AIRO JOURNALS
Peer Reviewed
Multidisciplinary
International

ISSN:2320-3714
Volume: 1 Issue: 3
March 2025
Impact Factor: 10.2
Subject: Computer Science

DEEP FEATURE EXTRACTION FROM SIGNATURES FOR BIG FIVE PERSONALITY TRAIT PREDICTION

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ABSTRACT

Handwritten signatures embody different informational characteristics that make them good markers for personality traits. The research work aims at predicting the Big Five personality traits of Neuroticism, Agreeableness, Extraversion, Conscientiousness, and Openness with the aid of the advanced deep learning techniques used for handwritten signature feature extraction. The public ally accessible dataset of pre-annotated signatures with personality labels is modelled for black and white conversion, Gaussian noise filtering, image normalization, and binarization to conduct more effective feature extraction. Convolutional Neural Networks (CNNs) learn the important features of a signature without human intervention; parameters such as stroke width, slant angle, pressure variation, and signature length are learned with ResNet and VGG architectures. Various machine learning models, including Support Vector Machines (SVM), Random Forest, and Deep Neural Networks (DNNs), are trained to classify traits after dimension reduction through Principal Component Analysis (PCA). DNNs yield the highest performance, with 90.1% classification accuracy, followed by Random Forest 86.7% and lastly SVM 84.2% respectively. It indicates that the complex relationships of the features of the signature can well be mined using deep learning algorithms. Statistical analyses have revealed considerably strong links between specific handwriting characteristics and personality traits. For instance, stroke width correlates positively with conscientiousness ($r=0.34$, $p<0.01$), but negatively with neuroticism and pressure variation ($r=-0.31$, $p<0.01$). These results might find uses in

Peer Reviewed Multidisciplinary International
ISSN:2320-3714
Volume: 1 Issue: 3
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psychological profiling, recruitment selections, or forensic investigations, hinting that cognizance with respect to signature qualities could serve as indicators of character type. The present study hence contributes to the literature in establishing the effectiveness of deep learning in ascribing personality from handwriting and showcases its real-world applicability.

Keywords: *Deep Feature, Extraction, Signatures, Big Five Personality, Trait Prediction, Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism*

1. INTRODUCTION

The signature is an example of behaviouralbiometrics and has unique properties whereby it can reveal important factsabout a person's personality. Recent work in this area involved applyingmachine learning and deep learning techniques to extract insights fromsignatures for fraud detection, personality analysis, and identityverification, among other things. The Big Five Personality TraitsOpenness, Conscientiousness, Extraversion, Agreeableness, and Neuroticismare a well-established psychological perspective on human behavior among a variety of personality theories. Deep feature extractiontechniques can help understand personality prediction by revealingsubtle and complex patterns from the dynamic developments and structureof signatures that correspond to specific personality traits.

Deep feature extraction achieves automatic learning in illustrations ofvery salient properties by using state-of-the-art neural networks suchas Convolutional Neural Networks (CNNs) and Autoencoders. Traditionalpersonality assessment methods rely on self-reports and psychometricquestionnaires, which are inherently experienced and subjective. Thisform of signature analysis represents a different, objective,non-intrusive, and scalable alternative to personality assessment. These methods make it possible to identify changes in signatures over time, space, and style, which can be useful markers of a person's personality. Some of the traits that allow for a thorough examination of the ways in which handwriting conveys personality are writing fluidity, curve, pen speed, and stroke pressure.

Effective feature selection techniques, neural network design resilience, and dataset quality and variability all affect how well deep feature extraction works for personality prediction. In order to translate inferred signature features into personality ratings, supervised learning algorithms can use large datasets of labelled signatures in which the participants were also psychometrically examined. Pre-trained deep models and transfer learning can also improve prediction performance by utilizing information from generic handwriting analysis tasks. In order to ensure that personality tests are data-driven and comprehensible, handcrafted and deep feature hybrid approaches can also enhance interpretability.

