ISSN 1870-4069

Automated Handwriting Analysis for Personality Traits Recognition Using Image Preprocessing Techniques

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Abstract. In this paper, we approach the problem of automated recognition and analysis of handwriting, applied in the context of personality trait estimation. Handwriting presents a singular and distinct expression for every individual, carrying valuable insights into the writer's personality and psychological traits. Despite several proposals already made to tackle this issue, there are still obstacles to overcome, such as the selection of algorithmic techniques for image quality enhancement. Our proposed methodology is based on analyzing handwritten text images, where we seek to identify patterns and features that allow us to infer specific personality traits. To achieve this, we have relied on the theoretical framework of the Big Five model, one of the most widely accepted models. The proposed methodology involved preprocessing images using a U-Net neural network and a convolutional layer-based architecture to classify personality traits.

Keywords: Personality, traits, handwritten text, big five, image preprocessing.

1 Introduction

The automated recognition and analysis of handwritten or cursive writing is emerging as a highly fruitful field of research in neuropsychology, psychology, and computer science. This latter domain seeks to automate a traditionally performed by psychologists and specialists in calligraphic analysis, known as graphologists. While individual handwriting may share similarities or common traits with others, it remains distinctive and a personal hallmark.

As a result, analyzing the characteristics of strokes is a challenging task; on the contrary, it requires diverse techniques and tools. Exploring patterns and features in handwriting can provide valuable information about a person, including their age, gender, and motor control, and it may even serve as an early indicator of potential neurodegenerative disorders, given that writing involves coordinating hand movement, vision, and brain commands.

For instance, a brain injury, known as agraphia, could manifest as a loss of hand control. Furthermore, analyzing handwritten text allows us to identify personality traits, enabling us to understand, to some extent, a person's moods or motivations.

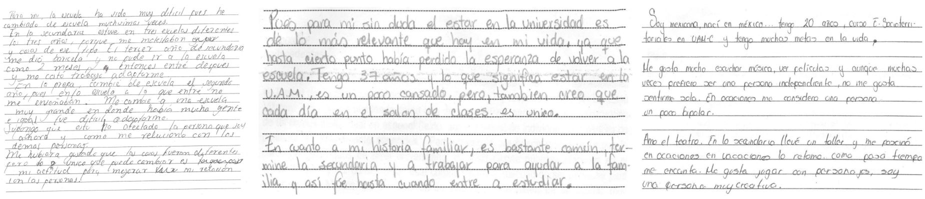


Fig. 1. Example of images included in the HWxPI dataset [12].

In psychology, numerous definitions have been proposed to explain the concept of personality. However, one of the most accepted is the proposition put forth by Allport, who defines personality as a dynamic organization within the individual of psychophysical systems that create characteristic patterns of behavior, thoughts, and feelings [1]. On the other hand, the evolution of personality concepts and components has led to the development of the so-called trait theory, wherein the trait is the central notion of personality psychology.

Traits are considered continuous entities along which individuals vary. We cannot directly observe a trait, but we can infer a person's level of trait based on their behavior. Several models and psychological tests within the trait theory attempt to describe the essential traits that define personality. One of the most robust models we rely on for this work is the Big Five personality model [2]. This model posits that personality can be summarized into five core factors:

1. Extroversion,
2. Agreeableness,
3. Conscientiousness,
4. Neuroticism,
5. Openness to Experience.

This paper addresses the problem of estimating personality traits from handwritten texts using Deep Learning techniques, leveraging the capabilities of Deep Learning, and specifically employing Convolutional Neural Networks (CNNs). The dataset used consisted of digitised versions of autobiographical essays handwritten by university students.

As for the methodology, this consisted of doing prior work on image processing and cleaning them of noise, using various methods, both classical mathematical morphology techniques and an encoder-decoder type network such as U-Net. Once the images were cleaned of noise, a neural network with five convolutional layers and three densely connected layers was used to perform the classification.

