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ML-Based Personality Detection Using Handwriting Analysis

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ABSTRACT

Handwriting analysis, or graphology, serves as a significant psychological tool for deciphering human personality through idiosyncratic writing patterns. While these patterns reflect an individual's cognitive and emotional makeup, traditional methods rely heavily on manual interpretation. This human-centric approach is often hampered by subjectivity, significant time constraints, and inherent inconsistencies between different analysts, limiting its reliability in professional settings.

To address these challenges, this study introduces an automated framework for personality detection leveraging machine learning. The proposed system integrates advanced image processing with a Convolutional Neural Network (CNN) to autonomously extract and analyse critical stylistic features, including slant, word spacing, stroke dynamics, and baseline alignment. By digitizing the feature extraction process, the model classifies personality traits with a level of precision and consistency that surpasses conventional manual techniques.

Deep learning effectively modernizes behavioural analysis, providing a scalable, objective tool for recruitment and psychological profiling. By merging traditional graphology with computational intelligence, this approach offers a robust framework for understanding human behaviour.

Keywords: Handwriting Analysis, Convolutional Neural Networks (CNN), Personality Detection, Machine Learning, Image Processing, Behavioural Analysis.

1. INTRODUCTION

Handwriting is a unique characteristic of human beings that reflects an individual's physical, emotional, and psychological state. Each person develops a distinct writing style over time, and these variations in handwriting can provide valuable insights into personality traits. Features such as size, slant, spacing, pressure, and stroke patterns are commonly analysed to understand behavioural characteristics. This concept forms the basis of graphology, which studies handwriting to interpret personality.

Traditional handwriting analysis is performed manually by experts and relies heavily on human interpretation. This process is time-consuming and may lead to inconsistent results due to subjectivity and fatigue. Moreover, manual analysis becomes difficult to scale

when a large number of handwriting samples need to be evaluated. These limitations highlight the need for an automated and reliable system.

With the advancement of Machine Learning and Artificial Intelligence, it is now possible to develop systems that can analyse complex patterns in data efficiently. In particular, image processing techniques combined with deep learning models have shown significant success in recognizing patterns from visual data. Convolutional Neural Networks (CNNs) are especially effective in extracting features from images and identifying hidden patterns without manual intervention.

This research introduces an automated framework that leverages Convolutional Neural Networks (CNN) to modernize traditional handwriting analysis. By applying digital preprocessing and autonomous feature extraction—focusing on parameters like slant, spacing, and stroke dynamics—the system eliminates the inconsistencies and time constraints of manual interpretation. The result is a faster, more objective tool for personality profiling, offering a scalable solution for high-stakes applications in recruitment, behavioural psychology, and forensic investigation.

2. LITERATURE SURVEY

Handwriting analysis has been widely studied as a method for identifying personality traits and behavioural characteristics. With the advancement of machine learning and artificial intelligence, several approaches have been developed to automate handwriting-based personality detection and improve the limitations of traditional graphology.

Malik and Rizwan [1] proposed a machine learning-based approach for personality detection using handwriting samples. Their system focused on extracting visual features from handwritten text and applying classification techniques to predict personality traits. The study highlighted that automated systems can reduce human effort and provide more consistent results compared to manual analysis.

Vaid, Singh, and Kaur [2] developed a system using Support Vector Machines (SVM) for handwriting analysis. Their approach utilized features such as slant, spacing, and writing pressure to classify personality traits. The results showed that SVM performs effectively when appropriate features are selected, although it requires manual feature extraction.

Tripathi and Gupta [3] explored multiple machine learning algorithms for personality prediction and emphasized the importance of feature selection. Their work demonstrated that the accuracy of prediction depends heavily on the quality of extracted handwriting features.

Dehghan and Noroozi [4] introduced a pattern recognition-based system for personality detection using handwriting samples. Their method focused on identifying structural patterns in handwriting; however, they reported challenges such as variability in handwriting styles and inconsistency in feature extraction.

