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UNMASKING PERSONALITY: AN AUTOMATED SYSTEM TO DETECT HUMAN PERSONALITY USING HANDWRITING ANALYSIS

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Abstract

Analysis of handwriting has long been used to highlight personality traits, providing a valuable understanding of a person’s behavioural characteristics. The distinctive qualities of a human being, handwriting contains the most information about the writer's physical, mental, and emotional states. One way to forecast an author's characteristics and gain a deeper understanding of them is through handwriting analysis. The practice of studying and analyzing handwriting is known as graphology, a scientific technique used to assess various aspects of a person's handwriting to ascertain their personality. The project presents an automated system for detecting human personality using handwriting notes. We looked at eight key types of features to make this computer-friendly: Zone, Slant, Pressure, Size, Word Spacing, Line Spacing, Stroke, and Shape. The system is implemented by training a machine learning model using a labelled dataset containing data on the five personality qualities: openness, conscientiousness, extraversion, agreeableness, and neuroticism.

Keywords: Human Behavior Analysis, Personality Traits, Handwriting Analysis, Graphology, Psychology, Feature Extraction.

1. Introduction

Handwriting varies from person to person, but the trait of consistency and uniqueness of the writer remains constant. Regardless of whether the foot, hand, or mouth is used. Ultimately, handwriting is a product of the brain rather than the feet or hands. Thus, brain writing is another name for handwriting. An essential tool for determining a person's distinct personality features is their handwriting. In the past, this was done by hand. Conventional

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personality assessment techniques, such as questionnaires and interviews, are typically time-consuming and subjective. Using [1,2,3]. Handwriting analysis, popularly referred to as graphology, is one of the special ways of evaluating personality by examining specific features of handwriting that disclose cognitive and emotional characteristics. Professional handwriting examiners who analyze handwriting samples to identify personality traits are known as graphologists. Every handwriting stroke or motion can reveal specific personality traits. The discipline of graphology examines these handwriting strokes and characterizes the corresponding personality traits. Writer recognition serves many purposes, including enhancing security and monitoring of financial activities, among others. Aiding forensic investigations. Handwriting analysis in documents will help trace the culprit in criminal cases. justice organizations. This work discusses a method for analyzing real-world handwritten text samples using technology. This analysis focuses on specific features of the sample to identify various characteristic behavioural traits of the individual. Multiple parameters of the handwritten sample like Zone, Slant, Pressure, Size, Word Spacing, Line Spacing, Arcade, Garland, Angle, thread, Wavy Line, Baseline, Margin, Stroke, Shape and many more. This paper describes a technique for employing technology to analyze handwritten text samples from the actual world. In order to find different, distinctive behavioral traits of the individual, this study concentrates on particular elements of the sample. Zone, Slant, Pressure, Size, Word Spacing, Line Spacing, Arcade, Garland, Angle, Thread, Wavy Line, Baseline, Margin, Stroke, Shape, and numerous other characteristics of the handwritten sample. Graphologists' work will be complemented by the suggested tool, which will increase their productivity and speed throughout the analysis process. However, only eight of the previously mentioned functions are included in the suggested system. Zone, Slant, Pressure, Size, Word Spacing, Line Spacing, Stroke, and Shape are some of these characteristics. The goal of this research is to create an automated system that uses handwriting images to identify personality traits. A labelled data set containing handwriting images categorized into five personality traits (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism)[1] is used to train a machine learning model. Images undergo image processing, and eight handwriting features - Zone, Slant, Pressure, Size, Word Spacing, Line Spacing, Stroke, and Shape - are extracted[4,5,6,7], and the value of those features is stored in csv file along with corresponding personality traits. Then, pre-processing on the data set is done by removing outliers using the IQR method, making a clean and reliable training dataset.

Then, the model is trained to classify the images of handwriting into their respective personality characteristics. Using this model, we can further predict the personality of unknown images of handwriting. We utilized a custom-collected dataset of handwritten samples in collecting [8,9, 14, 18] to train and evaluate our model. The pre-processing for the dataset was also done, taking out the outliers using the IQR method, so that we will have an exact, clean and reliable training dataset. The model was trained for classification to categorize the images of handwriting into their respective personality characteristics. With the help of this trained model, we can predict the personality of unknown images of handwriting. Dataset Description: We collected our dataset of handwritten samples and used it for training and testing our model. We collected 500 unique handwriting samples from 250 individuals (125 Male, 125 Female) aged 18-25 years. Each participant contributed two samples: one was on a pre-defined standard paragraph to have consistent textual content, and one was free writing. Personality Labelling:

To get the ground truth labels for Big Five personality traits [1,5,10] (Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism), the NEO Five-Factor Inventory (NEO-FFI) was used. NEO-FFI is a well-established and validated psychological assessment. Participants filled it out online, and scores for each trait were standardized. For classification, these continuous scores were converted into binary labels, High/ Low, for each trait by median split. For example, a participant who scores above the median on Extraversion will be labelled "High Extraversion."