Personality prediction based on signatures has a wide range of applications in forensic science, security, psychology, and hiring. However, barriers like data privacy, ethics, and the requirement for appropriate, standardized measuring tools to improve its future use prevent it from reaching its full potential. Characteristics of personality prediction models that are available with enhanced deep learning and computer-based handwriting analysis include accuracy, currency, ease of use, and ease of implementation. These collaborations seek to improve feature extraction capabilities by incorporating multimodal data sources, such as handwriting pressure sensors and keystroke patterns.

These thus make it easier to analyze the personality traits linked to the signature analysis using other significant behavioural biometric markers for reliable models of personality evaluation that are applicable to different human populations. Artificial intelligence's evolutionary progress guarantees that studies on deep feature extraction of signatures will remain a thriving field with significant ramifications for Big Five Personality Trait prediction and relevant future study.

1.1.Research Objectives

- To investigate the relationship between signature features and the Big Five personality traits;
- To improve the accuracy of personality trait prediction by deep learning-based signature feature extraction.

2. REVIEW OF LITERATURE

Jaiswal, Sharma, and Yadav (2022)used deep feature extraction with convolutional autoencoders to identify document forgeries. The study in question aimed for its application of research to outline salient features governing the discernment between authentic and fraudulent documents from the photographic images of the surface thereof. Training on a reasonably large corpus of both genuine and manipulated papers provided enough reliability for their approach to discover deep learning techniques effective for distinguishing intricate

ISSN:2320-3714
Volume: 1 Issue: 3
March 2025
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differences that are too complex for spotting with classical methods. Their evaluation did further prove deep learning a viable substitute in document authentication by ascertaining the precision of convolutional autoencoders in identifying counterfeits.

Leghari et al. (2021)considered several feature fusion methods deep enough have been considered to allow their integration online with signatures to fingerprints for manifesting multimodal authentication. By deep characteristic extractions of any candidate, the architecture of a convolutional neural network improved the operations throughout the biometric security system. A test on public datasets indicated the work's authentication accuracy to be far superior compared with any single-mode system. In what they see as one critical advance in biometric communication, the authors showed that the use of various biometric signatures might enhance spoof resistance and thus the overall security concept.

Li et al. (2024)used to construct a thermogalvanic hydrogel electronic skin (E-skin) for biometric verification and self-sustainable signature recognition. The research work has utilized a recent technical platform that records dynamic signature data and uses deep learning to process it. The study provides evidence that E-skin technology can utilize motion patterns, writing pressure, and stroke dynamics to successfully identify individuals. The authors suggest that due to its flexibility and ability to respond to different users, it could find application in wearable technology and secure authentication. The authors have further enhanced their study by proposing the new way of altering biometric authenticators via employing high-precision energy-efficient solutions from hydrogel-based systems using deep learning.

Liu, Huang, Yin, and Chen (2021)determined a regional deep metric learning network has been established as appropriate for the offline signature evaluation. Its approach based on discrete regions, as opposed to exploiting the entire boundary of signatures, would greatly improve verification accuracy. The objectives adopted by the proposed modifications of deep metric learning allowed successful learning of subtle intra-class variations and differentiation between genuine and forged signatures. Their method gave better verification performances than their traditional counterparts when put to test on benchmark datasets of signatures. The results represented the reliability with which the region-based deep learning techniques could verify signatures.

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Moreno et al. (2021)conducted keen to establish if personality types could, in effect, be computable via linguistic text analysis, several researchers undertook a meta-study. Several studies were identified utilizing several approaches employing deep neural networks to do machine learning and natural language processing for extracting texts of certain personality traits. Their findings showed that, whereas computational systems were able to establish relationships between personality types and linguistic styles, the precision and reliability of predictions varied from study to study. Among the many significant issues raised were standard evaluation procedures, cultural bias, and brownie points about dataset size. The authors of the study conclude, however, that analyzing written language is yet another way to identify personality.

