Decoding Personalities Through Handwriting Analysis

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Abstract - **A person's personality is made up of all of their unique traits and attributes. The development and evolution of a person's ideals, characteristics, connections with the community, recollections of specific life experiences, routines, and abilities may all have an impact. An individual's decisions and behaviors are primarily influenced by their personality. Based on a person's handwriting characteristics, one can identify such a personality attribute. Everybody has a different handwriting, and from it, one can deduce information about that person's personality, behavior, and even some psychiatric traits. The study of graphology is presented to examine handwriting to determine personality. We saw that a lot of studies had focused on using handwriting to identify personality and/or behavior, but most of them had only looked at a small number of characteristics. Graphology claims that a wide variety of handwriting stroke qualities reflect the writer's psychological traits. In this survey, we look at various methods for feature extraction to predict a writer's personality and show the connections between personality psychology and handwriting. Understanding personality traits is aided by handwriting features that have psychological backing. The study links these characteristics and promotes computer-based graphology as a tool for personality prediction.**

Keywords* — *Graphology, Psychology, Handwriting Analysis, Personality Prediction, Feature Extraction, Psychological Traits

I. INTRODUCTION

Physical attributes include things like height, weight, and complexion, while ability traits include things like creativity, efficiency, and intelligence. Social traits include things like sensing, intuition, thinking . Personality traits can also give an individual other types of features. These personality traits can be described as “emotional, interpersonal, experiential, attitudinal, and motivational styles”[5]."That which permits a prediction of what a person will do in a given situation" is how Raymond Cattell defined personality. By using personality traits, Cattell was able to anticipate behavior.

According to Cattell, a personality trait is "that which defines what a person will do when faced with a defined situation." A person's personality can be identified using a variety of methods, including plain text, documents, handwriting, and signatures [5]. This article describes how personality traits can be determined from handwritten English text; many scholars are interested in studying the same thing for other languages and scripts. Handwritten texts in Devanagari and Latin scripts, Farsi, Arabic, and other languages have all been investigated, such as however, our survey is limited to English. Graphologists typically analyze a person's handwriting and signature manually.

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Numerous handwriting samples of particular individuals were examined, and it was discovered that these persons had unique traits. Graphologists search for characteristics in these handwriting samples that are more common than in the handwritten texts of the general public. The ability of the graphologists to recognize the author from a tiny sample of handwriting varies. But it's a slow and error-free process. Researchers have been developing computer graphology, which can predict a person's personality automatically, as a solution to this issue. Furthermore, it is evident that every individual has a distinct handwriting style; one may infer information about a person's personality, conduct, and even some psychiatric features from their handwriting traits. Thus, researchers were drawn to this brainwriting. Using handwritten text, our primary objective is to analyze graphology research and offer insights into various facets of an individual's behavior and personality. We also go over personality psychology, measuring traits, and several other aspects of handwriting analysis. We highlight the outcomes of earlier research utilizing computational graphology to discover these qualities and relate them to personality traits. The apps that employed handwriting-based customization features are listed below in comparison to earlier research[4] In [1], we offer extensive handwriting characteristics suitable for personality identification. We also included connections between possible personality factors and handwriting characteristics. We wrap off our work with issues that have been pointed up in a particular field.

II. METHODOLOGY

The methodology for personality prediction using handwriting analysis follows a structured approach, including data collection, preprocessing, feature extraction, model training, classification, and result interpretation. The system is designed using Support Vector Machines (SVM) for classification, ensuring robust and accurate predictions based on handwriting traits.

A. Personality Psychology and Graphology

Graphology, the study of handwriting and its correlation with personality, forms the foundation of this research. It is supported by personality psychology theories, such as:

Trait Theory – Analyzing traits like extraversion, conscientiousness, openness, neuroticism, and agreeableness.

Psychodynamic Theories – Understanding subconscious influences on handwriting.

Cognitive Psychology – Investigating how attention, memory, and emotions affect handwriting variations.

Behavioral Genetics – Evaluating how handwriting is shaped by genetic and environmental influences.

B. Data Collection

A dataset of 456 handwriting samples was collected under controlled conditions. Participants were required to write a predefined paragraph in English, ensuring uniformity across samples. The personality labels were assigned using psychological assessments based on established personality trait models.

Data Parameters:

Age Group: 18–45 years

Handwriting Style: Cursive, Print, Mixed

Personality Labels: Assigned based on Big Five Personality Traits

Each sample was scanned and converted into JPEG or PNG format, maintaining quality for further processing.

C. Image Preprocessing

To improve data quality, the uploaded handwriting images undergo multiple preprocessing steps:

Grayscale Conversion – Reducing color complexity to enhance feature extraction.

Noise Reduction – Applying Gaussian blur to remove unwanted artifacts.