While the results obtained were not outstanding compared to other results in the state of the art in terms of accuracy, it is important to highlight that considerable performance could be achieved using only images without the need to work with text processing. We believe this is significant in terms of the approach to personality trait estimation using handwritten text. The rest of this paper is organized into the following sections: Section 2 addresses the state of the art, Section 3 presents the methodology used, and

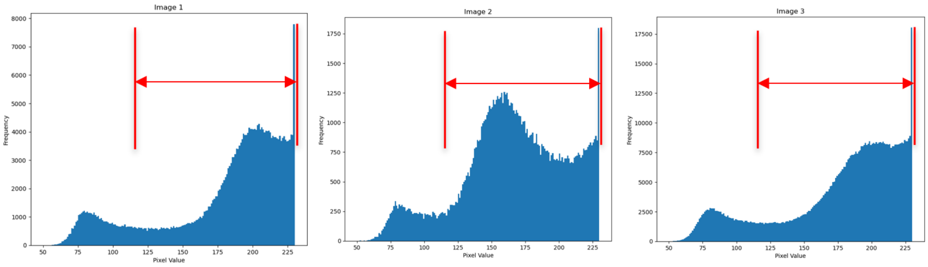


Fig. 2. Histograms of some selected images from the dataset were generated to analyze the distribution of pixel intensities in the handwritten texts. The defined range, which was carefully chosen, ensures that the text's details and readability are preserved during image processing and analysis.

some results derived from the proposed image preprocessing are shown, and Section 4 presents the obtained experimental results. Section 5 contains the conclusions. Finally, Section 6 briefly presents the limitations that arise when tackling the problem of trait estimation, and we discuss them.

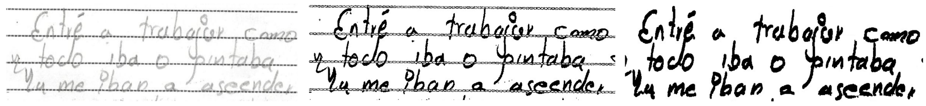
2 State-of-the-Art

The following is a review of state-of-the-art papers related to identifying personality traits from handwritten texts, focusing exclusively on studies that utilized the same dataset as ours. Valdez-Rodríguez et al.[3] propose a Convolutional Neural Network (CNN) called DeepWriter, based on the AlexNet model. This architecture uses five convolutional layers with Rectified Linear Unit (ReLU) activation function to extract features from the images, such as the shape of the strokes in each author's letters.

Subsequently, two fully connected layers with hyperbolic tangent activation functions are included for classification, and finally, an output layer with two neurons is added. The model was classified using the Area Under the Curve (AUC) metric, which describes the classifier's ability to distinguish between different classes. Additionally, Costa et al. [4] present a method that combines features extracted from handwritten text images and their transcriptions.

For the analysis of transcriptions, the representation of a bag-of-words model is extracted considering a TF-IDF (Term frequency-Inverse document frequency) scheme. For feature extraction, they rely on the Linguistic Inquiry and Word Counter (LIWC) software, which is a resource that, given a text, analyzes the proportion of words that reflect different emotions and psycholinguistic aspects that can be inferred from texts [5]. As for the analysis of the essay images, the characters were segmented.

For this task, the datasets of EMNIST [6] and Chars74 [7] were trained with a Faster R-CNN model. Finally, they relied on Support Vector Machines (SVM) for classification. They used the AUC as an evaluation measure. Mekhaznia et al. [8] propose an approach to evaluate personality traits through various handwriting characteristics. Their method involves extracting features from handwriting samples and classifying them using an artificial neural network (ANN) algorithm.



(a) (b) (c)

Fig. 3. a) Partial sample of image prior to filtering, b) Result after passing through the filter, and c) Result after applying morphological opening.

The primary experimental process consists of three phases: noise removal, construction of feature vectors, and feature classification. For noise removal, they adopted the idea by Dos Cardoso et al. [9], which introduces the concept of a stable path. A staff line is then considered an extended object of black pixels with a homogeneous width supported by a given shortest path. Removing staff lines involves replacing their pixels with white color and preserving other things that exceed the width.

Regarding constructing feature vectors, they retained the slants, writing direction, and ink trace features for experiments. The proposed classifier consists of three layers with a feed-forward architecture. The overall results for the Edge-Hinge Distribution and Run-Length Distributions features range from 50% to 60%.

3 Methodology

3.1 Dataset

The dataset used in this paper consists of 418 handwritten essays in Spanish written by undergraduate students from Mexico [10]. For each essay, two files are available: a manual transcription and a digitized image (Fig. 1). For this work, we solely utilized the images. Each essay has five classes corresponding to the Big Five personality traits.