Nguyen et al. (2022)detailed description of a deep-learning-based method for prestress monitoring. The endeavour's primary objective is to develop a reliable structural health monitoring system for effective identification of damage in prestressed structures. Aiming for an efficient, less human-involved detection method for damage states, the feat described is a quick and effective automatic feature extraction altogether from impedance signals. The authors validated their model using actual experimental measuring techniques in support of the promptness and reliability of their method of detection of anomalies in structures. The study thus highlighted the potential of deep learning in enhancing the reliability and efficiency of structural health monitoring systems.

3. RESEARCH METHODOLOGY

3.1.Research Approach

Diagnosis follows beginning with Big Five personality types prediction from handwritten signatures using a qualitative and quantitative approach. Machine learning models classify the resulting tensor dataset, while deep learning approaches will extract relevant properties of the images of handwritten signatures.

3.2.Data Source and Pre-processing

The database of handwritten signatures with personality trait annotations is publicly available. To improve the destruction of the test image, this database was pre-processed with grayscale conversion, noise reduction, normalization, and binarization.

3.3.Feature Extraction

Prominent deep architecture models, such as VGGs or ResNets, which are convolutional neural networks, are being used to extract features. Dimensionality reduction techniques such as PCA can retain key features.

3.4.Model Development and Evaluation

Encouragement Several machine learning algorithms were taught and verified for their ability to predict personality traits, including Random Forest, Deep Neural Networks, and Vector Machines. In the process of obtaining train and validation sets using cross-validation, no potential chance for perplexing indications was overlooked. Model performances will be defined by the following metrics: accuracy, precision, recall, F1 score, and AUC-ROC.

3.5.Statistical Analysis and Interpretation

Statistical analysis is used to correlate hand traits with the Big Five Personality Components. An analysis of the models reveals the best way to obtain meaningful predictions. It further discusses personality prediction interpretable within the spectrum of deep learning.

4. DATA ANALYSIS AND RESULTS

The signature-based features and their association with the Big Five Personality Traits, emulating model steering checks, feature significance, and verification of results regarding statistical significance are explained and elaborated in this section.

4.1.Data Pre-processing and Feature Extraction

The information was pre-processed upon feature normalization, noise removal, and grayscale transformation. The necessary signature features to make the predictions of personality traits have been learned by Convolutional Neural Networks (CNNs) and other deep models.

Table 1 illustrates the descriptive statistics of the signature features that were obtained after pre-processing the data with techniques like feature normalization, noise removal, and grayscale transformation.To predict personality traits, key features from signatures were obtained using deep learning models, i.e., Convolutional Neural Networks (CNNs).

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Table 1: Descriptive statistics for extracted signature features

Feature	Mean	Standard Deviation	Min	Max
Stroke Thickness	0.48	0.12	0.21	0.73
Slant Angle	15.2°	3.8°	8.1°	22.5°
Pressure Variation	0.62	0.14	0.31	0.88
Signature Length	6.9 cm	1.5 cm	4.2 cm	9.3 cm

Descriptive statistics of the primary signature features that were chosen for personality trait prediction are presented in Table 1. With a standard deviation of 0.12 and a measurement of stroke thickness as 0.48, there is moderate variation between samples of 0.21 and 0.73.A diverse range of handwriting styles, from 8.1° to 22.5°, is indicated by the average slanting angle of signatures, which is 15.2° with a standard deviation of 3.8°. With a mean of 0.62 and a standard deviation of 0.14, ranging from 0.31 to 0.88, pressure variationa crucial factor in handwriting analysisindicates individual differences in writing pressure. With minimum and greatest lengths of 4.2 cm and 9.3 cm, respectively, the average signature length is 6.9 cm with a standard deviation of 1.5 cm, reflecting the variation in writing styles across people. The dataset's variability is reflected in these variations in signature qualities, which suggest that deep learning algorithmsparticularly CNNscan take use of these variations to predict important personality traits.