Binarization – Using Otsu’s thresholding to separate handwriting strokes from the background.

Resizing & Normalization – Standardizing image dimensions (e.g., 840×840 pixels) for uniformity.

These preprocessing steps remove inconsistencies and ensure optimal feature extraction.

D. Feature Extraction

Handwriting analysis involves extracting key graphological features that correlate with personality traits. The extracted features are categorized into:

1. Structural Features:

Letter Slant – Measures emotional expressiveness.

Letter & Word Spacing – Determines social tendencies and cognitive organization.

Pen Pressure – Indicates determination and emotional intensity.

Stroke Shape & Size – Reflects confidence, precision, and openness.

2. Statistical Features:

Baseline Consistency – Examines alignment and steadiness.

Aspect Ratio – Width-to-height ratio of individual characters.

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Loop Formation – Identifies loops in letters like 'g', 'y', and 'l', which reflect openness.

3. Graphological Features:

Curvature Analysis – Measures smoothness and uniformity of handwriting strokes.

Stroke Direction – Determines writing rhythm and flow.

These features are numerically encoded into a structured dataset for machine learning.

E. Feature Representation & Dimensionality Reduction

The extracted features are stored in vector form, allowing numerical representation for machine learning. To optimize processing, Principal Component Analysis (PCA) is used to reduce feature dimensions while preserving essential traits.

F. Model Training Using Support Vector Machines (SVM)

The preprocessed dataset is split into 80% training and 20% testing sets. The SVM algorithm is used for classification due to its effectiveness in high-dimensional feature spaces.

1. SVM Model Configuration

Kernel Function: Radial Basis Function (RBF) for non-linear classification.

Regularization Parameter (C): Adjusted for optimal margin width.

Gamma (γ) Parameter: Tuned for feature scaling and model accuracy.

2. Training Process

The feature dataset is input into the SVM classifier.

The model learns patterns between handwriting features and personality traits.

Hyperparameter tuning is performed using Grid Search Cross-Validation.

G. Model Evaluation & Performance Metrics

To ensure reliability, the model undergoes rigorous testing using:

Accuracy Calculation – Measures correctly classified personality traits.

Precision & Recall Analysis – Evaluates reliability across different personality categories.

F1-Score – Ensures a balanced evaluation between precision and recall.

III. SYSTEM ARCHITECTURE

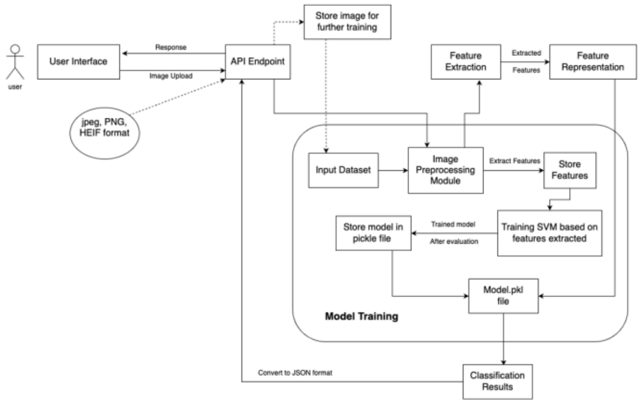

Figure 1: Proposed Architecture diagram

1. Image Processing Module

Image Acquisition

When an image is uploaded through the React frontend, it is sent to the backend API. The API triggers the

image processing module to prepare the image for analysis.

Format Validation: The module first validates that the uploaded file is in an acceptable format (e.g., JPEG, PNG) and size. If the image doesn't meet these criteria, the system flags it requests the user to upload a suitable file.

Resizing

Process: Images are resized to a predetermined width and height (e.g., 840x840 pixels), ensuring that the model can handle each image uniformly. Resizing helps standardize images for efficient processing, as large variations in image dimensions can reduce the accuracy of feature extraction.

Grayscale Conversion

The module converts the image to grayscale, reducing it to a single intensity channel. This step is crucial

because color information is typically irrelevant in handwriting analysis. Grayscale images allow the model to focus on the texture, shape, and contrast of strokes without additional processing overhead.

Noise Reduction and Binarization

Noise Reduction: Techniques like Gaussian blurring are applied to smooth out minor inconsistencies, such as paper texture or background blemishes.

Binarization: The module uses a thresholding algorithm (such as Otsu's thresholding) to convert the grayscale image into a binary (black-and-white) format. This approach distinguishes handwriting strokes from the background, making it easier for the model to detect handwriting features like letter spacing and pen pressure.

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Feature Extraction Preparation

Edge Detection: Detects edges within the handwriting strokes, which assists in measuring features like letter size and baseline alignment.

Stroke Thickness Analysis: This step assesses pen pressure by analyzing stroke thickness variations across the writing.