The courses for each trait are represented as 1 and 0, corresponding to each trait's high and low poles, respectively. To assign each label in the dataset, the TIPI test was used [11]. This standardized and widely used instrument provides a set of norms to determine the direction of each trait among four classes: high, medium-high, medium-low, and low. For this dataset, the creators binarized the classes to 1 for subjects with high and medium-high traits and 0 for standard and medium-low traits.

3.2 Preprocessing

One of the main reasons for performing a dataset treatment was that, when reviewing the state-of-the-art works, it was observed that no attention was given to the ruled line removal process. Only the work of Mekhaznia et al. proposes a method to clean the images. Despite the emergence of convolutional neural networks, there must be more exploration in line removal and even in the general denoising of document images using neural network models.

In a recent study by Gold, a synthetic dataset was developed that creates lines and combines them in a sequence of handwritten word images using a proposed architecture with three convolutional layers. However, we encountered a problem with the dataset we obtained as it did not include corresponding lineless images.

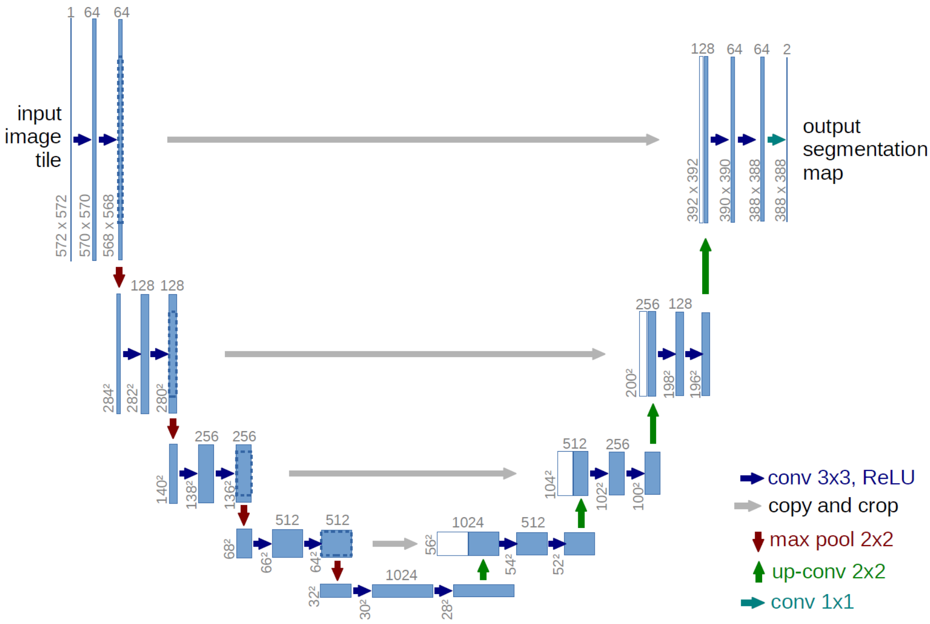


Fig. 4. U-Net architecture [13].

To solve this issue, we proposed an automated method for removing ruled lines, which is described below. First, we created images without lines by selecting a subset from the HWxPI dataset. We aimed to match the original images with their corresponding line-free versions, which would serve as labels for training the neural network model in line removal. We applied classical preprocessing techniques and mathematical morphology to construct this dataset. All images in the dataset were cropped to retain only the areas with text.

Next, we randomly selected 100 images, which were then converted to grayscale and processed with a Gaussian filter. This filter is typically used to reduce noise and flaws in images. By replacing each pixel with a weighted combination of its neighboring pixels, the filter smoothed the image and removed noise and minor variations in pixel intensity. We used a Gaussian filter with a kernel size of 3 x 3 and an auto-detector for the standard deviation.

Finally, we analyzed the histogram and pixel values that made up the lines in the essays to determine a suitable threshold. Defining a single threshold value for images with even minor variations can be complex and challenging. Factors such as the pressure applied while writing with a pencil or pen, continuous or dotted lines, and stains on the sheet can significantly alter pixel values.