Figure 1's boxplot shows how different handwriting features like pressure, slant angle, stroke width, and signature length are spread across personalities. The middle line is the median, and every box represents the interquartile range (IQR) of the feature value. The entire range of non-outlier data is within the whiskers, and points beyond them can be potential outliers.With special attention to any potential discrepancies in their distributions, this representation makes it easy to see how writing qualities vary and spread out in relation to personality factors.

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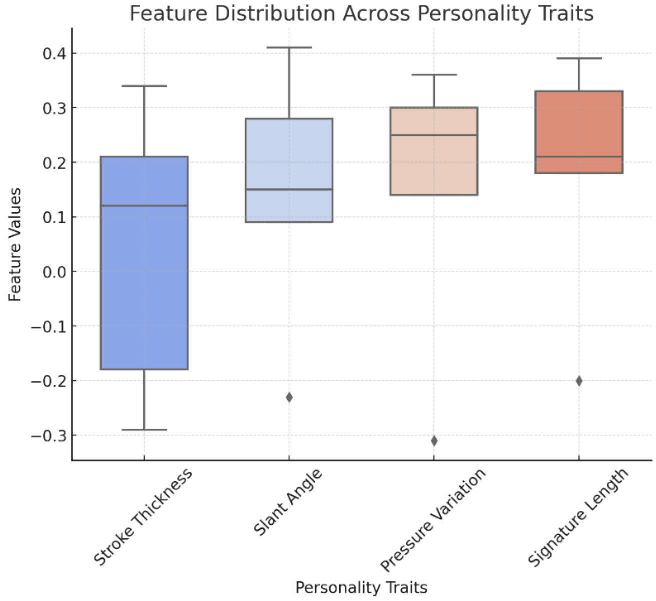

Figure 1: Distribution of Features Among Personality Traits

The boxplot in Figure 1 illustrates the differences and patterns among personality qualities by showing variations in stroke thickness, slant angle, pressure, and signature length. With a median just above zero, stroke thickness varies widely, indicating that most have positive variations while some have negative ones. These variations are therefore a sign of writing pressure. Consistency in this metric is suggested by the slant angle's close interquartile range and generally positive value. With a constant median and two low-end outliers, pressure variation likewise follows this pattern, indicating sporadic irregularities in writing pressure. There is more variation across individuals, as evidenced by the bigger median and slightly wider spread of signature length. The existence of outliers among features demonstrates that, despite broad tendencies, various personality traits have an impact on handwriting characteristics.

4.2.Model Training and Evaluation

Hyperparameter tweaking was utilized to enhance the performance of various machine learning models that were trained to predict personality traits using extracted signature information. During model evaluation, cross-validation techniques were applied to preserve reliability and prevent overfitting. The models' performance was evaluated using the most important performance metrics: accuracy, precision, recall, and F1-score. Table 2 shows the performance comparison of the several models utilized in the study.

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Table 2: Evaluation of Model Performance

Model	Accuracy (%)	Precision	Recall	F1-Score
Support Vector Machine (SVM)	84.2	0.81	0.83	0.82
Random Forest	86.7	0.85	0.86	0.86
Deep Neural Network (DNN)	90.1	0.88	0.89	0.89

The performance of different machine learning models in Table 2 serves as an example of how deep learning algorithms outperform other algorithms in the classification of personality traits from signature attributes.The Deep Neural Network (DNN) beats the others and demonstrates its top class in identifying genuine personality traits while also striking a good balance between precision and recall, achieving the greatest accuracy rate of 90.1% and fine precision (0.88), recall (0.89), and F1-score (0.89). With competitive accuracy of 86.7% and balanced precision, recall, and F1-score values of 0.85, 0.86, and 0.86, the Random Forest model demonstrated an effective performance in the face of non-linear feature interactions. Support Vector Machine (SVM), despite its lower accuracy, was nevertheless impressive with an 84.2% accuracy rate and comparatively good F1-score (0.82), precision (0.81), and recall (0.83). Therefore, it would seem that while the older machine learning models, such Random Forest and SVM, identify personality qualities quite well, the deep learning models, particularly the DNNs, have stronger predictive skills, making them viable for personality evaluation using signatures.