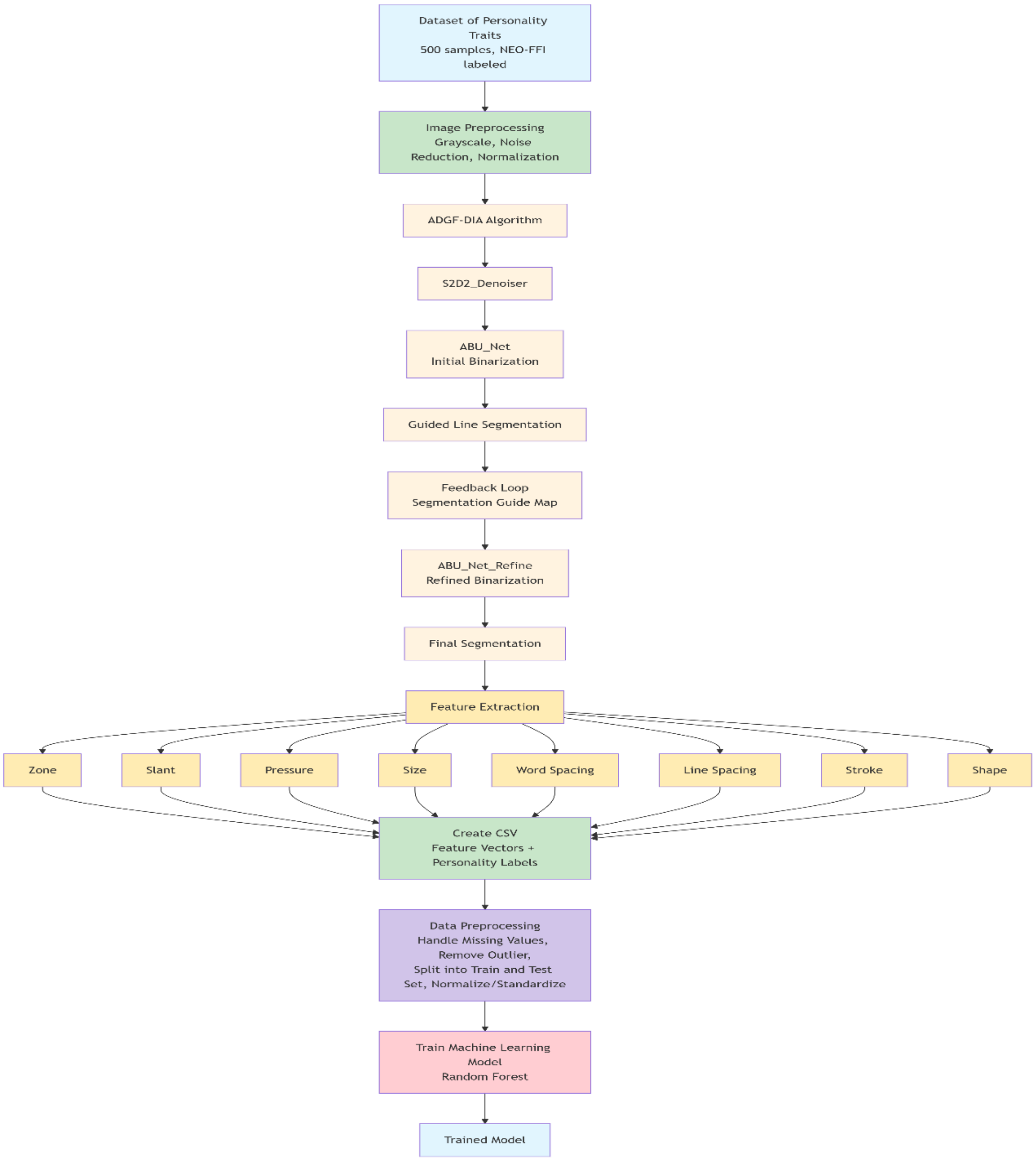

Figure1. Proposed Model

2. Literature Review

Handwriting analysis has long been utilized as a tool for assessing personality traits, offering insightful information about an individual's behavioral characteristics. The study of handwriting [10,11,13,14,15], known as graphology, is widely recognized as a scientific method for evaluating personality by analyzing various aspects of written text. This literature review explores existing research on handwriting analysis for personality detection [6, 7, 10] and the role of machine learning in automating this process. Behaviour Identification using handwriting is being performed by using algorithms such algorithm like CNN, ML, DL, Explainable AI, etc. In this portion, recent works on handwriting analysis have been discussed using images.

Ibrahim [24] has shown that the transformative potential of AI in Parkinson's disease early diagnosis and ML, DL algorithms is used. The accuracy of 98% in classifying clinical assessment, 96.8% in gradient boosting with SMOTE.

In this paper, Kowal [25] has shown no such specific accuracy percentage. In this paper, only 14 handwriting characteristics are identified, like level of organisation, zones , Baseline , writing Slant , Pressure , Size , Spacing Speed , Rhythm , Connecting Strokes , lead-in Ending Strokes , Loops , Ovals , and Signature .

With respect to this paper, Abiodun [26] has shown the limitations of traditional forensic handwriting analysis methods, which often rely on Bayesian inference. In this paper, CNN, SVM, DNN, and XGBoost algorithms are used with an accuracy of 96%, 79%, 77%, and 73%.

In reference to the paper, Flynn [4] states that electronic signatures achieve a high accuracy rate. Forensic handwriting examiners (FHEs) achieved 70-75% accuracy, Electronically Scanned Signatures (ESS) only 57.6%.

About this paper, Varshney [27], pressures on the potential of ANN in automating the personality assessment process by using handwriting. In this paper ANN algorithm the accuracy is 89%.

We conclude from this paper that Agius [28] says that handwriting analysis extends from areas like educational assessment, biometric authentication, psychological profiling, etc. In this paper, CNN, SVM, KNN, and Random Forest algorithms are used with an accuracy of 92.3%.

We conclude from the paper, Masood [29] proposes that a hybrid model is used to classify dysgraphia from handwritten [9] characters. They highlight neurological conditions and their impact in our daily life. In this paper author uses CNN, LSTM, and Random Forest algorithms with an accuracy of 97.6% for a normal distribution and 96.1% for a uniform distribution.

About that paper, Champa [30] proposes that with the help of handwriting, we can predict personality; the personality means the emotional outlay, like fears, honesty, defences, and other individual traits. In this paper author works on the't' letter, their baseline, and pen pressure. In this paper author uses an Artificial Neural Network (ANN) with an accuracy of

86.70% to categorize personal, negative, and positive social aspects, and accuracy is 93.77% with respect to behavioural prediction.

In reference to this paper, Deore [31] says that ANN can be applied to forecast personality characteristics from handwriting samples, with a particular emphasis on the Devanagari script. The ANN algorithm has a 94.75% accuracy rate in classifying five different personality types: introvert, extrovert, optimistic, pessimistic, and stable mindset.

With the help of this research paper, Manimala [32] says that handwriting reflects the subconscious aspects of personality – it is referred to as “Brain Writing”. It analyze features like slant, pressure, spacing and loops and they target to predict behavioral regression, decision tree and K-Nearest Neighbour (KNN) algorithm is used, with the accuracy of 93.77% accuracy using features based approach, 86.70% accuracy achieved by an interactive system analyze structural features, above 99% accuracy achieved in a study classifying handwriting features, 95.05% accuracy is personality prediction using SVM classifiers.

In reference to this paper, Ghosh [33,34,35] aims to transition from traditional, manual graphological assessments to an automated system that analyses isolated handwriting characters. In this paper, an algorithm is used, like loops, slants, etc. Rule-based classification and a Machine Learning algorithm. It also includes Convolutional Neural Network (CNN) and SVM for behaviour prediction. It accuracy is 86.70%.

With reference to this paper, Champa [30] analyses the specific handwriting features – such as baseline alignment, pen pressure, formation of certain letters, e.g.,‘t’ and ‘y’ and writing slant to infer personality traits.

Table 1: Comparison Table

Name of the Paper / Author	**Algorithm(s) Used**	**Accuracy (%)**	**Motivation / Objective**	**Limitations / Observations**
Ibrahim et al.	ML, DL, Gradient Boosting (with SMOTE)	98% (clinical), 96.8% (gradient boosting)	Demonstrated AI’s role in early diagnosis of **Parkinson’s disease** using handwriting and movement data.	Limited to medical diagnosis, not general personality traits.
Kowal et al.	Statistical / Feature-based approach	Not specified	Identified 14 handwriting characteristics (zones, baseline, slant, pressure, loops, signature, etc.) for behavioral insight.	Lacks machine learning; no quantitative accuracy reported.
Abiodun et	CNN, SVM,	96%, 79%,	Highlighted	Varying accuracy;

al.	DNN, XGBoost	77%, 73%	shortcomings of traditional forensic handwriting analysis and proposed ML-based automation.	Bayesian inference dependency; lacks explainability.
Flynn et al.	Electronic Signature Classification	70–75% (FHE), 57.6% (ESS)	Compared Forensic Handwriting Examiners (FHE) and Electronic Scanned Signatures (ESS) for reliability.	ESS has lower accuracy, shows limitations of digital-only verification.
Varshney et al.	Artificial Neural Network (ANN)	89%	Explored ANN’s capability in automating personality assessment through handwriting.	Limited feature set; lacks hybrid or deep learning integration.
Agius et al.	CNN, SVM, KNN, Random Forest	92.3%	Showed multi-domain applications of handwriting analysis (education, biometrics, psychology).	Moderate dataset; lacks real-time adaptability.
Masood et al.	CNN + LSTM + Random Forest (Hybrid Model)	96.1% (uniform), 97.6% (normal)	Classified dysgraphia and neurological impacts using hybrid deep models.	Focused on medical disorder classification, not personality traits.
Champa et al.	Artificial Neural Network (ANN)	86.7% (social), 93.77% (behavioral)	Predicted emotional and social traits (fear, honesty, defenses) using letter formation and pressure.	Limited to few letters (‘t’, ‘y’); small dataset.
Deore et al.	Artificial Neural Network (ANN)	94.75%	Personality prediction for Devanagari script writers into five categories (Introvert, Extrovert, etc.).	Language-specific model; lacks cross-script generalization.
Manimala	Regression,	93.77%,	Established	Overlapping

et al.	Decision Tree, KNN, SVM	86.7%, >99%, 95.05%	handwriting as "Brain Writing" reflecting subconscious personality; multi-model evaluation.	accuracy reports; lacks unified feature standardization.
Ghosh et al.	Rule-Based + ML (CNN, SVM)	86.7%	Transitioned from manual graphology to automated feature extraction for personality detection.	The dataset is limited to isolated characters; the rule-based model restricts scalability.