Output: These processed images, now with enhanced edge clarity and consistency, are ready for feature extraction. They serve as input to the machine learning model, which evaluates the seven targeted handwriting traits.

Error Handling

If any step of the processing fails, the system captures the error, logs it, and returns a clear message to the frontend. For instance, if noise reduction produces an insufficiently clear image, the module may reprocess the image with adjusted settings or request a new upload from the user.

2. Model for Personality Prediction

Feature Extraction: For handwriting analysis, we use SVM to classify based on extracted features such as baseline angle, top margin, letter size, line spacing, word spacing, pen pressure, and slant angle.

Model Architecture: The model, trained with labeled data, outputs a prediction for each trait. Each prediction level corresponds to a personality trait intensity.

Storage: Performance metrics and model parameters are stored in a pickle file to allow for easy loading and analysis.

3. API Layer

API Endpoints:

Image Upload Endpoint: Accepts an image file, initiates the preprocessing steps, and passes it to the model.

Prediction Endpoint: Receives the processed image, runs predictions through the model, and returns personality trait scores in JSON format.

Metrics Retrieval Endpoint: Serves model performance metrics (accuracy, precision, recall) for frontend display, sourced from a stored pickle file.

Error Handling: Implements CORS headers to resolve cross-origin requests between the frontend and backend, ensuring smooth communication across platforms.

4. Frontend Interface

Objective: Provides a user-friendly interface for uploading images and viewing predicted personality traits and model metrics.

User Flow:

Image Upload: Users upload an image via a React component, which triggers a call to the image upload API.

Prediction Display: Upon receiving JSON predictions, the frontend displays the trait levels in a clear and visually appealing format.(e.g. In Radar Chart)

Metrics Visualization: The React app retrieves model performance metrics via API and visualizes these using charting libraries, providing users insight into model reliability.

Design Considerations:

Implements error messages for invalid uploads and provides feedback on the processing status. Responsive design ensures accessibility across devices, allowing users to interact with the app seamlessly.

IV. Implementation Details

The implementation of the handwriting-based personality prediction system involved a combination of computer vision techniques, machine learning algorithms, and a robust software stack to create a scalable and effective solution. This section delves into the technical aspects of the project, covering the software stack, data preparation, model training configuration, and deployment strategies.

A. Technical Stack

To build a comprehensive system capable of automated handwriting analysis, a blend of frontend and backend technologies was used:

Programming Languages: The core system was implemented in Python for its rich ecosystem of data processing and machine learning libraries. The front end was built with JavaScript using React to create an interactive and responsive user interface.

Libraries and Frameworks:

OpenCV: Utilized for image preprocessing tasks such as resizing, grayscale conversion, noise reduction, and binarization.

scikit-learn: Chosen for implementing Support Vector Machines (SVMs) to train and evaluate the personality prediction model.

NumPy and Pandas: Used for numerical computations and data manipulation during feature extraction and model training.

Flask: Employed as the backend framework to create RESTful API endpoints for handling data communication between the front end and the machine learning model.

Chart.js or Recharts: Integrated into the front end for visualizing model performance metrics such as accuracy and precision.

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B. Data Preparation

The dataset used for training the model consisted of handwriting samples collected from individuals, each annotated with personality labels based on psychological assessments. The data preparation phase included:

Data Acquisition: Handwriting samples were digitized and stored in a suitable format (e.g., PNG or JPEG).

Data Cleaning: Ensured that the dataset was free from corrupted or low-quality images that could skew the model's learning.

Annotation: Each handwriting sample was labeled according to the target personality traits (e.g., emotional stability, and mental energy).

Data Augmentation: Techniques such as rotation, scaling, and flipping were applied to expand the dataset artificially, enhancing the model's ability to generalize.

C. Training Configuration

The training of the model was conducted using an ensemble of eight Support Vector Machines (SVMs), each dedicated to predicting one of the eight personality traits. Key aspects of the training process included:

Feature Scaling: Input features, including letter size, slant, baseline, pen pressure, spacing, and top margin, were standardized to ensure uniform influence during training.

Kernel Selection: The radial basis function (RBF) kernel was selected for the SVMs due to its ability to handle non-linear relationships effectively.

Hyperparameter Tuning: Grid search cross-validation was employed to find the optimal hyperparameters (e.g., C and gamma values) that maximized model accuracy.

Validation Strategy: A 10-fold cross-validation method was used to ensure robust model performance and reduce the risk of overfitting. The training dataset was split into training and validation sets in a 90-10 ratio to fine-tune the model and evaluate its generalizability.

D. Feature Extraction Implementation

The feature extraction module was critical for converting preprocessed handwriting images into structured data for model input. Each image underwent the following extraction procedures:

Letter Size Calculation: Determined by analyzing the average height and width of individual characters.

Slant Analysis: Measured by detecting the angle of strokes relative to the vertical axis.