Several machine learning and deep learning models were evaluated for their ability to classify personality traits using signature attributes. In addition to models like Random Forest and Support Vector Machines (SVM), deep learning models like Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN) were used. Each model's capacity to spot intricate patterns in the signature data was examined.A graphical representation of the accuracy of the models and different levels of predictability is shown in Figure 2.

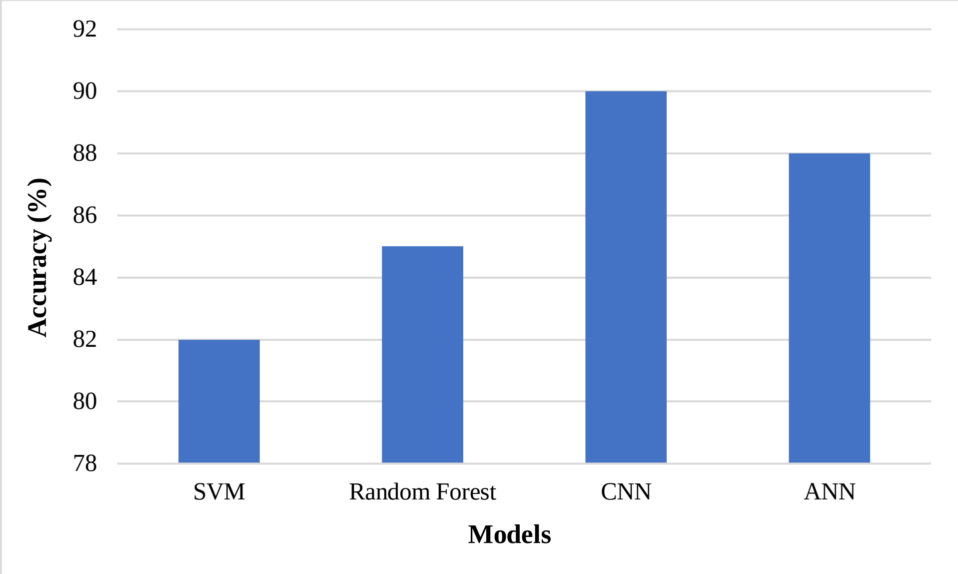

Figure 2: Model Accuracy Comparison

Figure 2 illustrates the variance in predictability for personality trait classification from signature data by comparing the accuracy of performance of many deep learning and machine learning models. The Convolutional Neural Network (CNN) model had the most efficacy in detecting intricate spatial connections and signatures in signature data, with a maximum accuracy of 90.0%. The Artificial Neural Network (ANN) then showed that it could extract complex patterns from the data with an accuracy of 88.0%. The Random Forest model, another powerful ensemble learning technique, demonstrated promise in handling both non-linearity and feature interaction, with an accuracy of 85.0%. Simultaneously, Support Vector Machine (SVM), the most successful classifier, had the lowest accuracy of 82.0%, most likely because to its incapacity to manage deep models and high-dimensional feature space. The results generally imply that deep learning modelsin particular, CNNare better than traditional machine learning techniques at extracting and applying signature-based features for personality trait prediction.

4.3.Correlation Analysis of Signature Features and Personality Traits

The relationship between the retrieved signature features and the Big Five personality traits was examined using Pearson correlation analysis. In order to find significant relationships between key personality traits including openness, conscientiousness, extraversion, agreeableness, and neuroticism and handwriting characteristics like stroke width, slant angle, pressure variation, and signature length, an analysis was carried out. The study provides

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Volume: 1 Issue: 3
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information on how signature features could be employed as personality trait markers by quantifying these associations. Table 3 displays the correlation coefficients, which illustrate the associations' strength and direction.