Thus, removing lines entirely or partially from all images is impossible, as the image characteristics vary. Due to this variability, only a percentage of the images can be successfully processed for line removal. Once the necessary modifications were made, it was determined that the most suitable pixel range for thresholding was between 120 and 230 (Fig. 2).

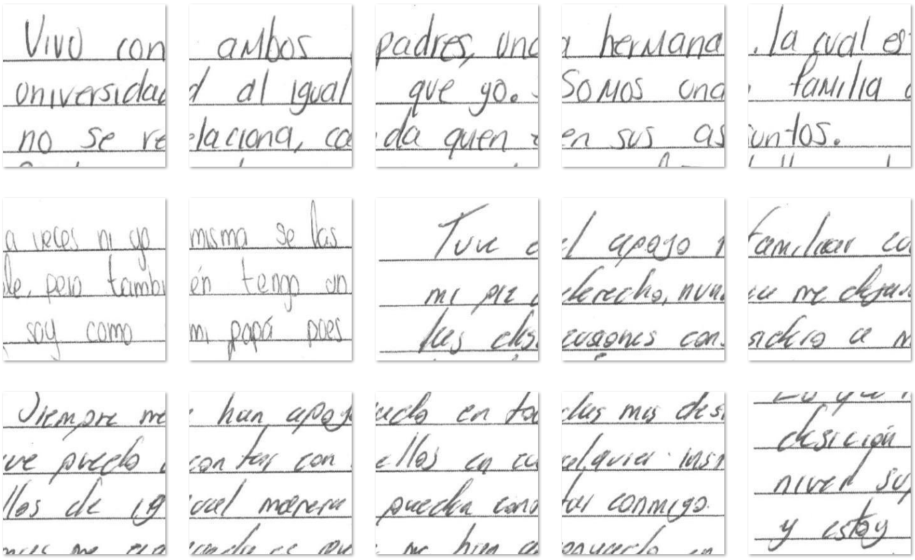


Fig. 5. Sample of Generated Patches.

Consequently, a filter was created to preserve only the grayscale values within that range. Out of the 100 images, applying the filter resulted in 40 images with almost complete line removal. Fig. 3 (a) and Fig. 3 (b) provide an example of a section of the image before and after passing through the filter. The filter effectively removed the filling in the lines, leaving only their outlines. To remove any remaining excess, an opening morphological operation was applied using Equation 1:

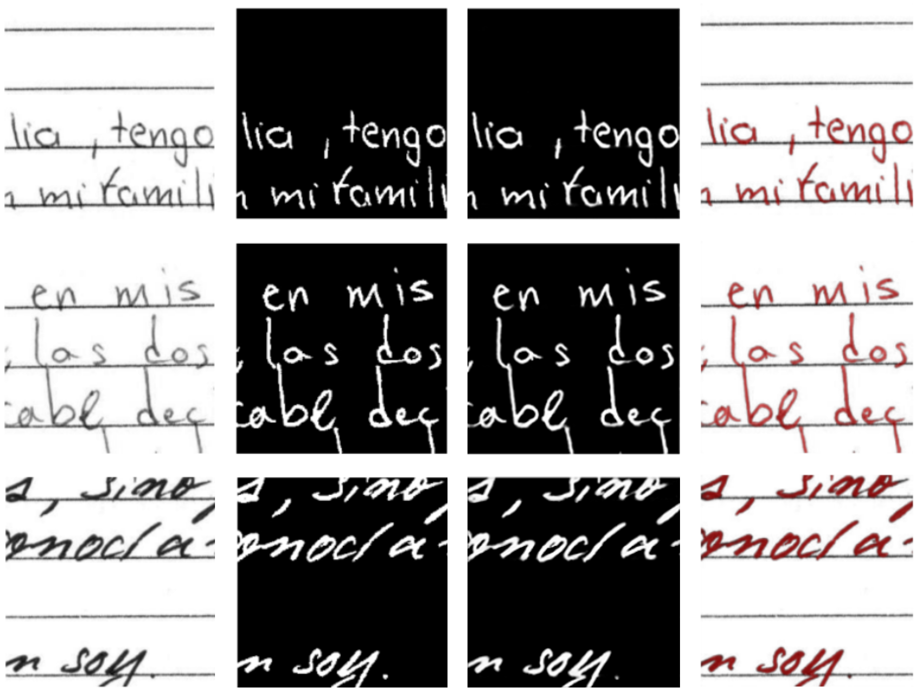
$$A \circ B = (A \ominus B) \oplus B. \tag{1}$$

This operation performs an erosion followed by dilation using the same structuring element for both procedures. Different structuring elements were experimented with, and the circular shape with a size of 3×3 worked best. The erosion completely removed the surplus contours, and the dilation helped preserve the letters' original structure (Fig. 3 (c)). Since some images had points of a particular area that could not be removed with erosion, an area opening was applied.

