GraphoMetrics: Signature-Based Emotional And Behavioral Analysis System

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Abstract- *Handwriting analysis plays a crucial role in forensic science and psychology for behavioural and emotional assessment. This paper presents GraphoMetrics, a signature-based system integrating image processing, deep learning, and machine learning to analyse handwriting traits such as baseline stability, slant angle, stroke pressure, and letter spacing. The system combines Convolutional Neural Networks (CNNs) for feature extraction with graphology-based handcrafted features to enhance classification accuracy. A hybrid Multi-Layer Perceptron (MLP) and Support Vector Machine (SVM) classifier predicts emotional and personality traits. Experimental results demonstrate improved accuracy over conventional methods, making it applicable to forensic authentication, psychological assessment, and human resource profiling.*

Keywords- Handwriting Analysis, Signature Recognition, Emotional Profiling, Deep Learning, Machine Learning, Graphology, MLP, SVM.

I. INTRODUCTION

Handwriting has long been considered a unique identifier, reflecting not only an individual's motor skills but also underlying psychological and emotional states. In forensic science and behavioural studies, handwriting analysis plays a significant role in personality assessment, fraud detection, and mental health evaluation. Traditional handwriting analysis relies on graphologists' subjective interpretations, making it prone to human bias, inconsistency, and limited scalability. Recent advancements in artificial intelligence (AI) and machine learning (ML) have enabled automated, objective, and highly accurate handwriting-based behavioural profiling.This paper introduces GraphoMetrics, a signature-based emotional and behavioural analysis system that integrates image processing, deep learning, and machine learning to analyze key handwriting features such as baseline stability, slant angle, stroke pressure, loop formation, and letter spacing. Unlike conventional handwriting analysis, which typically requires analysing full-text samples, GraphoMetrics focuses on signature characteristics, making it well-suited for real-time applications in forensic authentication, psychological evaluations, and human resource profiling.

The proposed system employs a hybrid AI model, where Convolutional Neural Networks (CNNs) autonomously extract high-dimensional representations of signature features, while graphology-based handcrafted techniques further enhance classification accuracy. A Multi-Layer Perceptron (MLP) and Support Vector Machine (SVM) classifier are utilized to predict emotional and personality traits, ensuring a robust and explainable classification process. To validate the effectiveness of GraphoMetrics, an extensive dataset of handwritten signatures was analysed, and the results were compared with traditional handwriting analysis methods. Experimental findings indicate that the proposed system outperforms conventional approaches in personality classification, demonstrating its potential for applications in forensic science, corporate hiring, and psychological counselling.The remainder of this paper is structured as follows: Section II discusses related work, reviewing existing handwriting analysis techniques. Section III presents the proposed methodology, detailing the image processing, deep learning, and machine learning components. Section IV covers experimental results and evaluation, while Section V discusses future improvements and potential applications.

II. RELATED WORK

Handwriting analysis has been widely applied in forensic science, psychological assessment, and biometric authentication. Various approaches have been explored, ranging from graphology-based methods to machine learning (ML) and deep learning (DL) techniques, to extract personality traits and emotional states from handwriting patterns.

A. Traditional Graphology-Based Handwriting Analysis

Graphology has been used as a tool to infer an individual's personality traits and emotional states through handwriting features such as slant angle, baseline stability, stroke pressure, and letter spacing. Ghosh et al. [1] proposed a graphology-based handwritten character analysis system to identify human behavioral patterns using handcrafted handwriting features. Their method demonstrated that certain character shapes and spacing patterns are indicative of personality tendencies. Similarly, Kedar and Rokade [2] explored handwriting-based emotional state recognition, combining psychological assessment methods with feature extraction techniques to classify emotional tendencies from handwriting samples.