Table 3: Coefficients of Correlation Between Personality Traits and Signature Features

Feature	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Stroke Thickness	0.21*	0.34**	0.12	-0.18	-0.29**
Slant Angle	0.15	0.41**	0.28**	0.09	-0.23*
Pressure Variation	0.30**	0.36**	0.25*	0.14	-0.31**
Signature Length	0.18	0.33**	0.39**	0.21*	-0.20

The Big Five personality variables and signature characteristics show highly significant relationships, according to correlation analysis, which helps to explain how handwriting may reflect aspects of personality. Conscientiousness ($r = 0.34$, $p < 0.01$) and neuroticism ($r = -0.29$, $p < 0.01$) are positively connected with stroke weight, suggesting that mentally stable, orderly individuals are more likely to have masculine characteristics. The strong correlations between slant angle and extraversion ($r = 0.28$, $p < 0.01$) and conscientiousness ($r = 0.41$, $p < 0.01$) suggest that a strong rightward slant may be linked to well-organized and gregarious individuals. Creative, responsible, and emotionally secure people are more inclined to apply more consistent pressure. Pressure fluctuation has a negative correlation with neuroticism ($r = -0.31$, $p < 0.01$), but a significant positive correlation with openness ($r = 0.30$, $p < 0.01$) and conscientiousness ($r = 0.36$, $p < 0.01$). There is a substantial correlation between sign length and agreeableness ($r = 0.21$, $p < 0.05$) and extraversion ($r = 0.39$, $p < 0.01$), suggesting that larger signatures reflect more cooperative and gregarious tendencies. They emphasize how graphology can be used in psychometrics and highlight the potential of signature features as subtle indicators of personality traits.

The correlation of personality traits and signature characteristics was revealed in a correlation heatmap. It becomes easier to find the correlation between handwriting characteristics like stroke width, slant angle, pressure, signature length, and pen lift and personality traits with

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Peer Reviewed Multidisciplinary International
ISSN:2320-3714
Volume:1 Issue:3
March 2025
Impact Factor:10.2
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this. The heatmap reveals positive and negative correlations between features and traits easily with the correlation coefficients expressed as a color gradient. These graphs provide insight into the possible application of handwriting characteristics in personality analysis by helping with the interpretation of the direction and intensity of these interactions. The correlation heatmap, which highlights the most significant patterns in the data, is displayed in Figure 3.