This functional filtering operation removes all connected components whose size in some pixels is smaller than the proposed threshold value. Ten additional images without ruled lines were added to the initial set of 40, but these were obtained by manually removing lines instead of using morphological operations. As a result, a small dataset composed of 100 images was generated: 50 original images and 50 line-free images.

3.3 U-Net

The U-Net architecture (Fig. 4) is advantageous because it can be trained with relatively few images, making it ideal for applications where a small dataset or real-time segmentation is needed [13].



(a) (b) (c) (d)

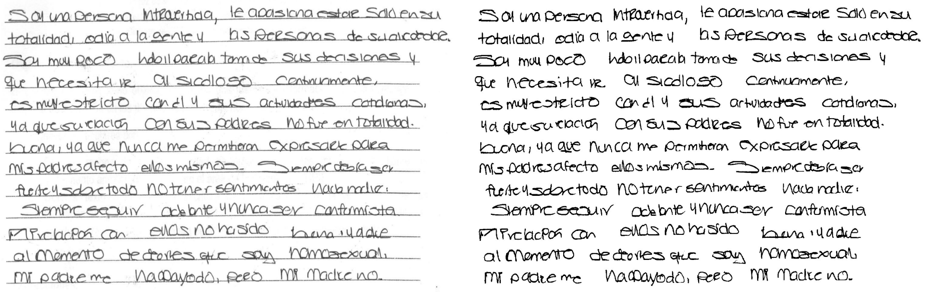
Fig. 6. Samples of some results: a) Original patches with lines, b) Ground Truth, c) Predictions, d) Intersection of the original patch with the prediction: the red color in the letters highlights a successful intersection between the original image and the prediction.

Due to this reason, we chose to work with this architecture, as the HWxPI image dataset obtained after line removal was limited. The U-Net is a deep Convolutional Neural Network (CNN) consisting of two main parts: the encoding pathway (encoder) and the decoding pathway (decoder). The encoding pathway is similar to the architecture of a typical CNN, where the input image is gradually reduced in size by applying convolutional layers and pooling.

On the other hand, the decoding pathway gradually increases the size of the image by applying convolutional layers and upsampling. Additionally, the U-Net uses a technique called "skip connections," which connects the encoding and decoding layers, allowing high-resolution information to be directly transmitted to the decoding layers, helping to avoid the loss of essential details in the image.

3.4 Training for Line Removal

Experiments were conducted with the images obtained from the HWxPI dataset. To expand the training set, dividing each image into patches of 256×256 pixels was proposed. Before this, each image was resized to multiples of 256 to avoid information loss and ensure capturing all regions of the image.



(a) Original Image (b) Image after processing.

Fig. 7. Result of U-Net model for an image.

As a result, a dataset consisting of 668 patches was generated (Fig. 5). Furthermore, data augmentation was performed, resulting in 64 additional images. This augmentation included rotation, mirroring, zooming, and stretching in height and width. One of the advantages of data augmentation is that it helps reduce overfitting by introducing variations in the training set, making the model less prone to memorizing the samples and enhancing its generalization capability. We used 64 filters, a dropout of 0.3, a batch size of 32, a definition of hyperparameters, and a sigmoid activation function. On the other hand, the metric used to evaluate the model was the Intersection over Union (IoU) (equation 2):

