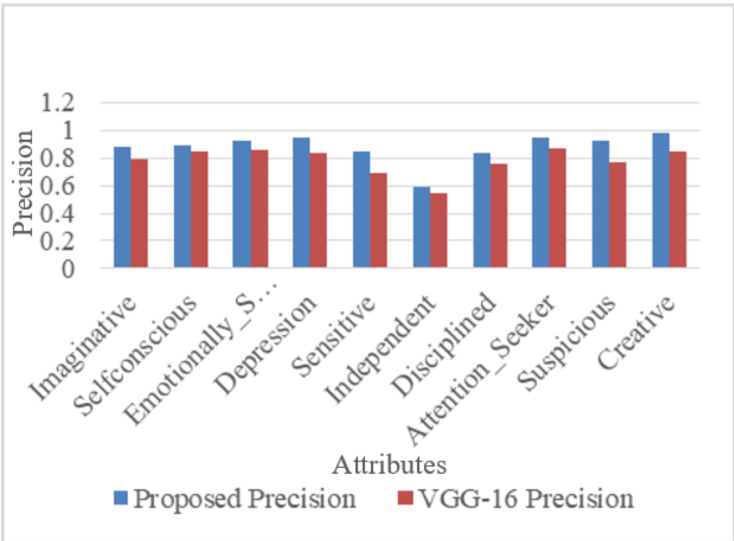

Figure 3. Comparison of precision

3.2. Comparison with other techniques

Table 1 summarizes the findings from a comparison of the suggested handwritten recognition with some of the existing methodologies. The proposed algorithm's detection accuracy is proved to be higher than the existing techniques. This is mainly because of the combination of histogram enhancement with MRA followed by classification using dense CNN. Further we have created our own dataset for worst case writing and achieved close to 98% accuracy with 99% precision compared to existing techniques.

Table 1. Performance comparison

Authors	Technique	Maximum accuracy in %
Xing and Qiao [25]	Multistream CNN	91.35
Pathak *et al*. [26]	Discrete mathematical science	97.7
Proposed	MRA+CNN	97.85

4. CONCLUSION

The study of people's personalities has the potential to provide insights on the behaviors, qualities, and features of individuals. The occurrence of these phenomena provides insights on the functioning of people's thoughts, the ways in which people act, and the ways in which individuals thrive in unique circumstances. Using data from an individual's handwriting and using machine learning algorithms, this research reveals a ground-breaking method for assessing an individual's personality traits in a consistent manner. In the first stage of this novel method for characterizing textual information by means of a signature-based structural representation, MRA is used. In the subsequent step, we use a deep dense network in order to further enhance the general image. The objective of this inquiry is to get a deeper understanding of handwriting in the sense that is more conventionally understood. The proposed approach obtained more accuracy compared to existing methods. In order to achieve the ultimate objective of being able to predict individual characteristics, the basic intention in future is to develop a computerized program which will perform behavioral analysis.

REFERENCES

[1] A. McNichol and J. A. Nelson, *Handwriting Analaysis: Putting It to Work for You*. McGraw Hill Professional, 1994.

[2] F. Laganaro, M. Mazza, G. Marano, E. Piuzzi, and A. Pallotti, "Classification-based screening of depressive disorder patients through graph, handwriting and voice signals," in *2023 International Workshop on Biomedical Applications, Technologies and Sensors (BATS)*, Sep. 2023, pp. 6–10, doi: 10.1109/BATS59463.2023.10303104.

[3] P. Porwik, "The compact three stages method of the signature recognition," in *6th International Conference on Computer Information Systems and Industrial Management Applications (CISIM'07)*, Jun. 2007, pp. 282–287, doi: 10.1109/CISIM.2007.65.

[4] S. Mushtaq and A. H. Mir, "Signature verification: a study," in *2013 4th International Conference on Computer and Communication Technology (ICCCT)*, Sep. 2013, pp. 258–263, doi: 10.1109/ICCCT.2013.6749637.

[5] Y. Tang, X. Wu, and W. Bu, "Offline text-independent writer identification using stroke fragment and contour based features," in *Proceedings - 2013 International Conference on Biometrics, ICB 2013*, 2013, pp. 1–6, doi: 10.1109/ICB.2013.6612988.

[6] H. N. Champa and K. R. AnandaKumar, "Automated human behavior prediction through handwriting analysis," in *Proceedings - 1st International Conference on Integrated Intelligent Computing, ICIIC 2010*, 2010, pp. 160–165, doi: 10.1109/ICIIC.2010.29.

[7] M. Naghibolhosseini and F. Bahrami, "A behavioral model of writing," in *Proceedings of ICECE 2008 - 5th International Conference on Electrical and Computer Engineering*, 2008, pp. 970–973, doi: 10.1109/ICECE.2008.4769353.

[8] I. Zaarour, L. Heutte, P. Leray, J. Labiche, B. Eter, and D. Mellier, "Clustering and bayesian network approaches for discovering handwriting strategies of primary school children," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 18, no. 7, pp. 1233–1251, 2004, doi: 10.1142/S0218001404003745.