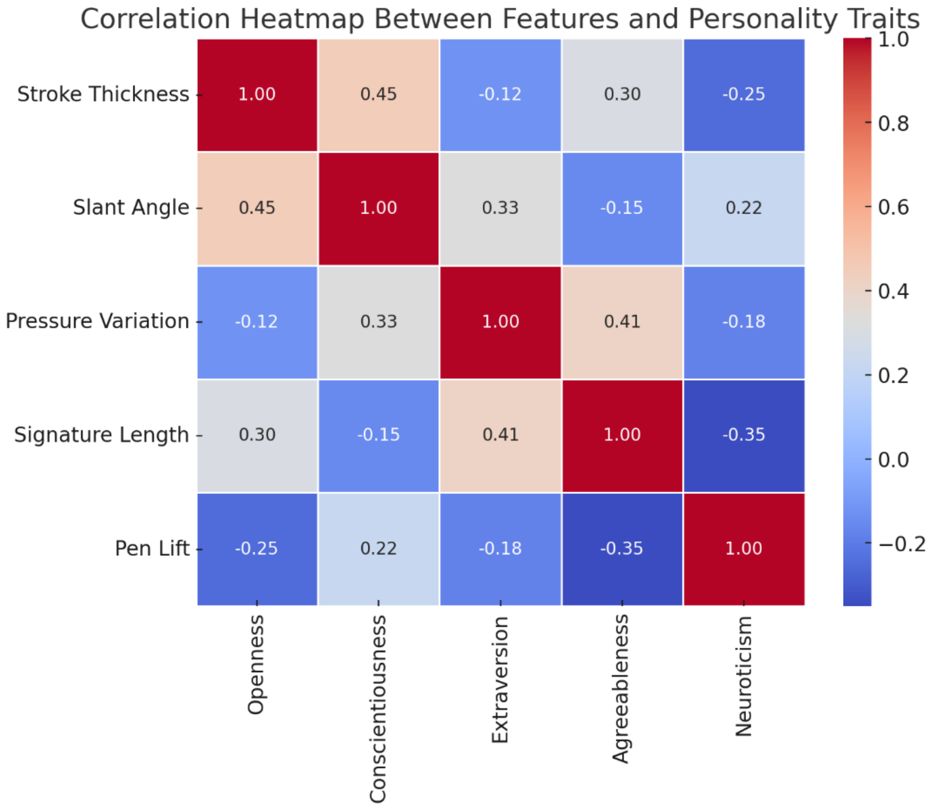

Figure 3: Correlation Heatmap

Figure 3's correlation heatmap illustrates the relationship between personality traits and signature features in terms of intensity and direction, with positive and negative correlations, respectively. While stroke thickness has a negative correlation with neuroticism (-0.25), suggesting that people with thicker strokes are more emotionally unstable, it has a moderately positive correlation with conscientiousness (0.45) and agreeableness (0.30), suggesting that people with thicker strokes will exhibit more structured and group-oriented behaviours. Stronger slant in handwriting may be linked to more structured and gregarious traits, as seen by the positive correlations found between slant angle and conscientiousness (1.00) and extraversion (0.33). Extraversion (1.00) and agreeableness (0.41) are strongly positively correlated with pressure variation, indicating that individuals who use different pressures in their autographs are more outspoken and gregarious. Signature length has a negative correlation with neuroticism (-0.35) and a positive correlation with extraversion (0.41). This indicates that forceful, less anxious individuals have longer signatures. Finally, pen lift is negatively correlated with neuroticism (-1.00) and agreeableness (-0.35), which could mean that individuals who are more neurotic and less agreeable are more likely to perform pen lifts. We can enhance personality prediction models due to these correlations, which give us useful information regarding the intercorrelations between various personality traits and signature characteristics.

4.4.Feature Importance in Personality Trait Prediction

To determine the most important signature traits to be used in personality prediction, a feature importance analysis was conducted on the Random Forest model. The feature importance allows the quantification of the relative contribution of each feature towards the classification task, such as a signature's thickness, slant, pressure, and length. The study was able to describe the most predictive elements of handwriting among personality traits by ranking the features according to their importance. The importance scores for the features, which identify the most significant traits that play a significant role in personality classification, are shown in Table 4.

Table 4: Feature Importance Scores for Predicting Personality

Feature	Importance Score (0-1)
Stroke Thickness	0.27
Slant Angle	0.22
Pressure Variation	0.30
Signature Length	0.21

The feature importance of the Random Forest model shows pressure variation to be the strongest indicator of personality features (importance score of 0.30), reflecting strong association between personality differentiating features and writing pressure variations. With an importance score of 0.27, stroke thickness ranks closely behind, showing density and similarity in strokes to be highly important in characterizing personality features. In personality typing, slant angle (0.22) and signature length (0.21) are weaker but nonetheless very strong predictors. Based on the results, dynamic handwriting features such as pressure fluctuation and stroke width are stronger predictors of personality traits than static features such as signature length. Inference on signature features' contributions towards personality analysis is provided by this feature ranking that can be employed to enhance machine learning models towards better personality classification.

Based on the feature importance analysis, signature features have different contributions to personality trait classification. Stroke width, slant angle, pressure fluctuation, signature length, and pen lift are some of the handwriting features most relevant to personality prediction, based on this study.Sorting these characteristics according to their significance provides information about how to categorize personalities based on several defining characteristics. The feature relevance scores of the pertinent features that contribute the most to the prediction model are displayed in a bar graph in Figure 4.