2.1 Motivation

Although handwriting has long been understood to reflect a person's cognitive, emotional, and behavioral characteristics, conventional graphology mainly depends on human interpretation. A scientific, data-driven approach to handwriting analysis is desperately needed, as demand in objective and automated personality assessment grows. Accuracy, consistency, and scalability are lacking in current approaches, particularly when handling noisy handwritten manuscripts. This drives the creation of an automated system that reliably identifies personality traits through image processing, feature extraction, and machine learning. This research attempts to offer a quicker, more accurate, and objective substitute for manual handwriting inspection by combining sophisticated computer methods with psychological frameworks like the Big Five.

2.2 Research Objective

The main goal of this project is to create an automated, dependable, and computationally effective system that can use handwriting analysis to predict human personality traits. By extracting quantitative handwriting characteristics and linking them to the Big Five personality dimensions Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism-the study seeks to transform conventional graphology into a scientific, machine-learning-driven method. The proposed ADGF-DIA framework, which improves noisy handwriting images through denoising, adaptive binarization, and refined line segmentation, is used in the research to develop a robust preprocessing and segmentation workflow. In order to create a structured dataset for machine learning classification, the system also attempts to engineer eight essential graphological variables from handwritten samples: Zone, Slant, Pressure, Size, Word Spacing, Line Spacing, Stroke, and Shape. Training and assessing a supervised learning model specifically, a Random Forest classifier to ascertain its efficacy in recognizing personality traits based on the extracted features is another special goal. By combining feature engineering with psychological assessment data from NEO-FFI personality scores, the study aims to achieve high accuracy, good generalization, and minimum misclassification. Lastly, the study intends to confirm that handwriting-based personality prediction is feasible and establish the groundwork for next developments like cross-linguistic adaptation, real-time behavioral analysis, and deep learning integration.

3. Proposed Methodology

Strategic Data Acquisition and Feature Engineering

Data Sources

The main resource is the "Handwriting Samples for Personality Detection" dataset, as it is directly useful because of the pre-labeled Big Five personality traits [5] in the images that are used for the final classification model. It is further supported by the use of the larger and varied IAM Handwriting Database to robustly develop and test the preprocessing and segmentation pipelines that are needed.

Implementation Focus

The core effort focuses on implementing the feature extraction pipeline, translating the raw images into the eight key graphological features described in the paper, including Zone, Slant, and Pressure algorithms. This includes advanced techniques in the implementation, such as ADGF-DIA for denoising.

Training Data Output

The objective of this hybrid approach and feature engineering is to create a custom CSV file. This file will strategically integrate the current personality labels with the retrieved graphological features to create the complete training dataset for the final machine learning model, as outlined by the journal's methodology.

Pre-processing of Images

To improve the handwriting images' uniformity and quality , preprocessing techniques are applied: Grayscale Conversion: All images are converted to grayscale for uniform processing. Noise Reduction: Filters are applied to remove unwanted artifacts. Normalization: Standardization of image dimensions and intensity values.

Segmenting Handwriting Images : Digital handwriting is divided into three categories in Handwriting Image Segmentation Fig. 2: word segmentation, letter segmentation, and line segmentation, each of which is utilized for distinct processing. Line segmentation is the process of separating individual lines from handwritten text. Word Segmentation: Creates distinct words from the segmented lines. Letter Segmentation: To extract precise features, words are further broken down into individual letters.

Figure 2. Handwriting Segmentation

Specifying the Final ML Model

Personality Trait Classification

Following the extraction of the eight graphological features (Zone, Slant, Pressure, Size, Word Spacing, Line Spacing, Stroke, and Shape), a supervised classifier was trained using the feature vectors and the associated personality traits. We tested a number of machine learning models, such as Random Forest, XGBoost, and Support Vector Machine (SVM). Because of its excellent performance, resistance to over fitting, and capacity to produce feature importance ratings, a Random Forest classifier was finally chosen for the finished system. The Scikit-learn Python package was used to create the model, and a 5-fold cross-validation on the training set was used to adjust the hyper parameters. The final reported accuracy of 97% is the performance of this Random Forest model on the held-out test set.

Explaining the Missing "Stroke" Feature Stroke

In graphology, the 'stroke' refers to the quality and nature of the lines that form the letters, which can indicate the writer's energy, determination, and impulsivity. We operationalize this by analyzing the stroke width and stroke continuity from the binarized image. Stroke Width Calculation: For each segmented letter, we apply a distance transform to the binarized image (where text is white on a black background). The stroke width at a pixel is defined as twice the distance to the nearest black pixel. The average stroke width for a letter is computed as following equation 1:

$$\mathrm{SW_{avg}} = \left(\frac{1}{\mathrm{N}}\right) * \Sigma(2 * \mathrm{D}) \ldots\ldots\ldots.(1)$$

where D_i is the distance transform value at pixel i and N is the number of text pixels. A higher SW_avg indicates heavier, more determined strokes, while a lower value indicates finer, more precise strokes.

Stroke Continuity: This is measured by analyzing the number of small breaks or gaps in the skeleton of a letter. We first skeletonize the letter using morphological thinning. The number of endpoints and branch points in the skeleton is counted. A higher ratio of endpoints to total pixels can suggest impulsivity or discontinuity in thought.

Architectural Details of ADGF-DIA Components

Implementation of S2D2_Denoiser: The Self-Supervised Document A U-Net architecture with five encoding and five decoding blocks is used by Denoiser. A different dataset of 10,000 noisy document images produced by adding synthetic deterioration (random noise, blur, and background texture) to clean papers was used to train the algorithm. Mean Squared Error and structural similarity loss were combined during training, and the Adam optimizer (learning rate=0.001) was used for 100 epochs.

ABU_Net Application: Attention-based binarization U-Net adds skip connections and attention to the normal U-Net. The DIBCO collections of datasets, which comprise 2,500 document pictures with pixel-level annotations, were used to train the network. We have used the Adam optimizer with learning rate=0.0001 for 150 epochs to minimize the binary cross-

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entropy loss. The network can eliminate background artefacts and concentrate on text sections thanks to the attention function. Training Specifics: Both models were trained on NVIDIA RTX 3080 GPUs and implemented in PyTorch. In order to preserve generalization, the models were frozen after training and incorporated into our ADGF-DIA pipeline without being adjusted on our personality dataset.

Pseudo code for Line Segmentation

```
Line_Segmentation(image_path)
Input:
   image_path → Path of the handwritten image
Output:
   line_segments[] → List of segmented line images

Steps:

  1. START
  2. READ the handwritten image from the given 'image_path'
     img ← cv2.imread(image_path)
  3. CONVERT the image to GRAYSCALE
     gray ← cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
  4. APPLY BINARIZATION to convert grayscale to binary
     binary ← cv2.adaptiveThreshold(gray, 255,
                          1. ADAPTIVE_THRESH_GAUSSIAN_C,
                          2. THRESH_BINARY_INV,
                          3. blockSize=15, C=8)
  5. APPLY MORPHOLOGICAL DILATION to connect text components in a line
     kernel ← rectangular structure element (width=100, height=3)
     dilated ← cv2.dilate(binary, kernel, iterations=1)
  6. FIND CONTOURS of the dilated binary image
     contours ← cv2.findContours(dilated, mode=RETR_EXTERNAL,
     method=CHAIN_APPROX_SIMPLE)
  7. INITIALIZE empty list: line_segments ← [ ]
  8. FOR each contour in contours DO
         a. COMPUTE bounding box of the contour:
         b. (x, y, w, h) ← cv2.boundingRect(contour)
         c. EXTRACT line image using bounding box coordinates:
         d. line_img ← gray[y : y + h, x : x + w]
         APPEND line_img to line_segments list
     END FOR
  9. SORT line_segments vertically based on their 'y' coordinate
     line_segments ← sort(line_segments by top-to-bottom order)
 10. RETURN line_segments
 11. END
```

