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Article

Augmented Backpropagation Neural Networks for Handwriting Analysis Based on Multi-Task Learning for Detecting Personality Attributes

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Abstract: Handwriting analysis has been explored as a potential indicator of personality traits, though traditional approaches remain subjective. Many prior researches have shown a correlation between personality and handwriting variances, although the data is mostly anecdotal. Each individual's handwriting is distinctive which may serve as indicators of underlying personality traits, behavioural patterns and psychological characteristics. This study proposes a machine learning-based framework using a Modified Backpropagation Neural Network (MBPNN) integrated with multi-task learning to objectively identify personality traits from handwriting samples. Feature extraction is performed using Discrete Wavelet Transform (DWT), enabling effective representation of handwriting characteristics. The incorporation of multi-task learning enhances the network's ability to generalize across related prediction tasks while minimizing computational overhead compared with training separate single-task models. The findings suggest that integrating DWT-based feature extraction with an optimized neural learning architecture provides an accurate, robust, and computationally efficient solution for automated handwriting-based personality assessment. The proposed model achieves an accuracy of 91% in multi-trait personality classification, demonstrating improved performance over conventional approaches. The results highlight the capability of the proposed method to extract robust features and provide reliable personality predictions.
Keywords: Handwriting, Personality Traits, Modified BPNN, DWT.

1. INTRODUCTION

Graphology is the systematic analysis of an individual's cognitive and emotional state, as inferred from the characteristics of their handwriting at the time of writing. A Structured method of analysis and interpreting personality based on strokes and patterns is referred to as graphology. An entity's handwriting may be used to predict the emotional state. Handwriting is a unique behavioural characteristic that reflects the complex interaction between an individual's cognitive processes, neuromuscular coordination and psychological state. Unlike printed text handwritten scripts exhibit distinctive variations in stroke formation writing pressure, spacing slant, curvature and character dimensions. These variations have motivated researches to investigate whether handwriting can provide useful information regarding an individual's behavioural tendencies and personality traits.

A few applications which could be useful are employment, selection, team building, confabbing and career planning which may prove to be helpful. Individual variances may make it possible for a person's handwriting to disclose aspects of their personality, conduct and psychological characteristics. In comparison to more conventional techniques like surveys or interviews, graphology might be a more effective approach, particularly when assessed by machine learning. It is possible that this is of utmost significance in situations involving a large volume, such as early screenings or recruitment attempts. When compared to self-reported traits, graphology may provide additional information. Examining someone's handwriting can reveal secret facets of their personality which they may not be aware of or are reluctant to share with others.

When attempting to identify behavioral or personality traits in a person's handwriting, graphologists manually search for analytical conclusions. There are two techniques: The German method, frequently known as the holistic approach and the French method, referred to as the atomistic method [1]. The French approach is considered an isolated trait method because it examines individual components of handwriting separately. In contrast, the German method, also known as the gestalt approach, analyzes handwriting as a complete entity to interpret behavior [3]. This holistic perspective helps avoid issues related to character segmentation and inconsistencies in form, offering a more intuitive understanding of the overall writing style. In some instances, graphologists may adopt a hybrid approach, combining elements of both methods [2].

There is a possibility that handwriting analysis will reveal new insights into aspects of personality. Distinct characteristics may be gleaned from strokes, slants, and loops. The journey into understanding oneself and others via the written word is an absorbing experience worth taking. The field of computational graphology makes use of these components as distinctive traits. Because the association between handwriting features and personality qualities does not have a scientific foundation that is generally accepted, graphology is considered to be a pseudoscience within the field of study. There is a possibility that the outcomes of graphology analysis are subjective and dependent on the analyst's expertise. Despite the fact that they still need a great deal of research, machine learning algorithms are now being created in order to improve accuracy.

An individual's handwriting is a distinguishing characteristic that, similar to a person's fingerprint, cannot be identical between two different people. Additionally, it assists us in recognizing the emotional condition of a person.

The process of handwriting recognition is often carried out in a conventional fashion. This involves a professional handwriting expert collecting handwriting samples from an individual and analyzing them for various personality traits. The method requires a significant amount of time and effort from the person providing the samples. There is a possibility that the author's personality might be deduced from the kind of writing that occurs, such as signatures and stroked letters. Signatures, on the other hand, are often used to identify certain personalities. Signatures may range from the look of dots and streaks to the appearance of shapes, shells, and bottom lines [4]. The methodology's limitations make it much harder to validate the finding that handwriting and personality are related. As an example, the traditional analysis of handwriting scripts is confronted with a significant obstacle in the form of relying on subjective assessment of the frozen handwritten outputs. This means that the interpretation is largely dependent on the professional talents and graphological theories used by the analyst. Through this research, we aimed to study a technique that is more comprehensive and objective establishing an analogy between personality and handwriting. This was achieved by investigating patterns of brain activity that developed while the dynamic handwriting process. To address the limitations of existing methods, this work proposes a handwriting-based personality trait identification framework that combines DWT-based feature extraction with a Modified Backpropagation Neural Network (MBPNN) and a multi-task learning strategy. Unlike conventional neural networks that independently predict individual personality traits, the proposed architecture learns a shared feature representation that simultaneously predicts multiple behavioural attributes. Sharing feature representations among related tasks improves learning efficiency, enhances generalization capability, and reduces overfitting, particularly when the available training data are limited.