Baseline Detection: Identified by mapping the horizontal alignment of writing across the sample.

Pen Pressure Analysis: Evaluated using pixel density to estimate the force applied during writing.

Spacing Features: Calculated as the average distance between letters and words to infer spacing habits.

Top Margin Measurement: Quantified by analyzing the space between the top edge of the text and the top of the page.

These features were stored in JSON format for consistency and ease of processing by the backend.

E. API Development and Integration

The backend API, built with Flask or Django, played a pivotal role in facilitating communication between the frontend and the model. The API was structured with the following endpoints:

/upload-image: Accepted image uploads from the front end and initiated preprocessing and feature extraction.

/predict-traits: Processed the extracted features through the trained SVM ensemble and returned personality predictions in a JSON response format.

/get-metrics: Provided the frontend with stored model performance metrics, allowing users to view the system's reliability.

F. Deployment Strategy

The system was deployed on a local server or cloud platform to ensure seamless access. The deployment process included:

Containerization: Used Docker to package the application and its dependencies for consistent operation across different environments.

Cloud Hosting: Options such as AWS or Heroku were considered for remote deployment to enhance scalability

Security Measures: Implemented CORS policies and secure data handling practices to protect user data and maintain privacy.

This structured and detailed implementation laid the foundation for a reliable and scalable handwriting-based personality prediction system that can be extended and adapted for future needs.

V. RESULTS AND EVALUATION

Emotional Stability had 90.2% accuracy but struggled with class imbalances, while Mental Energy or WillPower and Personal Harmony performed well with accuracies around 80-93%. Modesty achieved 98.5% accuracy, though smaller classes affected recall and precision. Lack of Discipline had lower performance at 86.3%, but Poor Concentration and Non-Communicativeness excelled with near-perfect accuracies (99.8% and 99.1%). Social

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Isolation also performed well with 98.3% accuracy. Overall, class imbalance affects performance, especially in smaller categories.

Figure 2: Output

Personality Trait	Accuracy	F1 Score	Recall	Precision
Emotional Stability	0.9021	0.86	0.90	0.83
Modesty	0.8043	0.80	0.80	0.80
Lack of Discipline	0.9848	0.98	0.98	0.97
Poor Concentration	0.9304	0.93	0.93	0.93
Non-communicativeness	0.8630	0.80	0.86	0.74
Social Isolation	0.9978	1.00	1.00	1.00

Table 1: Performance Metrics Results

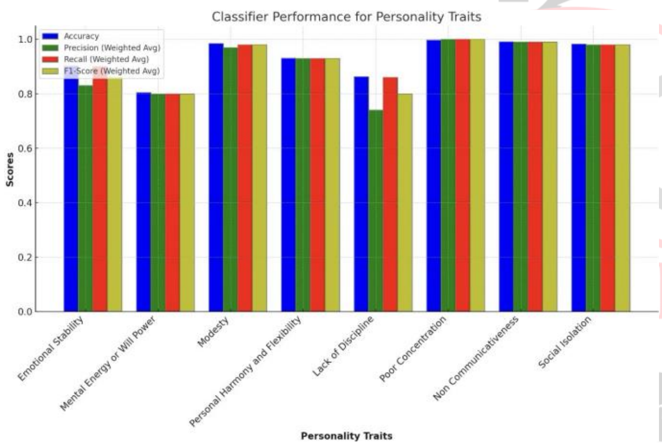

Figure 3: Classifier Performance for Personality Traits

VI. Future Scope

There is a lot of room for improvement and wider use of this handwriting-based personality prediction system. By adding more handwriting characteristics, future research could broaden the scope of personality traits examined and produce a more comprehensive personality profile. The method would be more useful in a variety of cultural contexts if it could be made to accommodate multilingual handwriting. Furthermore, real-time personality tests might be possible with the system optimized for mobile devices, improving user accessibility and convenience. Reliability and privacy will also be ensured by bolstering data security procedures and improving user input through interactive visualizations. Finally, tailoring the system for uses in domains like hiring and mental health may yield focused insights, making it a useful instrument for a range of sector.

VII. Conclusion

The paper aimed to develop a machine learning-based system for predicting personality traits through handwriting analysis. Utilizing support vector machines (SVMs), the system analyzed handwriting samples and extracted relevant features to classify individuals across eight personality traits. These traits include emotional stability, willpower, modesty, personal harmony and flexibility, lack of discipline, poor concentration power, non-communicativeness, and social isolation. By integrating handwriting analysis with advanced machine learning algorithms, the system offers applications in psychological assessment, counseling, recruitment, education, forensic analysis, and personal development. The paper successfully addressed the need for automated and objective personality assessment methods, contributing to advancements in understanding human behavior and facilitating tailored interventions to enhance individual well- being.

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