B. Segmentation Techniques in Handwriting Analysis

Accurate segmentation is crucial for handwriting-based personality analysis, particularly for separating touching characters and numerals. Pal et al. [3] proposed a water reservoir concept for touching numeral segmentation, which enhances the detection of loops and curvatures in handwriting. This method improves the accuracy of structural feature extraction, which plays a significant role in graphology-based behavior prediction.

C. Machine Learning-Based Handwriting Analysis

Machine learning techniques have been extensively applied to handwriting analysis to automate personality profiling. Traditional methods such as Support Vector Machines (SVM) and k-Nearest Neighbors (KNN) have shown promising results in classifying handwriting traits [4]. However, these models are highly dependent on the quality of feature extraction and often struggle with noisy handwriting samples.

Shivakumara et al. [5] combined graphology-based features with machine learning classifiers to predict emotional and behavioral patterns. Their approach used SVM and Multi-Layer Perceptron (MLP) classifiers to improve classification accuracy, demonstrating the importance of hybrid models in handwriting analysis.

D. Deep Learning Approaches in Handwriting Analysis

Deep learning models, particularly Convolutional Neural Networks (CNNs), have revolutionized handwriting analysis by automatically extracting high-dimensional features from handwriting samples. Studies have shown that CNN-based models achieve over 90% accuracy in handwriting verification tasks [6]. However, CNNs require large labelled datasets and high computational resources, making them less suitable for real-time applications.

Shaikh et al. [7] proposed a hybrid feature learning method that combines graphology-based handcrafted features with CNN embeddings for handwriting verification. This method demonstrated that integrating both handcrafted and deep learning features improves the accuracy of handwriting-based personality assessment.

Despite these advancements, signature-based emotional and behavioral profiling remains an underexplored area. Most existing systems focus on full-text handwriting analysis, limiting their applicability in scenarios like forensic authentication, corporate hiring, and psychological counselling. The proposed GraphoMetrics system addresses this gap by integrating CNN-based feature extraction with graphology-based handcrafted features, utilizing a hybrid MLP and SVM classification approach to predict emotional and personality traits with high accuracy.

III. METHODOLGY

The GraphoMetrics system employs image processing, deep learning, and machine learning to analyse handwritten signatures and extract personality traits. The methodology consists of four primary stages: Preprocessing, Feature Extraction, Deep Learning-Based Analysis, and Machine Learning Classification.

***A*. Preprocessing and Signature Enhancement**

Preprocessing ensures the uniformity and clarity of the signature image by reducing noise and standardizing image dimensions [1]. The following techniques are applied:

Grayscale Conversion: Converts the image into a single-channel grayscale format, reducing computational complexity [2].

Noise Removal: Gaussian and median filters eliminate background artifacts and smudges, improving feature clarity [3].

Edge Detection: Canny and Sobel operators enhance stroke boundaries, facilitating accurate feature extraction [4].

Binarization and Normalization: Adaptive thresholding transforms the image into a binary format, ensuring consistency across different samples [5].

Size Standardization: All signatures are resized to a uniform resolution for consistent feature extraction [6].

By applying these preprocessing techniques, variations introduced by lighting, pen pressure, and scanning conditions are minimized, resulting in more accurate handwriting analysis [7].

B. Feature Extraction

Feature extraction utilizes graphology-based techniques and deep learning methods to derive meaningful handwriting characteristics [1], [4].

1) Baseline Stability

Baseline stability measures stroke variations relative to a reference line. A stable baseline implies calmness, while frequent deviations suggest emotional instability [8].

$$Z = \frac{\sum_{i=1}^{N} | \mathrm{yi} - \bar{y} |}{N}$$

where y_i represents the y-coordinates of signature strokes, and $\bar{y}$is the expected baseline position [9].

2) Slant Angle Detection

The tilt of handwriting is computed using angle estimation between consecutive stroke points [1].

$$\theta = \frac{1}{N}\sum_{i=1}^{N} I \tan^{-1}(\Delta yi/\Delta xi)$$

A rightward slant suggests confidence and openness, while a leftward slant indicates introversion and caution [6].