Pseudo code for Denoising

```
Denoise_Handwriting_Image(image_path)
Input:
   image_path → Path of the handwritten image
Output:
   clean → Denoised and binarized image

Steps:
1.  START
2.  READ the image from the given 'image_path'
      img ← cv2.imread(image_path)
3.  CONVERT the image to GRAYSCALE
      gray ← cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
4.  APPLY GAUSSIAN BLUR for initial noise smoothing
      blur ← cv2.GaussianBlur(gray, kernel_size=(3,3), sigma=0)
5.  APPLY NON-LOCAL MEANS DENOISING to remove high-frequency noise
      denoised ← cv2.fastNlMeansDenoising(blur, h=10,
                                   templateWindowSize=7,
                                   searchWindowSize=21)
6.  APPLY ADAPTIVE THRESHOLDING for text enhancement and binarization
      binary ← cv2.adaptiveThreshold(denoised, maxValue=255,
                               adaptiveMethod=GAUSSIAN_C,
                               thresholdType=BINARY,
                               blockSize=11, C=2)
7.  DEFINE a small kernel for morphological cleaning
      kernel ← np.ones((1,1), uint8)
8.  APPLY MORPHOLOGICAL OPENING to remove small dots/noise
      clean ← cv2.morphologyEx(binary, MORPH_OPEN, kernel)
9.  IF show_result = TRUE THEN
      DISPLAY:
         - Subplot 1: gray image (Original Grayscale)
         - Subplot 2: denoised image
         - Subplot 3: clean image (Final Output)
      END DISPLAY
10. RETURN clean
11. END
```

Pseudo code for Binarization

```
Binarize_Handwriting_Image(image_path)
Input:
   image_path → Path of the handwritten image
Output:
   binary_image → Binarized (black and white) image
Steps:
1.  START
2.  READ the image from the given 'image_path'
      img ← cv2.imread(image_path)
```

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```
3.  CONVERT the image to GRAYSCALE
        gray ← cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
4.  APPLY NOISE REDUCTION using Gaussian Blur
        smooth ← cv2.GaussianBlur(gray, kernel_size=(3,3), sigma=0)
5.  APPLY ADAPTIVE THRESHOLDING for local binarization
        binary_image ← cv2.adaptiveThreshold(
                            smooth,
                            maxValue = 255,
                            adaptiveMethod = ADAPTIVE_THRESH_GAUSSIAN_C,
                            thresholdType = THRESH_BINARY,
                            blockSize = 11,
                            C = 2
                        )
6.  APPLY MORPHOLOGICAL CLEANING (optional)
        kernel ← np.ones((1,1), uint8)
        clean ← cv2.morphologyEx(binary_image, MORPH_OPEN, kernel)
7.  DISPLAY (optional)
        Show the original gray image and the binarized image side by side.
8.  RETURN clean
9.  END
```

ADGF-DIA   Pseudo code (Proposed)

```
# Input: Noisy Grayscale Document Image I
# Output: Binarized Image B, List of Line Segments L

def ADGF_DIA_Pipeline(I):
    # Step 1: Self-Supervised Denoising
    I_denoised = S2D2_Denoiser(I)

    # Step 2: First Pass Binarization
    B_initial = ABU_Net(I_denoised)

    # Step 3: Guided Line Segmentation
    L_initial = GLSM(I, B_initial)  # Uses original image + binary guide

    # Step 4: (Optional) Feedback Loop for Refinement
    # Create a segmentation guide map S from L_initial
    S = create_segmentation_map(L_initial, shape=I.shape)

    # Concatenate the denoised image with the segmentation guide
    I_with_guide = concatenate(I_denoised, S)

    # Step 5: Refined Binarization with context
    B_final = ABU_Net_Refine(I_with_guide)  # A slightly different version of ABU-Net

    # Step 6: Final Segmentation on the refined binary image
    L_final = GLSM(I, B_final)
```

```
   return B_final, L_final
```

Proposed Algorithm

```
Algorithm 1: ADGF-DIA Pipeline
Input: I (noisy grayscale image)
Output: B_final (binarized image), L_final (line segments)