The Modified Backpropagation Neural Network employed in this study incorporates an improved weight-update mechanism that accelerates convergence while maintaining stable learning behaviour. The extracted DWT features serve as compact and informative descriptors of handwriting characteristics, enabling the network to distinguish subtle variations associated with different personality traits. Experimental evaluation demonstrates that the proposed framework achieves superior performance compared with conventional KNN, CNN, and standard BPNN classifiers.

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to study a technique that is more comprehensive and objective establishing an analogy between personality and handwriting. This was achieved by investigating patterns of brain activity that developed while the dynamic handwriting process.

2. LITERATURE SURVEY

The authors Anari M., et al. provide a revolutionary real-time model that, for the very first time, makes predictions about the personality traits of individuals who speak Persian. The handwriting samples that were collected from people who speak Persian served as the basis for the model development. The decision-making model is developed using a Lightweight Deep Convolutional Neural Network (LWDCNN) architecture. It utilizes preprocessed image samples as input, enabling efficient feature extraction and accurate classification while maintaining low computational complexity. In order to determine whether or not a graphologist is able to predict personality characteristics based on knowledge about handwriting, the efficacy of the graphologist is the deciding factor. In the event that a computer-based method for assessing handwriting is developed, there is a chance that the capability to forecast certain personality characteristics may be significantly improved. Their model demonstrated improved classification accuracy while maintaining relatively low computational complexity [5].

Through the use of the machine learning algorithm KNN, the objective of the study that was carried out by the method discussed here was to develop an automated system that was capable of predicting the personality traits of a specific individual based on a sample of their handwriting [7]. Technique developed in [9] is based on handwriting and combines tasks that include sketching and handwriting. Additionally, the method includes a digital version of typical behavioural and practical measurements that have been accepted, confirmed and used in the field of neuroscience in the past. The discipline of neurology was the one that decided to use this method. Specifically, the approach is implemented in the form of a modular platform, which enables the enhancement, deletion and insertion of new processes in accordance with specific needs. The work discussed in [6] employed a convolutional neural network (CNN) in order to create a prediction about the five key personality qualities that the writer had at the time that the writing was being taken. In addition to agreeableness, conscientiousness, extraversion, neuroticism and openness, a few more characteristics were also present.

A transformer-based (TB) approach presented in [10] was developed for the purpose of personality identification. Traditional information extraction algorithms, on the other hand, often include text interpretation via the use of a Long Short-Term Memory (LSTM) Network, which is then incorporating a structural interpretation guided by signature patterns in the handwriting. This contrasts with the existing method, which represents such material using a signature. Three unique advanced handwriting parametrization techniques were developed with the intention of improving recognition via the use of online handwriting [8]. These methods make use of modulation spectra, fractional order derivatives and a Q-factor wavelet transformation that may be set in a variety of different ways.

Work discussed in [14] employed graphological analysis of three handwriting traits—baseline, word slant, and writing pressure—to construct novel methods to assess crucial facets of a person's personality. These techniques were carried out via the application of handwriting. To accomplish this, handwriting samples taken from a database were utilized to train three VGG-16 convolutional neural networks. The networks were trained on these samples. The method in [12] analyzes the spatial features of the environment concurrently with the activities. The displacement changes along the x and y axes are used to calculate the velocities. To classify the generated feature vectors, a neural network called a Bidirectional Long-Short Term Memory (BiLSTM) is considered. The research in [13] found that the word content and the amount of pen pressure felt when touching the markings left on the paper after the apology letter has been written affect people's assessments of the feelings of shame, humiliation, regret, and sincerity that are expressed in the letter. More specifically, they investigate the ways in which the words that are included in the letter influence people's perceptions of the sentiments that are being discussed.

Although existing studies demonstrate promising performance, several challenges remain unresolved. First, many approaches focus on predicting a single personality trait, requiring separate models for each behavioural attribute. Such independent models increase computational cost and ignore the correlations that naturally exist among personality traits. Second, convolutional neural networks generally require extensive labelled datasets and considerable computational resources, limiting their practical applicability in resource-constrained environments. Third, traditional graphological methods remain subjective and often produce inconsistent results because they rely heavily on expert interpretation.

To overcome these limitations, this work proposes a unified framework that integrates Discrete Wavelet Transform (DWT)-based feature extraction with a Modified Backpropagation Neural Network (MBPNN) employing a multi-task learning strategy. The proposed approach simultaneously predicts multiple personality traits using shared feature representations, thereby improving learning efficiency and reducing computational redundancy. In addition, the modified weight-update mechanism enhances convergence while maintaining stable training behaviour. Experimental results demonstrate that the proposed framework achieves superior classification accuracy compared with conventional KNN, CNN, and standard backpropagation neural network models.