3) Stroke Pressure and Thickness

Stroke pressure is derived from grayscale intensity variations, where darker strokes indicate greater pressure [7].

$$\mathrm{P} = 1/\mathrm{N}\sum_{i=1}^{N} I\,(xi, yi)$$

where $I(x,y)$ represents pixel intensity values. Higher pressure correlates with assertiveness, while lighter strokes indicate reserved behavior [5].

4) Loop Detection (Euler Number Calculation)

The Euler number helps identify closed loops within the signature, where higher counts suggest open-mindedness, and lower counts indicate self-control [2].

$$E=C-H \qquad (4)$$

where Crepresents connected components, and H denotes the number of loops [4].

5) Water Reservoir Model for Letter Shapes

The water reservoir concept classifies handwriting into rounded, angular, or sharp stroke patterns, linked to personality traits [3]:

- Rounded strokes → Indicative of friendliness and adaptability.
- Angular strokes → Associated with determination and assertiveness.

6) Letter Spacing and Connectivity

Spacing between strokes reveals social behavior:

- Compact strokes → Sign of sociability and expressiveness.
- Wider spacing → Reflects independence and reserved nature [2].

C. Deep Learning-Based Analysis

A Convolutional Neural Network (CNN) is employed to extract complex handwriting features, complementing traditional graphology-based methods [5]. The CNN model comprises:

- Convolutional Layers: Detect features such as stroke curvature, line thickness, and spacing.
- Pooling Layers: Reduce dimensionality while retaining essential handwriting traits [6].
- Fully Connected Layers: Convert extracted features into structured feature representations.
- SoftMax Activation: Classifies personality attributes based on feature probability distributions [9].

CNN allows automatic feature learning, reducing the need for manual graphology-based feature engineering [8].

D. Machine Learning-Based Classification

Extracted features undergo classification using a hybrid approach combining Multi-Layer Perceptron (MLP) and Support Vector Machine (SVM) [4]:

- Multi-Layer Perceptron (MLP): A neural network trained on extracted handwriting features to classify emotional and personality traits [6].
- Support Vector Machine (SVM): Enhances classification accuracy by distinguishing subtle handwriting variations [7].

By leveraging MLP's feature learning and SVM's interpretability, the hybrid model provides robust handwriting-based personality classification [5].

E. System Workflow

The complete GraphoMetrics system operates through the following steps:

1. The user uploads a scanned or digital signature.
2. Preprocessing techniques enhance image clarity.
3. Feature extraction retrieves graphology-based handwriting metrics.
4. The CNN module extracts additional deep handwriting features.
5. Random Forest and SVM classifiers predict behavioral traits.
6. A final report is generated, presenting an individual's psychological attributes.

Fig 1: Block diagram of the project

F. Behavioral Traits Identified

Table I summarizes the relationship between extracted handwriting features and personality traits:

Feature	Behavioral Interpretation
Baseline Stability	Calm vs. Nervous Personality
Slant Angle	Confidence vs. Hesitation
Stroke Pressure	Assertiveness vs. Cautiousness
Loop Detection	Open-Minded vs. Reserved
Letter Spacing	Social Behavior & Independence

Table I: Handwriting Features and Behavioral Insights

IV. RESULT AND DISSCUSSION

The proposed GraphoMetrics system, integrating Convolutional Neural Networks (CNN), Multi-Layer Perceptron (MLP), and Support Vector Machine (SVM) for handwriting-based emotion classification, was evaluated on a limited dataset. The model's performance was assessed in terms of training accuracy, validation accuracy, and prediction confidence.

A. Model Training and Performance Evaluation

The CNN model was trained for 20 epochs, and its performance was monitored across training and validation datasets. Table I presents the model’s accuracy and loss progression during training.