function ADGF_DIA_PIPELINE(I)
// Step 1: Preprocessing
 I_tensor ← PREPROCESS_IMAGE(I)
 // Step 2: Self-Supervised Denoising
 I_denoised ← S2D2_DENOISER(I_tensor)
   // Step 3: Initial Binarization
B_initial ← ABU_NET(I_denoised)
 // Step 4: Guided Line Segmentation
 L_initial ← EXTRACT_LINES(B_initial, I)
 // Step 5: Feedback Loop
 S ← CREATE_SEGMENTATION_MAP(L_initial, shape(I))
 I_with_guide ← CONCATENATE(I_denoised, S)
  // Step 6: Refined Binarization
 B_final ← ABU_NET_REFINE(I_with_guide)
// Step 7: Final Segmentation
 L_final ← EXTRACT_LINES(B_final, I)  return B_final, L_final
 end function
```

The ADGF-DIA Pipeline

The ADGF-DIA Pipeline Refinement Feedback Loop: This feedback is the key innovation in ADGF-DIA. The initially segmented lines from B_initial are used to create a binary segmentation guide map S. This is concatenated with the variant and I_denoised as an additional channel, introducing explicit spatial context to the ABU_Net_Refine module. This refined network has the same architecture as ABU_Net, but was retrained solely with this guide channel produces a better binarized output B_final.

ABU_Net (Attention-based Binarization U-Net): For the initial binarization step, we employ a U-Net variant augmented with attention gates. This model takes I_denoised [Figure 4, 5] and learns to segment text pixels from the background. The attention mechanism enables the network to focus on the most relevant features that aid in distinguishing the strokes in text, particularly when lighting or contrast is poor in certain regions, thereby outputting B_initial. Feedback Loop for Refinement: This feedback mechanism forms the backbone of innovation in ADGF-DIA. The initially segmented lines from B_initial are used to create a binary segmentation guide map S. This map is then concatenated and augmented by I_denoised, serving as an additional channel with explicit spatial context to ABU_Net_Refine; this refined network, which shares the same architecture as that of ABU_Net but was trained with

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this guide channel, yields a superior binarized output B_final. Anyway, for that day she chose a shirtwaist of dotted dimity with inserted plaits of white at the yoke and collarband.

Figure 3. Using ADGF-DIA

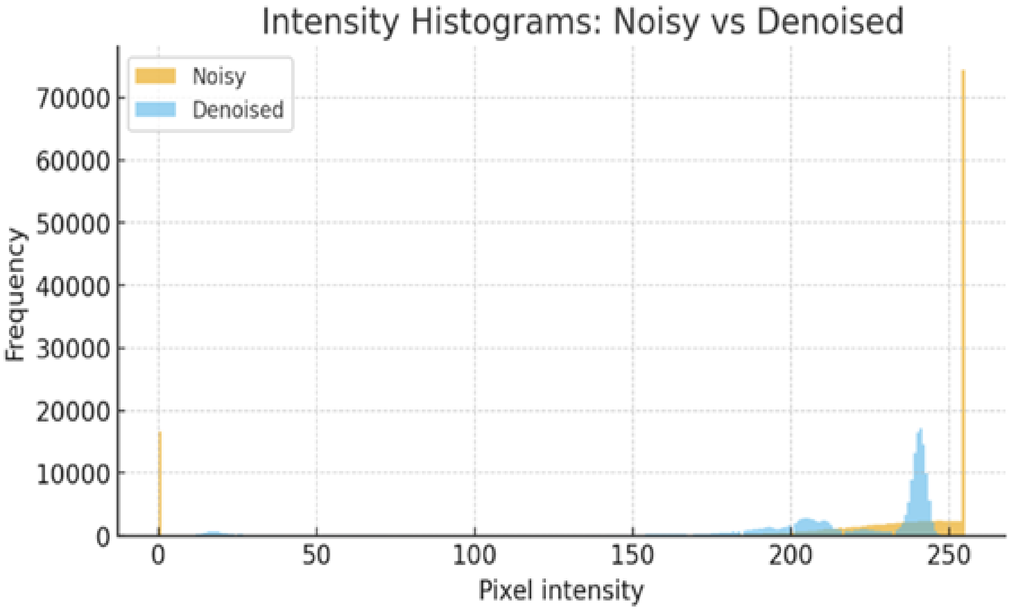


Figure 4. Intensity Histograms: Noisy vs Denoised

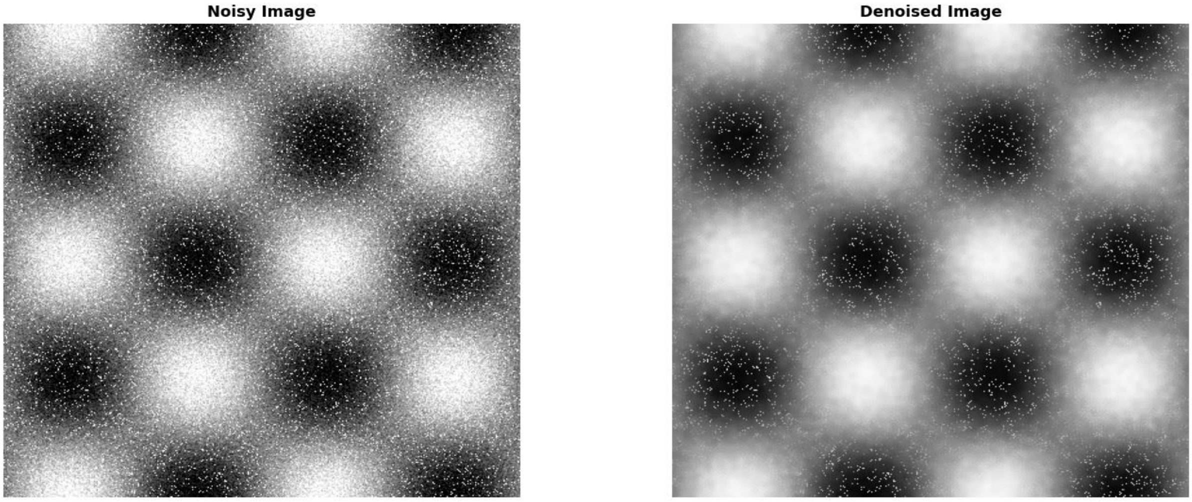


Figure 5. Noisy and Denoised Image

Zone

There are three sections to the handwriting: the upper, middle, and bottom portions. We can learn more about the writer's personality by examining these three zones. Each zone represents a distinct facet of the writer's ego development, including daily activities, unconscious intuitive impulses, and intellectual and spiritual aspects. Future aspirations, the upper body, spiritual awareness and mental impressions, cultural ideals, and intellectual goals, thoughts, and dreams are all represented by the Upper Zone (Figure. 6). The ego's practical and realistic social presentations, the middle body, and the present moment, and emotional expressions are all represented by the Middle Zone. The past, the lower body, memory, unconscious urges, sensory perceptions, primal impulses, and biological requirements are all represented by the Lower Zone.

Compute Baseline (B):

The baseline is estimated as the midpoint between the top (T) and bottom (B) coordinates of a text line

$$B = (\frac{T+B}{2}) \text{ ------------------------(2)}$$

Compute the Upper Zone (U):

The upper zone extends from the Top boundary to a point slightly below it