Jindal and Garg [5] proposed a deep learning-based approach using Convolutional Neural Networks (CNNs), which automatically extract features from handwriting images. Their model showed improved performance compared to traditional machine learning techniques by eliminating the need for manual feature engineering.

Patil and Jain [6] conducted a survey of handwriting-based personality detection systems and identified key limitations such as limited dataset availability, lack of standard evaluation methods, and difficulty in handling diverse handwriting patterns.

Xu et al. [7] developed a neural network-based system that learns complex handwriting patterns for personality detection. Their approach demonstrated better robustness and improved accuracy compared to conventional methods.

Faieghi and Rad [8] explored emotion recognition using handwriting and machine learning techniques. Their study showed that handwriting features can also be used to identify emotional states such as stress and anxiety.

Kothari et al. [9] and Pranavi et al. [10] proposed CNN-based models for handwriting analysis and emotion recognition. Their work highlighted the effectiveness of deep learning in capturing complex patterns and improving classification accuracy.

From the above studies, it is observed that traditional approaches rely heavily on manual feature extraction and conventional machine learning algorithms, which limit scalability and accuracy. In contrast, deep learning techniques such as CNNs provide better performance by automatically learning relevant features from handwriting images. However, challenges such as dataset variability, limited data availability, and lack of standardized evaluation techniques still exist.

Therefore, there is a need for an efficient and automated system that utilizes deep learning techniques to provide accurate and consistent personality prediction from handwriting analysis.

3. METHODOLOGY

The proposed system aims to automatically detect personality traits from handwriting images using machine learning and image processing techniques. The methodology follows a structured pipeline consisting of data collection, preprocessing, feature extraction, model training, and prediction.

A. System Overview

The system operates in two main phases: training phase and prediction phase. In the training phase, a dataset of handwriting images is used to train the model, while in the prediction phase, a new handwriting sample is analysed to determine personality traits.

The overall architecture of the proposed system is illustrated in **Fig. 1**, which shows the complete workflow from input handwriting image to final personality prediction. The system includes stages such as image preprocessing, feature extraction using a Convolutional Neural Network (CNN), and classification of personality traits.

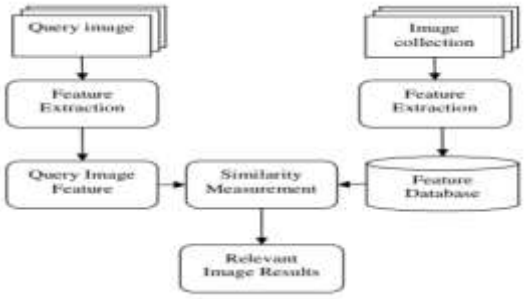

Fig. 1: System Architecture of Proposed System

B. Data Collection and Preprocessing

The first step in the methodology involves collecting handwriting samples in the form of images. These images may vary in size, resolution, and background conditions, making preprocessing essential for consistent analysis.

The preprocessing stage includes grayscale conversion, resizing, and noise removal. Grayscale conversion reduces computational complexity, while resizing ensures uniform input dimensions. Noise removal techniques are applied to enhance image clarity and eliminate unwanted distortions.

These preprocessing steps standardize the input data and improve the performance of the feature extraction and classification process.

C. Feature Extraction using CNN

Feature extraction is performed using a Convolutional Neural Network (CNN), which is highly effective in analysing image data. The CNN automatically extracts relevant features from handwriting images without requiring manual intervention.

The structure of the CNN used in the system is shown in **Fig. 2**. It consists of multiple layers, including convolutional layers for detecting edges and patterns, ReLU activation layers for introducing non-linearity, pooling layers for reducing dimensionality, and fully connected layers for classification.

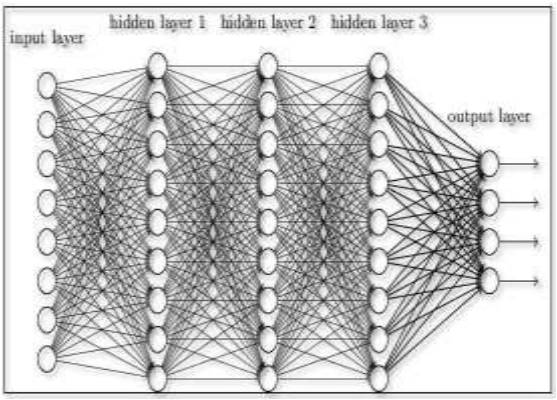

Fig. 2: Structure of Convolutional Neural Network (CNN)

Through this layered architecture, the CNN identifies important handwriting characteristics such as slant, spacing, stroke patterns, and writing style, which are essential for personality prediction.