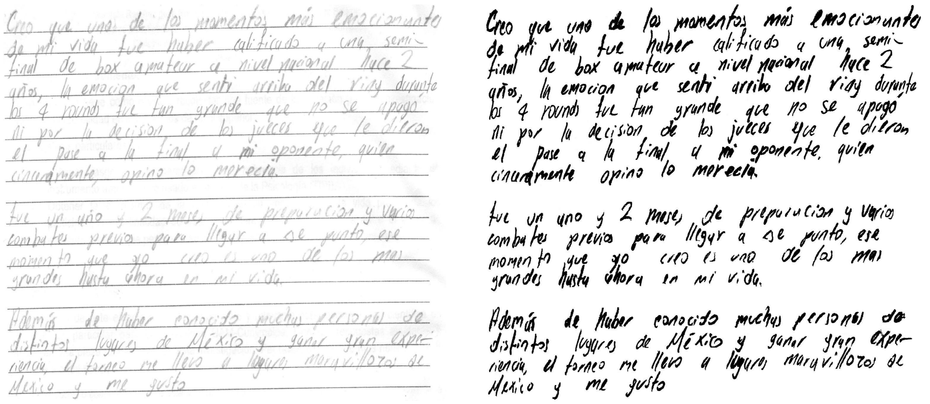
$$\mathrm{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}. \tag{2}$$

This metric involves dividing the intersection area between the model's predictions and the ground truth labels by the size of their union. It is widely used in segmentation tasks and allows measuring the similarity between the segmentation performed by the model and the accurate segmentation, where a value of 1 indicates a perfect segmentation and a value of 0 predicts an entirely erroneous segmentation. We employed the stochastic gradient descent algorithm and a binary cross-entropy loss function for model optimization.

During training, we obtained a loss value of 0.0667, while the Intersection over Union (IoU) coefficient resulted in a matter of 0.6847. When evaluating the model with the test set, we achieved an IoU value of 0.733. Once the model was established, all the images from the HWxPI dataset were utilized. A sample of the resulting patches are shown in Figure 6.

Below, we present some examples of the results in the preprocessing phase. The patches of each image were reassembled to restore each original image. Examples are shown in Figure 7 and 8. The use of an architecture like U-Net proved to be a valuable tool, allowing us to achieve good results in the removal of lines form handwritten texts without the need for additional exhaustive reconstruction work.

In only a few cases, a dilation followed by a morphological erosion was performed to close some gaps between letters. While this has demonstrated the potential of CNNs for line removal, it is essential to highlight that there are still areas that can be explored in future research. For instance, different network architectures can be proposed to further enhance result accuracy.



(a) Original Image (b) Image after processing.

Fig. 8. Result of U-Net model for an image.

3.5 Proposed Architecture for Personality Traits Recognition

After completing the preprocessing step successfully, each image of the complete dataset was divided into patches of 256 x 256 pixels, generating a total of 11,263 patch images. Each of these patches was processed to remove the existing lines. Also, it was ensured that for each generated patch, a copy of the label originally assigned to the original image was replicated.

Then, we proceeded with the model design for personality traits estimation. In this dataset, each image can belong to five different classes. However, we decided to build a model to train courses by category, as these classes are not mutually exclusive. The model comprises five convolutional layers, followed by normalization and max pooling layers. Then, there are dropout layers to prevent overfitting. Finally, there are dense layers that produce the model's output (Fig. 9).

The architecture is shown below, where **d** represents dimensions; **k** denotes kernel size; **p** is the pool size, **s** represents stride, and **f** indicates filters. The first layer of dropout had a value of 0.3, and the remaining two layers had a value of 0.7.

The dataset consisting of 11,263 line-free patches was partitioned into 80% for training, 10% for validation, and 10% for testing purposes. The model was trained from scratch using the Adam optimizer with a learning rate of 0.0001, a binary cross-entropy loss function, and the binary accuracy metric, considering the binary nature of the classes. In addition, a filtering process was implemented to remove patches containing no text.

This refers to situations where the sum of all pixels in a patch was zero or contained minimal strokes that did not contribute relevant information, such as dots or letter traces. This process left out 430 patches that contained no information. To ensure consistency, we utilized a batch size of 16, and the training went on for 300 epochs. Notably, when increasing the number of epochs, we observed a tendency for the training process to overfit.