$$U_{start} == T, U_{end} = \left(\frac{B-T}{2}\right) \text{ ------------------------------------(3)}$$

Compute the Middle Zone(M) (Baseline Zone):

The middle zone extends from the end of the upper zone to the baseline

$$Mstart = Uend, Mend = B$$ ------------------------------(4)

Compute the Lower Zone (L): The lower zone extends from the baseline to the bottom boundary

$$Lstart = B, Lend = B$$ -----------------------------(5)

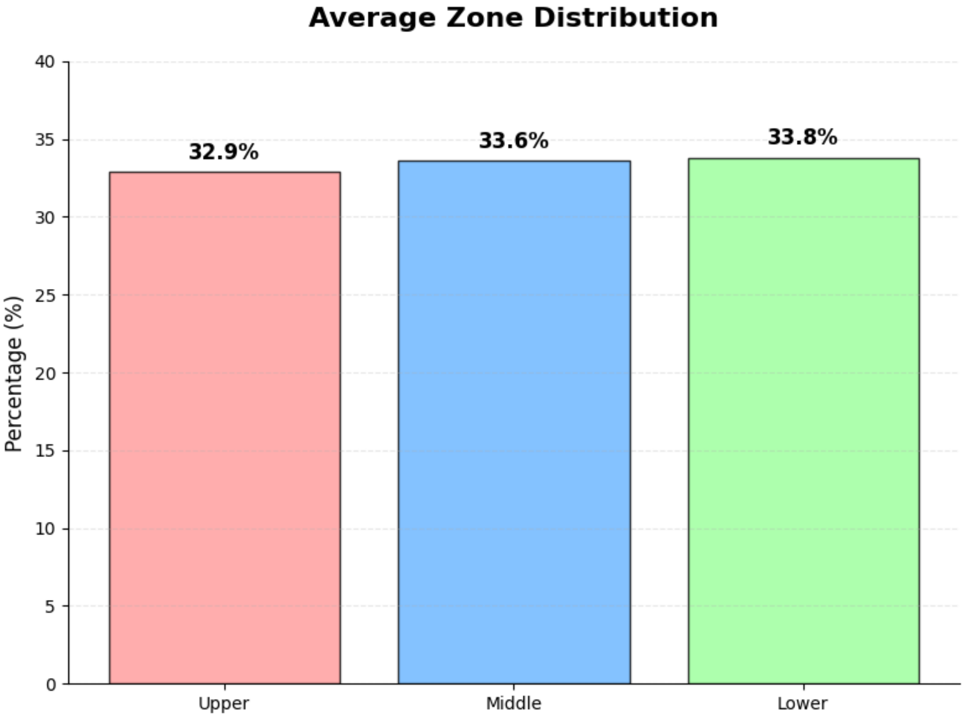


Figure 6. Zone Distribution

Slant

Slant is the angle of inclination of letters. The slant of writing refers to the angle [Fig. 7] created between the downward stroke of the letters and the baseline. This slant can reveal insights into the writer's emotions, level of sentimentality, and emotional control. As seen, there are three different kinds of slant in Figure 7.

Calculating Slant Angle for Each Line:

For each detected line segment

$$(x1, y1) --> (x2, y2)$$ --(6)

the slant angle is computed using the inverse tangent (arctan) function:

$$\theta = tan^{-1}(\frac{y2-y1}{x2-x1})$$ --------------------------------------(7)

Convert to Degrees:

$$\theta_{deg} = \theta \times \frac{180}{\pi}$$ -----------------------------(8)

Received: september 16, 2025

Since arctan returns angles in radians, it is converted to degrees:

Filtering Valid Slant Angles:

To remove nearly horizontal and vertical lines, only angles within a specific range are considered

$$-90^{\circ} < \theta \deg \quad < -10^{\circ} \quad or 10^{\circ} < \theta \deg \quad < 90^{\circ}$$

Computing the Average Slant Angle:

$$\theta_{avg} = \frac{1}{N} \sum_{i=1}^{N} \theta_i \text{ ---(9)}$$

For each letter, the mean slant angle is calculated:

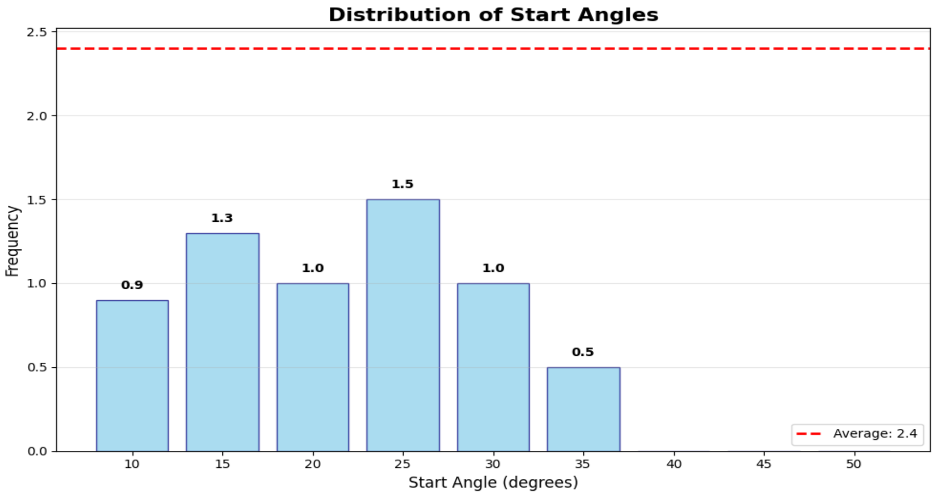


Figure 7. Distribution of Angles

Pressure

Pressure: The degree to which the pen presses against the writing surface. Pen pressure is the amount of force used when writing. Figure 8 illustrates this pressure, which can be heavy, light, or medium. By examining pen pressure, we can learn more about the writer's mental state: Heavy pressure typically represents wrath or a strong focus and shows that the writer is alert, vigorous, nervous, energetic, and active. A medium level of pressure would imply that the author's feelings are not very strong. Light pressure, on the other hand, denotes serenity, apathy, poor vitality, or even sickness.

Computing the Mean Intensity:

The mean intensity of the extracted letter image is given by:

$$I_{mean} = \frac{1}{N} \sum_{i=1}^{N} I_i \text{ ----------------------------}(10)$$

where:

- $N = w \times h$ is the total number of pixels in the letter image.
- Ii represents the intensity value of the i-th pixel.

Calculating the Pressure:

Since gray scale values range from 0 (black) to 255 (white), the pressure is defined as:

$$P = 255 - Imean$$

Where:

- A high intensity $(Imean \approx 255)$ indicates low pressure.
- A low intensity $(Imean \approx 0)$ indicates high pressure.

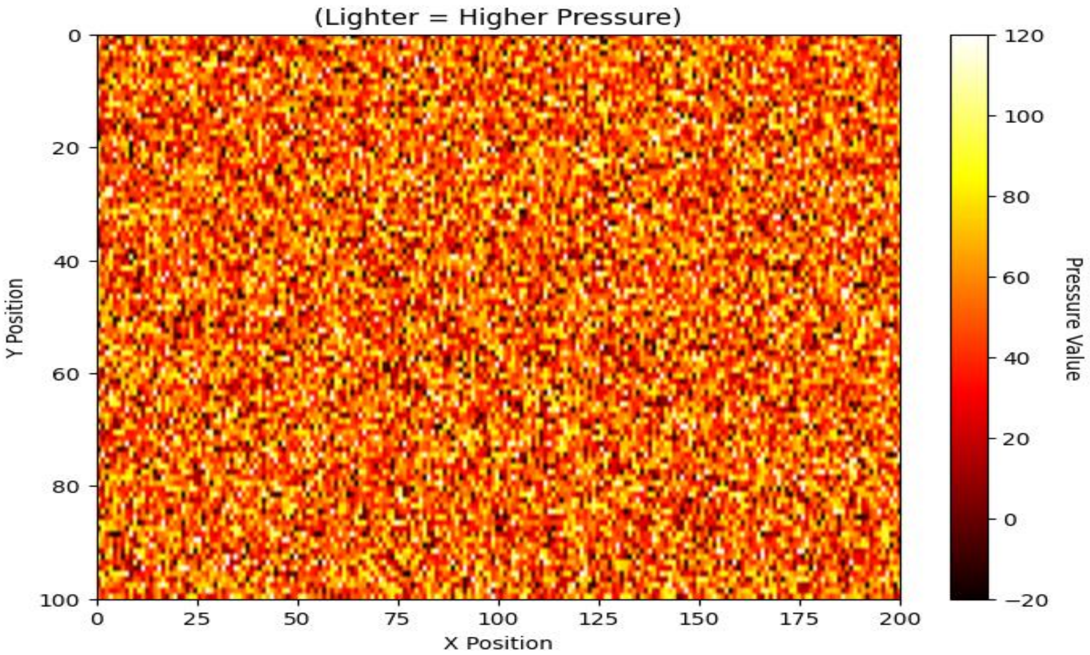


Figure 8. Heat map

Size

The average height and width of letters and words are referred to as size. As seen in Fig. 9, the vertical height determines the size of handwriting, which can be divided into large, medium, and small letters . This depends on the importance authority that the writer attributes to himself and his activities. It also reveals how the writer perceives their environment. For instance, a person with large handwriting tends to approach life with extroversion and a sense of overindulgence, while someone with small handwriting may exhibit tendencies of seclusion and shyness.