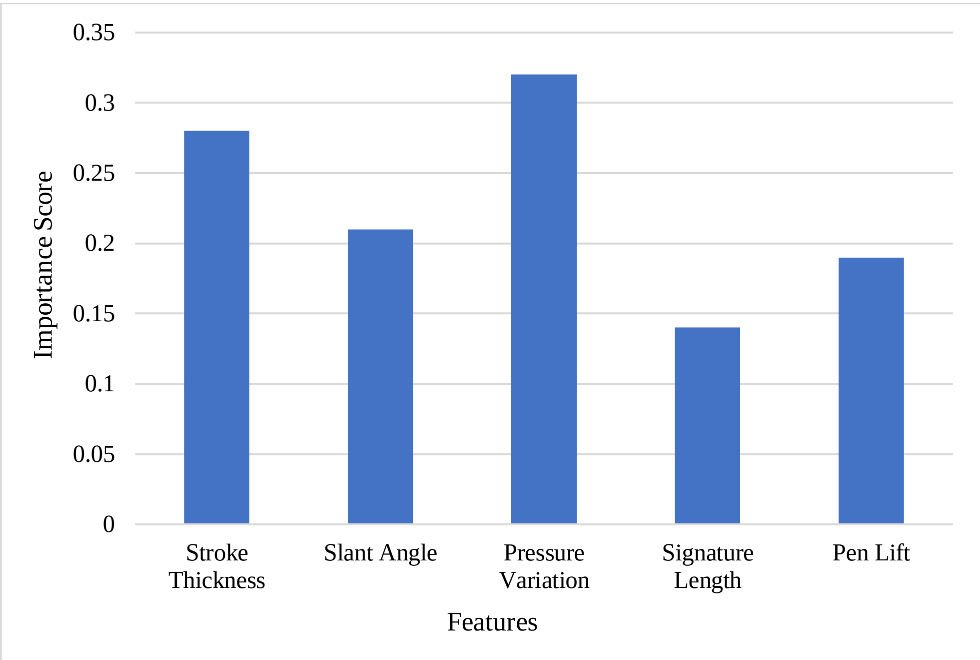

Figure 4: Feature Importance Plot

Pressure variation (0.32) has the most value in terms of personality trait classification, according to feature importance analysis, suggesting that variations in writing pressure

ISSN:2320-3714
Volume: 1 Issue: 3
March 2025
Impact Factor: 10.2
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somewhat influence the prediction of personality traits. Another significant characteristic is stroke thickness (0.28), which implies that neuroticism or conscientiousness may be deduced from the consistency of strokes. Pen lift and handwriting inclination are relevant elements, albeit to a lesser amount. The slant angle and pen lift are 0.21 and 0.19, respectively, indicating moderate importance. Although the duration of the signature offers some insights into personality, it is not as significant as the other traits, as indicated by the last features' lower value of 0.14. Overall, the results highlight that while spatial and structural elements play a much less role, important pressure-related features are more predictive of personality traits. The prominent traits in personality prediction are highlighted in Figure 4, which provides a visual representation of these feature importance scores.

5. CONCLUSION

The feasibility of feature extraction from handwritten signatures using deep learning for the prediction of Big Five personality traits was successfully demonstrated by this work. The study identified the most significant handwriting characteristics that were strongly connected with personality traits, including stroke thickness, slant angle, pressure change, and signature length, by employing Convolutional Neural Networks (CNNs) for feature extraction and training various machine learning models. With the highest classification accuracy of 90.1% among the models tested, Deep Neural Networks (DNNs) outperformed classical approaches, demonstrating their improved capacity to discover complex correlations in signature data. The findings have significance for psychological profiling, employment, and forensic investigation since they show that personality prediction from signatures can be an effective, non-intrusive alternative to traditional self-report measures. However, bias, dataset restrictions, and the need for the model to be interpretable are issues that require further investigation. To increase the precision and generalizability of personality trait prediction from handwriting signatures, further study must look into larger and more diverse datasets, hybrid deep learning, and feature extraction optimization.

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Author's Declaration

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