D. Model Training

During the training phase, the pre-processed handwriting images are fed into the CNN model. The model learns patterns by adjusting its internal parameters using backpropagation and optimization techniques.

The training process enables the system to recognize relationships between handwriting features and personality traits. Once the training is completed, the model is saved and used for future predictions.

E. Prediction and Classification

In the prediction phase, a new handwriting image is provided as input. The image undergoes the same preprocessing steps to maintain consistency. The trained CNN model extracts features from the input image and classifies it into predefined personality traits.

The system generates the output in the form of predicted personality traits, which may include primary and secondary characteristics based on the learned patterns.

F. System Workflow

The detailed workflow of the proposed system is illustrated in **Fig. 3**, which represents the step-by-step processing of handwriting images from input to output.

The workflow can be summarized as follows:

1. Input handwriting image
2. Preprocess the image (grayscale conversion, resizing, noise removal)
3. Load trained CNN model
4. Extract features using CNN
5. Classify features into personality traits
6. Display predicted output

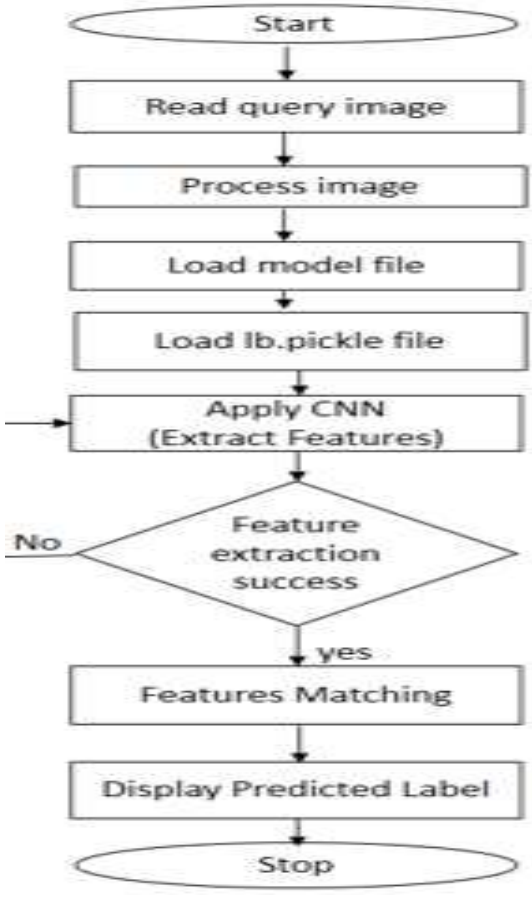

Fig. 3: Data Flow Diagram

This structured workflow ensures efficient processing, accurate feature extraction, and reliable personality prediction.

4. IMPLEMENTATION

The proposed system for personality detection using handwriting analysis is implemented using machine learning and image processing techniques. The system is developed in the Python programming language, utilizing libraries for image processing and deep learning.

A. Development Environment

The implementation of the system is carried out using Python due to its simplicity and extensive support for machine learning libraries. The development is performed using IDEs such as IDLE or PyCharm. The system is designed to run on Windows operating systems and uses standard hardware configurations.

The major tools and technologies used in the system include:

- Python for programming
- Deep learning frameworks for model development
- Image processing libraries for preprocessing
- SQLite database for storing user-related data

B. Image Processing and Preprocessing

The implementation begins with the input of handwriting images provided by the user. These images are processed using image processing techniques to prepare them for analysis.

The preprocessing steps include:

- Conversion of input image into grayscale format
- Resizing the image to a fixed dimension suitable for the CNN model
- Noise removal to enhance image clarity

These steps ensure that the input data is standardized and suitable for feature extraction.