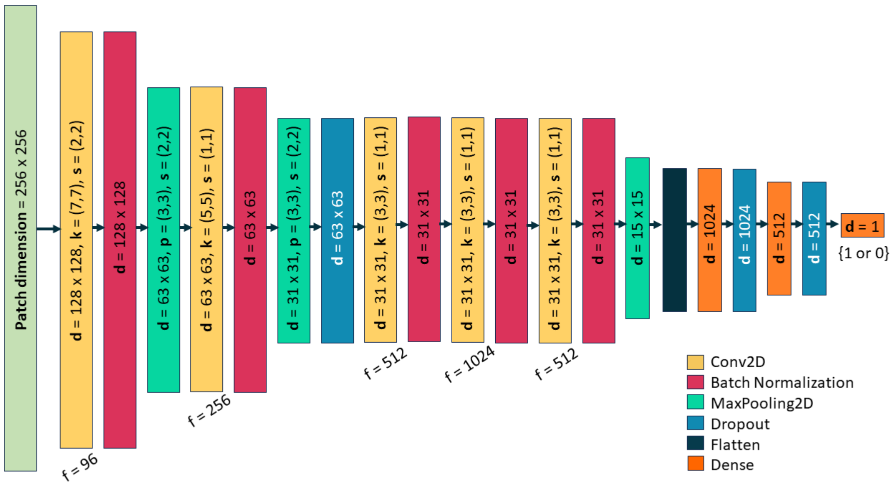


Fig. 9. Proposed Architecture.

Table 1. Evaluation of our method.

	AUC	Precision (weighted avg)	Recall (weighted avg)	F1-score (weighted)	Accuracy
Extraversion	**0.625**	**0.64**	**0.62**	**0.61**	**0.61**
Agreeableness	0.59	0.58	0.59	0.59	0.58
Conscientiousness	0.60	**0.63**	0.59	0.57	0.58
Neuroticism	0.50	0.31	0.56	0.40	0.55
Openness	0.50	0.25	0.50	0.33	0.50
Average	**0.56**	**0.48**	**0.57**	**0.50**	**0.56**

4 Experimental Results

The classifier received and rated each patch separately. However, the purpose was to evaluate each complete image, not just its patches. To achieve this, the ratings of all the patches from each image were averaged to obtain the final rating for that image. The individual patch ratings were combined to get an overall rating for the entire image.

Various metrics were used to evaluate the results (Table 1) and the average of all rankings per metric was also obtained. The personality trait of Extraversion received the highest scores, surpassing 0.60 in all metrics. The personality trait of Conscientiousness received the second-highest scores. Conversely, neuroticism and openness received the lowest values.

In Table 2 and Table 3, we present the results from other state-of-the-art studies to facilitate a comparison with our results. In the work by Valdez et al. [3], although the final scores for each emotion are not shown, the average score across all classes was 0.5023. On the other hand, in Costa et al.'s work [4], the best results using a combination of Natural Language Processing techniques with image analysis (Shape) were 0.53 for extraversion and openness using LIWC.

Table 2. Results by Costa et. al [4].

Features	Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness
LIWC	0.51	0.49	0.47	0.45	0.54
BoW	0.52	0.50	0.49	0.53	0.50
Shape	0.50	0.50	0.57	0.45	0.53
LIWC+BoW	0.43	0.47	0.49	0.48	0.50
LIWC+Shape	0.53	0.47	0.48	0.44	0.53
BoW+Shape	0.50	0.50	0.56	0.48	0.52
BoW+LIWC+Shape	0.43	0.47	0.48	0.48	0.49

Table 3. Results by Valdez et. al [3].

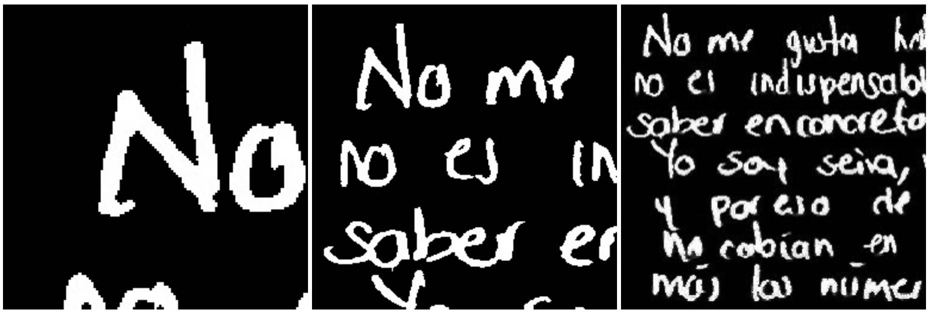
	Baseline (validation set)	Validation set	Final evaluation
AUC	**0.5014**	**0.5023**	**0.5009**
F1 (multiclass)	0.2629	0.1931	0.2025
F1 (multilabel)	0.2994	0.2916	0.2738
BAC (multiclass)	0.2091	0.1888	0.2011
PAC (multiclass)	0.0136	0.0136	0.0135
PAC (multilabel)	0.5028	0.5028	0.5063
Regression ABS	-0.0004	-0.0876	-0.1384
Regression R2	-1.0008	-1.1753	-1.2769