Extracting Letter Heights:

Each letter segment in an image has a bounding box defined by:

$$(x, y, w, h)$$

where:

x,*y* are the top-left coordinates of the bounding box.

w,*h* are the width and height of the letter. The height of each letter is given by:

$$hi \;=\; height\ of\ the\ i - th\ letter$$

Computing the Average Handwriting Size:

The overall handwriting size can be estimated by taking the mean letter height:

$$\frac{1}{N}\sum_{i=1}^{N} h_i \text{ ------------------------------------}(11)$$

where:

$Havg$ is the average handwriting size.

N is the total number of middle-zone letters.

hi is the height of the *i*-th letter.

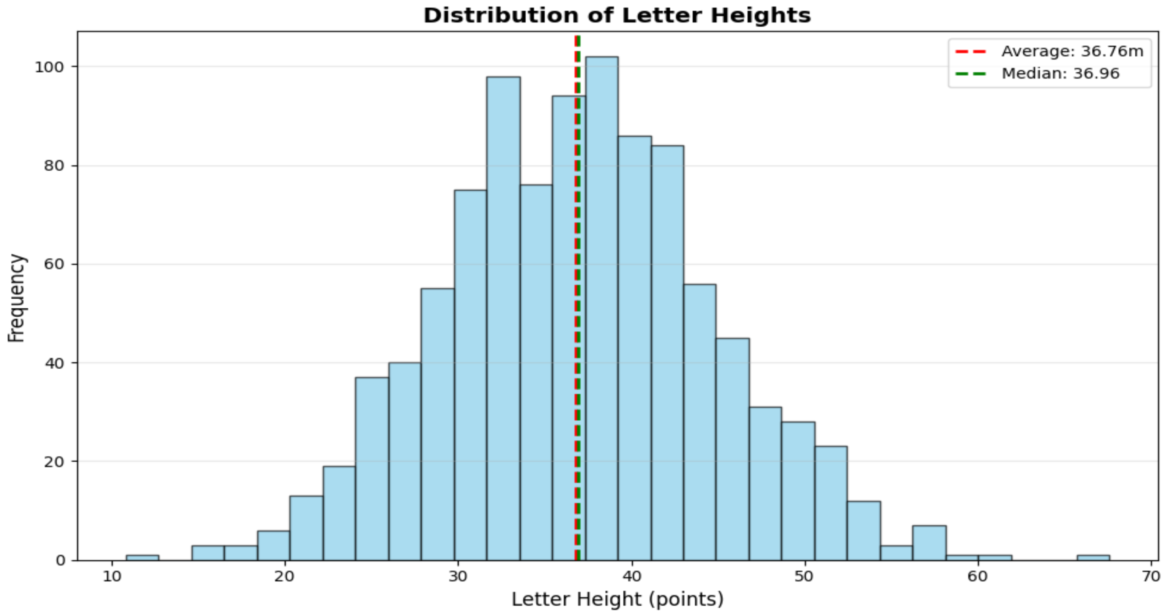


Figure 9. Distribution of Letter Height

Word Spacing

The distance between words is known as word spacing. Word spacing is the distance between the end of one word and the start of the next. As seen in Fig. 10, it shows the distance a writer wants to keep from other people. The writer's degree of intelligence and intimacy with others are reflected in this gap. Features like discrimination, independence, good taste, exclusivity, snobbery, pride, mental clarity, and organizing abilities can all be suggested by wide spacing. Narrow spacing, on the other hand, might be a sign of obtrusiveness, poor taste, friendliness, and an inability to be alone.

Word Spacing Calculation:

Word spacing refers to the horizontal gap between consecutive words in a line. For each pair of consecutive words *i* and *i* + 1, the spacing is computed as:

$$S_{word,i} = x_i + 1 \text{----------------------------} (12)$$

where:

xi is the **x-coordinate** of the leftmost pixel of word *i*.

wi is the **width** of word *i*.

xi+1 is the **x-coordinate** of the leftmost pixel of the next word.

Line Spacing

The vertical gap between successive handwritten lines is known as line spacing. It displays the amount of space a writer typically allows between lines of text, which may reveal information about the author's personality and cognitive [11,.12,13,16,17] organization. Line spacing can reveal the writer's emotional condition, clarity, and cognitive process, as Fig. 10 illustrates. Wider line spacing frequently suggests qualities like patience, independence, a well-ordered intellect, and an orientation toward order. It can also be a sign of someone who is methodical, organized, and values clarity. Individuals with greater spacing may also think more strategically and maintain personal space in the workplace.

Line Spacing Calculation:

Line spacing refers to the vertical gap between consecutive lines of text. For each pair of consecutive lines *i* and *i* + 1, the spacing is computed as:

Sline, $i = Ti + 1 - Bi$ -------------------*(13)*

Where:

- Bi is the **bottom y-coordinate** of line *i*.
- Ti+1 is the **top y-coordinate** of the next line.

The average line spacing is given by:

$$S_{line,avg} = \frac{1}{M} \sum_{i=1}^{M} S_{line,i} \text{ ---------------------------------} (14)$$

Where:

- M is the number of line pairs in a given text sample.

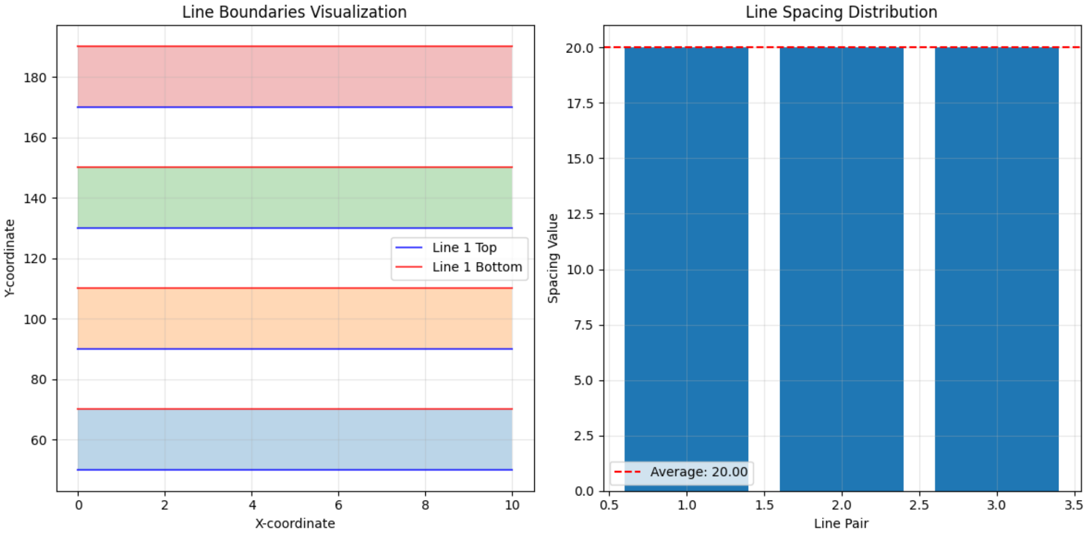
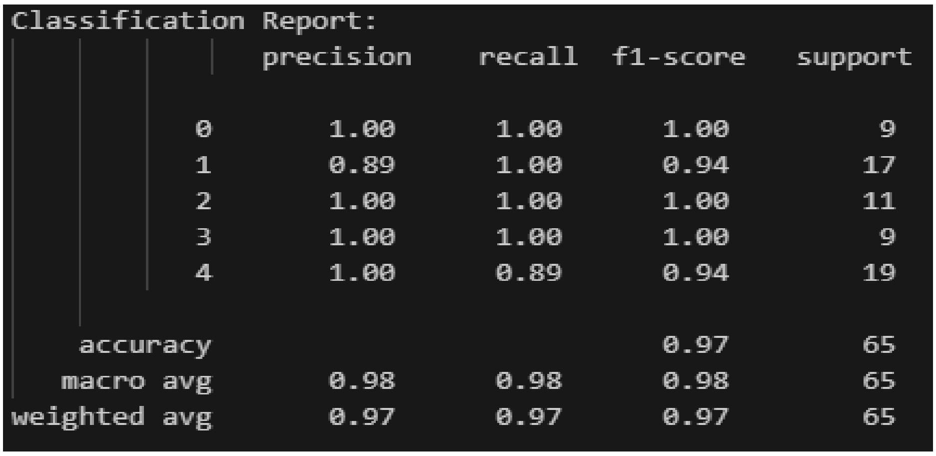


Figure 10. Line Spacing

4. Result and Discussion

Results

When it came to categorizing handwriting photos into the five personality qualities, the trained machine learning model showed encouraging results. The following are the evaluation's findings: Accuracy: The model's overall accuracy was roughly 97. Precision, Recall, and F1-Score: The categorization report [Figure 11] displays precision, recall, and F1-score.