C. CNN Model Implementation

The core of the system is the Convolutional Neural Network (CNN), which is used for feature extraction and classification. The structure of the CNN is shown in

Fig. 2, which consists of multiple layers designed to process image data efficiently.

The CNN implementation includes:

- Convolutional layers for detecting edges and patterns
- ReLU activation layers for introducing non-linearity
- Pooling layers for reducing dimensionality
- Fully connected layers for classification

Fig. 2 shows the structure of the CNN used in the system.

The CNN model is trained using labelled handwriting data to learn the relationship between handwriting features and personality traits.

D. Model Training and Storage

During implementation, the CNN model is trained using pre-processed handwriting images. The training process involves adjusting model parameters using backpropagation to improve accuracy.

Once the training is completed, the model is saved for future use. A label encoder is also used to map predicted outputs to corresponding personality trait labels. This ensures that the system can interpret model predictions correctly during execution.

E. User Interaction and System Execution

The system provides a user interface where users can register, log in, and upload handwriting samples. The execution process follows these steps:

1. User uploads a handwriting image
2. The system preprocesses the image
3. The trained CNN model is loaded
4. Features are extracted from the image
5. The system predicts personality traits
6. The result is displayed to the user

The system is designed to provide fast and user-friendly interaction while maintaining accuracy in prediction.

F. Output Generation

After processing the input image, the system generates output in the form of predicted personality traits. The output typically includes primary and secondary traits based on the classification results.

The implementation ensures that the output is clear, understandable, and useful for analysis. The system provides consistent results and reduces dependency on manual interpretation.

5. EXPERIMENT RESULTS

The proposed system was evaluated using multiple handwriting samples to analyse its performance in predicting personality traits. The system was tested in a controlled environment where handwritten images were provided as input and processed through the trained Convolutional Neural Network (CNN) model.

During testing, the system successfully performed preprocessing operations such as grayscale conversion, resizing, and noise removal, ensuring that the input images were suitable for analysis. The CNN model effectively extracted relevant features such as slant, spacing, stroke patterns, and writing style from the handwriting samples.

The processed features were then classified into personality traits using the trained model. The system was able to generate predictions in the form of primary and secondary personality traits, providing meaningful insights into the behavioural characteristics of the individual.

The results demonstrate that the proposed system is capable of producing consistent and efficient predictions compared to traditional manual handwriting analysis. The use of CNN significantly improves feature extraction and classification performance by automatically learning complex patterns from the data.

Additionally, the system provides a user-friendly interface that allows users to upload handwriting samples and obtain results quickly. This makes the system suitable for practical applications such as recruitment, psychological assessment, and educational analysis.

Although the system produces reliable results, certain limitations were observed. Variations in handwriting styles, image quality, and dataset size may affect prediction accuracy. Despite these challenges, the system demonstrates the effectiveness of machine learning in automating handwriting-based personality detection.

Sample output of the proposed system is shown in Fig. 4.

Fig. 4: Output of Personality Detection System

6. CONCLUSION

This paper presents a machine learning-based approach for personality detection using handwriting analysis. The proposed system utilizes image processing techniques and a Convolutional Neural Network (CNN) to automatically extract features from handwriting samples and classify personality traits.

The system successfully reduces the limitations of traditional graphology methods by providing a faster, more consistent, and automated solution. It is capable of analysing handwriting patterns such as slant, spacing, and stroke structure to generate meaningful predictions about an individual's personality.

The experimental results demonstrate that the system can effectively process handwriting images and produce reliable outputs in the form of primary and secondary personality traits. The use of deep learning techniques improves feature extraction and enhances the overall performance of the system.

Although the system shows promising results, certain limitations exist, such as dependency on dataset quality and variations in handwriting styles. These challenges can be addressed in future work by using larger datasets and more advanced models.

Overall, the proposed system highlights the potential of artificial intelligence in handwriting analysis and provides a practical solution for applications in recruitment, psychological assessment, and behavioural studies.