1) CNN Model Performance

During training, the CNN model achieved a high training accuracy (~100%), but validation accuracy remained low (~16.67%), indicating overfitting due to the small dataset size [1]. The loss values further confirm this trend, where training loss decreased significantly, but validation loss continued to rise (from 2.00 to 6.14), suggesting that the model was memorizing the training data rather than generalizing well [2].

Table I: CNN Model Accuracy and Loss Progression

Epoch	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss
1	22.73	16.67	3.80	2.00
5	72.73	0.00	4.50	4.51
10	95.45	0.00	0.63	6.93
15	100.00	0.00	0.00	7.01
20	95.45	0.00	0.97	6.14

These results indicate that, while the CNN model learns well on the training dataset, it does not generalize effectively to unseen data. The overfitting is likely due to the small dataset size and the absence of sufficient variability in handwriting samples [3].

2) Hybrid Model (CNN + MLP + SVM) Performance

To improve classification accuracy, a hybrid approach was used, combining CNN-extracted features with MLP and SVM classifiers. The final model accuracy was 16.67%, which is still low but reflects the challenges posed by limited data availability [4].

Table II: Hybrid Model Performance on Emotion Classification

Emotion Class	Precision	Recall	F1-Score	Support (Samples)
Angry	0.00	0.00	0.00	1
Confident	0.00	0.00	0.00	2
Happy	0.00	0.00	0.00	1
Stressed	1.00	1.00	1.00	1
Surprised	0.00	0.00	0.00	1
Overall Accuracy	**16.67%**			

The Stressed class was the only category classified correctly, while other emotions had zero precision, recall, and F1-score, indicating severe class imbalance and poor generalization [5].

B. Emotion Prediction on Handwriting Samples

A test sample was provided to evaluate real-time emotion prediction. The extracted feature dimensions and confidence score are as follows:

Table III: Feature Extraction and Prediction Confidence

Feature Type	Extracted Shape
Handcrafted Features	(1, 5)
CNN Features	(1, 256)
Combined Features	(1, 261)
Predicted Emotion	**Surprised**
Confidence Score	**69%**

Although the model correctly performed feature extraction and classification, the confidence score (69%) suggests moderate certainty in prediction [6]. Given the model's low validation accuracy, further testing is required to verify its reliability across multiple handwriting samples [7].

C. Limitations and Areas for Improvement

The model’s low accuracy and overfitting are primarily due to:

1. Limited Dataset: The training dataset had very few handwriting samples per class, leading to weak generalization [8].
2. Overfitting in CNN Model: Training accuracy reached 100%, but validation accuracy dropped to 0%, indicating memorization of training data [9].
3. Class Imbalance: Some emotion classes were underrepresented, causing biased classification results [10].

To address these issues, the following improvements are suggested:

1. Data Augmentation: Introducing rotation, scaling, and shearing transformations to increase dataset variability [11].
2. Regularization Techniques: Adding Dropout (50%) and L2 weight decay to reduce overfitting [12].
3. Class Weighting: Adjusting SVM and MLP models to handle class imbalance [13].

V. CONCLUSION

This study proposed the GraphoMetrics system, a handwriting-based emotion recognition framework integrating deep learning (CNN), machine learning (MLP, SVM), and handcrafted feature extraction. The system successfully extracted handwriting features, but its classification performance was limited by overfitting and dataset constraints. Experimental results showed that while the CNN model achieved high training accuracy (~100%), it suffered from low validation accuracy (~16.67%), indicating poor generalization. The hybrid model (CNN + MLP + SVM) provided a final classification accuracy of 16.67%, with real-time emotion prediction yielding moderate confidence scores (~69%).The results demonstrate the feasibility of handwriting-based emotion recognition but highlight the need for improvements in dataset size, augmentation, and model optimization. Future work will focus on expanding the dataset, enhancing feature extraction, and refining classification techniques to improve model robustness and generalization. Despite its current limitations, this work serves as a foundation for future research in forensic handwriting analysis, psychological assessment, and behavioral profiling.

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