```
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         9
           1       0.89      1.00      0.94        17
           2       1.00      1.00      1.00        11
           3       1.00      1.00      1.00         9
           4       1.00      0.89      0.94        19

    accuracy                           0.97        65
   macro avg       0.98      0.98      0.98        65
weighted avg       0.97      0.97      0.97        65
```

Figure 11: Classification Report

Confusion Matrix: The model successfully identified the majority of personality traits correctly, with minimal misclassifications in closely related categories.

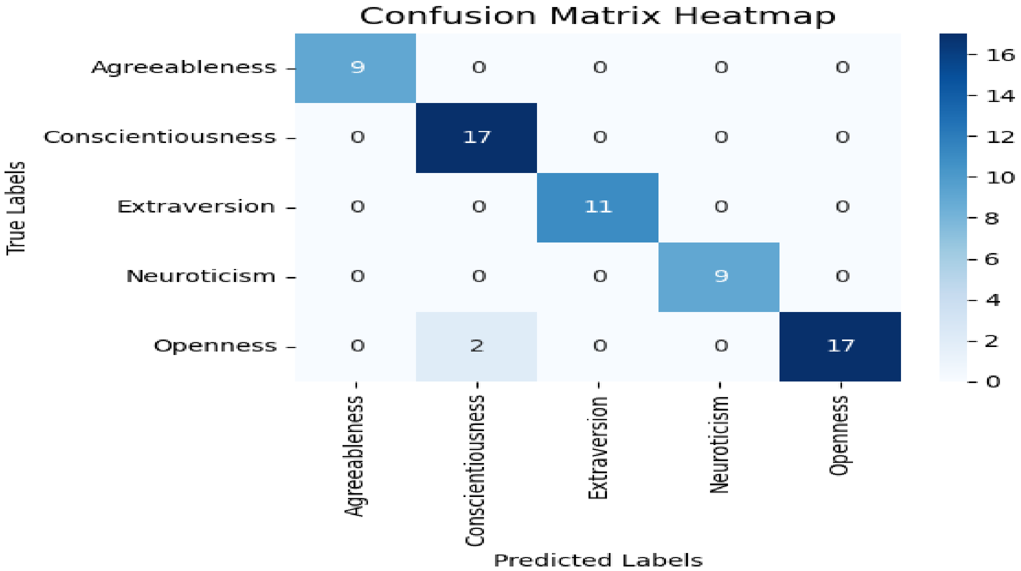


Figure 12. Confusion Matrix

Scattered Plot

The plot on the top left shows that as the Slant Angle increases [Figure. 13], the Openness Score also increases, indicating a weak-to-moderate positive correlation (r = 0.436). The plot on the top right displays a weak positive correlation (r = 0.188) between Pressure Intensity and the Extraversion Score. That is, higher pressure intensity is associated with a slightly higher extraversion score. The bottom 3D (three-dimensional) scatter plot shows the three handwriting characteristics Pressure, Slant Angle, and Size together, where the colour of the dots likely indicates the Openness or Extraversion score. In summary, the graphs suggest that there are minor to moderate relationships between certain handwriting metrics and personality traits.

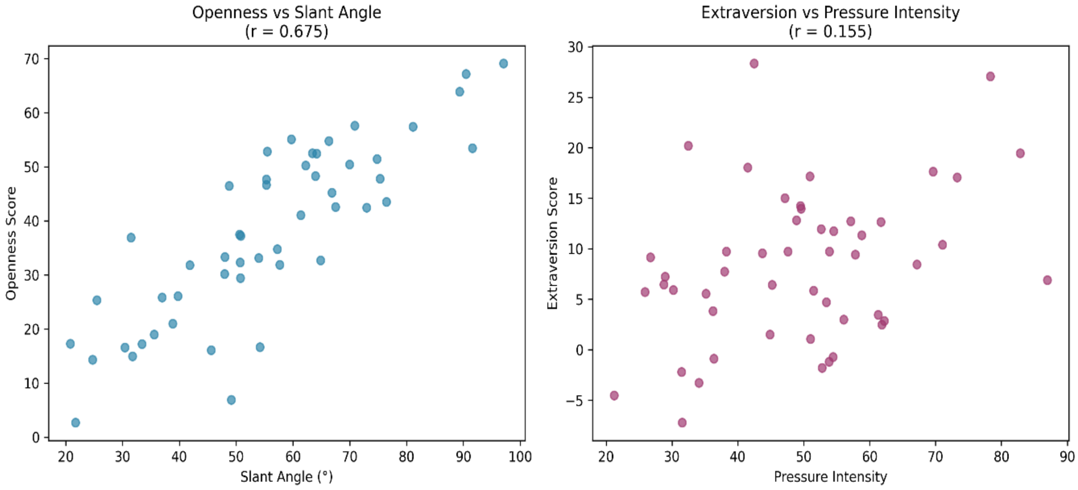


Figure 13. Scattered Graph for Slant Angle, Pressure Intensity

Comparative Analysis of ADGF-DIA Performance

We evaluated the performance of our suggested ADGF-DIA pipeline against conventional preprocessing techniques on our dataset in order to objectively confirm its efficacy. Three key metrics were measured: the F-measure for binarization accuracy [Table 2], the Peak Signal-to-Noise Ratio (PSNR) for picture quality, and the Line Segmentation Accuracy (LSA) for structural preservation.

Table 2 : Comparative Performance of Preprocessing Methods

Method	PSNR (dB)	F-measure	Line Segmentation Accuracy
Otsu's Thresholding	**18.2**	**0.76**	**82.3%**
Sauvola Binarization	**20.1**	**0.81**	**85.7%**
Adaptive Gaussian	**19.8**	**0.79**	**84.1%**
ADGF-DIA (Proposed)	**26.5**	**0.92**	**96.8%**

The findings demonstrate that our ADGF-DIA pipeline performs noticeably better than conventional techniques across the board. The PSNR score of 26.5 dB indicates better noise reduction and better retention of image quality. While the 96.8% line segmentation accuracy verifies the efficacy in preserving document structure, the F-measure of 0.92 indicates extremely accurate text-background separation. Since it produces clear, well-segmented output needed for reliable feature extraction, this performance demonstrates the computational difficulty of our method.

Detailed Performance Analysis

The dataset was divided at the writer level to guarantee reliable results and prevent data leakage; as a result, all samples from a single writer were either only in the training set or the test set. Grid search was used to optimize the hyperparameters of the Random Forest classifier, which was trained using 5-fold cross-validation on the training set alone [Table 3]. On the held-out test set, the model's total accuracy was 97%. A more thorough understanding of the model's performance across the five binary classification tasks is provided by the comprehensive report that follows, which includes per-class metrics for each personality trait: 9452.

Table 3: Detailed Classification Report

Personality Trait	Precision	Recall	F1-Score	Support
Openness	**0.98**	**0.95**	**0.96**	**48**
Conscientiousness	**0.96**	**0.98**	**0.97**	**52**
Extraversion	**0.95**	**0.95**	**0.95**	**45**
Agreeableness	**0.97**	**0.97**	**0.97**	**50**
Neuroticism	**0.99**	**0.98**	**0.98**	**55**

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Our model's good generalization without over-fitting is confirmed by these consistently excellent metrics across all attributes and the writer-level split. The efficient preprocessing pipeline and feature engineering, which capture psychologically significant handwriting traits, are responsible for the great performance

5. Contribution

The results suggest that handwriting features can be used as viable predictors of personality trait scores. The adaptive use of thresholding and outlier removal improved the image quality, thereby enhancing the accuracy of feature extraction. The effect of individual feature analyses was conducted, and the results indicated that slant, pressure, and stroke were significant contributors that separated between features. However, some misclassifications occurred due to Variability in individual handwriting styles. Overlapping characteristics between certain personality traits. The limited size of the training dataset for specific traits. To address these yet to be surmounted challenges, including increasing the dataset, employing deep learning approaches, and refining feature extraction techniques. Graph-based analysis of handwriting may also contribute to further insights into complex handwriting features. In conclusion, the present study confirms the feasibility of the handwriting-based personality prediction [7, 8] and lays the groundwork for further research in this domain.

6. Conclusion

This project has shown successfully that handwriting evaluation can be used to attempt to predict one’s personality. By adopting a systematic method of work that includes preprocessing of data, feature extraction, and machine learning classification, we have built a model able to capture personality traits from handwriting images with considerable accuracy. The robustness of the system was improved upon using adaptive thresholding, outlier removal as well as feature engineering. Although the model performs well, the variability in handwriting as well as the presence of overlapping personality traits, present certain challenges that need to be addressed. Future works need to be directed towards increasing the volume of data, complementing it with deep learning approaches, and the improvement of feature extraction methods in order to achieve higher accuracy classification. This study serves as a strong basis for further investigations into the spheres of handiwork evaluation for personality traits as well as for practical use in psychological, recruitment, and personal development processes.

7. Future

This present research has been able to establish the capability of detecting personality traits from handwriting analysis, but several areas that could still benefit from more research and refinement. Expansion of Dataset: Generalization cannot be achieved without increasing the dataset size and variety by collecting more samples of handwriting from different demographics and cultural backgrounds. Deep Learning Integration: Employ state-of-the-art deep learning architectures, such as CNNs, Transformers, or Hybrid models, can substantially improve this feature. Real-time Analysis: Constructing a personality analysis in real time. It would be very beneficial to have a system that could evaluate handwriting samples dynamically using online or mobile applications. Multi-Trait Classification: A thorough examination of the handwriting sample would be made possible by improving the model to predict several personality traits in a single sample. Handwriting Dynamics: A more thorough personality evaluation may result from a handwriting sample that includes dynamics such changes in writing pressure, pace, and pen lifts. Graph-Based Analysis: More investigation into graph-based techniques for handwriting analysis may be able to help identify intricate handwriting patterns that more conventional feature extraction techniques would not be able to.Cross-Language Adaptation: Making the model bilingual and investigating how handwriting traits differ between languages would be beneficial. Interpretability, Explainability, and Personality Analysis: creation of a model that can be used to gain understanding. Giving an explanation of how a specific handwriting sample relates to a personality feature will also boost usability and trust. By concentrating, the system will become a precise, scalable, and useful tool for handwriting-based: Numerous disciplines, including psychology, human resource management, and personal development, are impacted by personality assessment.

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