[9] R. Sudirman, N. Tabatabaey-Mashadi, and I. Ariffin, "Aspects of a standardized automated system for screening children's handwriting," in *Proceedings - 1st International Conference on Informatics and Computational Intelligence, ICI 2011*, 2011, pp. 49–54, doi: 10.1109/ICI.2011.19.

[10] N. M. Nor, A. Wahab, N. Kamaruddin, and H. Majid, "Post accident analysis of driver affection," in *Proceedings of the International Symposium on Consumer Electronics, ISCE*, 2011, pp. 278–283, doi: 10.1109/ISCE.2011.5973832.

[11] S. B. Bhaskoro and S. H. Supangkat, "An extraction of medical information based on human handwritings," in *2014 International Conference on Information Technology Systems and Innovation, ICITSI 2014 - Proceedings*, 2014, pp. 253–258, doi: 10.1109/ICITSI.2014.7048273.

[12] P. Drotár, J. Mekyska, Z. Smékal, I. Rektorová, L. Masarová, and M. Faundez-Zanuy, "Predicition potential of different handwriting tasks for diagnosis of Parkinson's," in *2013 E-Health and Bioengineering Conference (EHB)*, 2013, pp. 1–4.

[13] P. Singh, S. Verma, S. Chaudhary, and S. Gupta, "Personality trait detection using handwriting analysis by machine learning," in *Proceedings of International Conference on Recent Trends in Computing: ICRTC*, 2023, vol. 600, pp. 387–396, doi: 10.1007/978-981-19-8825-7_33.

[14] Y. R. Dhumal, A. Shinde, K. Chaudhari, S. Oza, R. Sapkal, and S. Itkarkar, "Automatic handwriting analysis and personality trait detection using multi-task learning technique," in *10th International Conference on Computing for Sustainable Global Development (INDIACom)*, 2023, pp. 348–354.

[15] D. Gagiu and D. Sendrescu, "Detection of handwriting characteristics using convolutional neural networks," in *2023 24th International Carpathian Control Conference (ICCC)*, Jun. 2023, pp. 157–160, doi: 10.1109/ICCC57093.2023.10178936.

[16] Samsuryadi, R. Kurniawan, J. Supardi, Sukemi, and F. S. Mohamad, "A framework for determining the big five personality traits using machine learning classification through graphology," *Journal of Electrical and Computer Engineering*, vol. 2023, pp. 1–15, Jan. 2023, doi: 10.1155/2023/1249004.

[17] A. U. Rahman and Z. Halim, "Identifying dominant emotional state using handwriting and drawing samples by fusing features," *Applied Intelligence*, vol. 53, no. 3, pp. 2798–2814, Feb. 2023, doi: 10.1007/s10489-022-03552-x.

[18] K. Sati and D. Kumar, "Identifying the personality traits based on handwriting using ANN and MLP concept," in *2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS)*, Jun. 2023, pp. 524–528, doi: 10.1109/ICSCSS57650.2023.10169354.

[19] S. Ghosh, P. Shivakumara, P. Roy, U. Pal, and T. Lu, "Graphology based handwritten character analysis for human behaviour identification," *CAAI Transactions on Intelligence Technology*, vol. 5, no. 1, pp. 55–65, Mar. 2020, doi: 10.1049/trit.2019.0051.

[20] A. U. Rahman and Z. Halim, "Predicting the big five personality traits from hand-written text features through semi-supervised learning," *Multimedia Tools and Applications*, vol. 81, no. 23, pp. 33671–33687, Sep. 2022, doi: 10.1007/s11042-022-13114-5.

[21] "Chapter 5 Wavelet signal processing," in *Wavelet Analysis and Its Applications*, vol. 8, no. C, 1998, pp. 167–190, doi: 10.1016/S1874-608X(98)80050-2.

[22] Á. Vázquez–Mayagoitia, W. S. Thornton, J. R. Hammond, and R. J. Harrison, "Quantum chemistry methods with multiwavelet bases on massive parallel computers," in *Annual Reports in Computational Chemistry*, Elsevier, 2014, pp. 3–24.

[23] A. Prieto-Guerrero and G. Espinosa-Paredes, "Linear signal processing methods and decay ratio estimation," in *Linear and Non-Linear Stability Analysis in Boiling Water Reactors*, Elsevier, 2019, pp. 269–314.

[24] P. Singh, S. Verma, S. Chaudhary, and S. Gupta, "Personality trait detection using handwriting analysis by machine learning," in *Proceedings of International Conference on Recent Trends in Computing, ICRTC*, 2023, vol. 600, pp. 387–396, doi: 10.1007/978-981-19-8825-7_33.

[25] L. Xing and Y. Qiao, "DeepWriter: a multi-stream deep CNN for text-independent writer identification," in *Proceedings of International Conference on Frontiers in Handwriting Recognition, ICFHR*, 2016, vol. 0, pp. 584–589, doi: 10.1109/ICFHR.2016.0112.

[26] A. R. Pathak, A. Raut, S. Pawar, M. Nangare, H. S. Abbott, and P. Chandak, "Personality analysis through handwriting recognition," *Journal of Discrete Mathematical Sciences and Cryptography*, vol. 23, no. 1, pp. 19–33, 2020, doi: 10.1080/09720529.2020.1721856.

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