For conscientiousness, they achieved 0.56 using BoW (Bag of Words). In contrast, using only images, their highest result was 0.57. It is worth noting that during training phase, when using patches of smaller and larger dimensions than 256×256, obtained by dividing each image, we obtained results equal or less than 0.40. In other words, our model was able to learn better from image samples that encompassed more words rather than focusing on isolated letters, which is interesting. To illustrate and have a better understanding of this, examples of the content covered by patches of larger and smaller dimensions are shown in Fig. 10.

A remarkable outcome of our work is that we achieved a maximum score of 0.62 in the AUC metric and a precision score of 0.61 solely through image analysis. This contrasts with other state-of-the-art works that obtained lower values using natural language processing, image analysis techniques, or even a combination of both. It is also important to note that there was no need for prior feature extraction, unlike other state-of-the-art works [15, 16] that performed an initial feature extraction process, such as handwriting inclination, letter size, writing pressure, and whether strokes were connected or not, among other aspects.

5 Conclusions

In this work, we have presented a method for estimating personality traits from handwritten text images. The method involved two stages. The first stage was preprocessing, which aimed to create line-free images from the HWxPI dataset.



(a) (b) (c)

Fig. 10. Example of the original image division using patches of different dimensions. a) 125×125 px, b) 256×256 px, and c) 512×512 px.

To achieve this, a subset of the original dataset was selected and the images were cleaned by cropping them to capture only the area where the text was present. Classic techniques were used, such as Gaussian filtering, grayscale conversion, thresholding, and mathematical morphology techniques like simple opening, area opening, and dilation. Once this set was cleaned, we had a paired dataset: images with lines alongside their respective line-free images. This small dataset was used to train the line removal model using a U-Net-type neural network.

All of the above had to be done almost from scratch, except for having the HWxPI dataset as a reference, as there is currently no dataset designed explicitly for the task of line removal in document images. The second stage was the selection of the architecture for trait identification. Different layer arrangements and hyperparameters were tested, but the best results were obtained using the architecture shown in Fig. 9. While our results could not surpass 0.64, we believe that they still managed to stand out compared to other results in the state of the art.

6 Limitations and Discussion

When comparing our results with those obtained by other studies that used the same dataset and were based on the same psychological evaluation model, the Big Five, we can see that surpassing the 0.5 barrier in accuracy or AUC is challenging. Why is this the case? It is a difficult question to answer, as it could depend on several factors, such as the dataset used. Even the dataset creators mention that personality identification is quite challenging with a small sample of handwritten texts. This is reflected in their proposed baseline, where scores range from 0.47 to 0.54 with the AUC metric [10].

However, Samsuryadi [14] provides an excellent compilation and analysis of works related to personality analysis from handwritten text. Although some studies are not included, and the compilation needs to be updated due to recent publications in this field over the past two years, a contrast can be observed among the results of studies that apply different methods and rely on different tools. For example, there is a significant leap in scores between studies that use different psychological models for personality evaluation and those that rely solely on graphology or even combine both tools.

Additionally, differences are observed in studies that use different datasets, apply various preprocessing techniques, utilize diverse architectures, and extract different features, among other factors. Undoubtedly, one of the future tasks in the area of personality estimation from handwriting is to establish a clear division between the methods to follow. For instance, it is essential to define which psychological evaluation models are the most robust to work with or to create a database with samples in different languages. This is necessary to conduct an objective assessment of the state-of-the-art, as without clear rules or guidelines, results that appear to be good may not be truly reliable.

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