Based on the existing literature, the following research gaps are identified:

- Most existing graphology-based systems depend on subjective manual interpretation, limiting reproducibility and consistency.
- Conventional machine learning models generally predict only a single personality trait and fail to exploit relationships among multiple behavioural attributes.
- Deep learning approaches often require large annotated datasets and significant computational resources.
- Limited research has investigated the integration of wavelet-based feature extraction with multi-task neural learning for handwriting-based personality assessment.
- Few studies have explored modified backpropagation strategies to improve convergence speed and classification performance for handwriting analysis.

Motivated by these observations, the present study develops a computationally efficient multi-task learning framework that combines DWT feature extraction with a Modified Backpropagation Neural Network to provide accurate and objective personality trait identification from handwriting samples.

3. METHODOLOGY

Using the time-scale analysis characteristics is what the wavelet transform technique is intended to do. An approach that seems to be successful for obtaining minute signal details is the use of MRA and sequential signal selection. Considering the fact that the Daubechies wavelet family is so similar to the electrocardiogram (ECG) signal, it was considered to be the most suitable choice for wavelet analysis [1]. A scaling filter and a wavelet filter are the two filters that are used to provide a comprehensive description of an orthogonal wavelet. In order to get the approximation coefficients (A), a wavelet transform is accomplished by convolutioning the input signal X(n) with the scaling function H(n). Here, H(n) represents the impulse response of the Low Pass filter. By convolving X(n) with the wavelet function G(n), which serves as a representation of the impulse response of the High Pass filter, the detailed coefficients (D) may be produced. The first method produces twice as much information as it did at the beginning of the process. A total of N detail coefficients D and N approximations are produced by the set of n input samples. For this issue to be resolved, the filter output should be down sampled by two, with every second coefficient being discarded. By first upsampling the signals and then reversing the technique, it is possible to recreate the signal that was presented as input [2, 3]. This figure depicts the whole architecture for the purpose of dismantling and rebuilding. Through repeated iterations of the decomposition process, the input signal is broken down into a number of components with a lower resolution. The wavelet decomposition tree is depicted in Fig 1 as shown. There is a three-level breakdown.

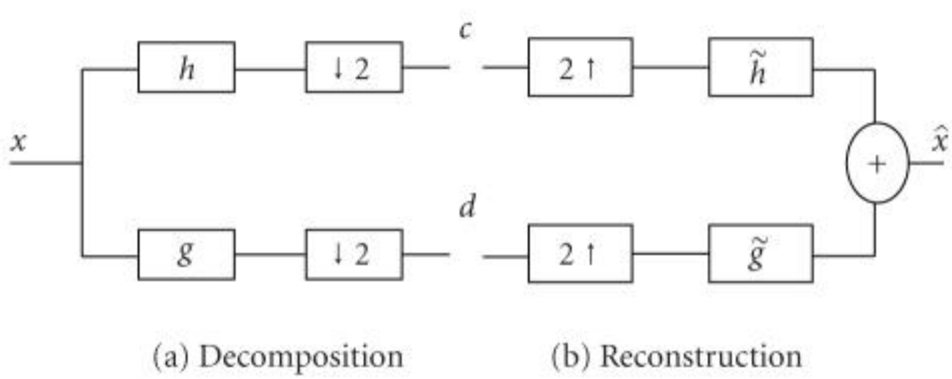

Fig 1: DWT decomposition and reconstruction

Fig 1 presents the operational framework of the Discrete Wavelet Transform (DWT), which consists of two sequential stages: decomposition and reconstruction. During the decomposition stage, the input signal $x$is simultaneously processed through a low-pass filter (h) and a high-pass filter (g). The low-pass filter captures the coarse or approximation information, while the high-pass filter extracts the detailed or high-frequency information, such as edges and texture. The filtered outputs are then downsampled by a factor of two, reducing the data size and generating the approximation coefficients (c) and detail coefficients (d).

In the reconstruction stage, the approximation and detail coefficients are first upsampled by a factor of two to restore their original sampling rate. These upsampled signals are then passed through the synthesis filters ($\tilde{h}$ and $\tilde{g}$), which reconstruct the low- and high-frequency components, respectively. Finally, the reconstructed components are combined through an adder to obtain the output signal $\hat{x}$, which closely resembles the original input signal. This multiresolution decomposition and reconstruction process enables efficient feature extraction while preserving important signal characteristics, making DWT highly suitable for image compression, denoising, and deep learning-based image analysis.

Sinusoidal functions are global in the spatial coordinate (position/time), but they are precisely localized in the frequency domain. Temporally or spatially limited functions cannot be expressed at all using a Fourier basis. However, during the course of the analysis, a wavelet basis is roughly localized in both the frequency and spatial domains. All basis functions must be localized in both conjugate variables and must be mutually orthogonal and normalized. As a result, the permitted functions are severely restricted. These features are obtained by the scaling function applied to the data at each wavelet transform phase. The wavelet transform step will apply the scaling function to determine N/2 smoothed values if the data set contains N values. The smoothed values are retained in the lower half of the N element input vector in the ordered wavelet transform.

Wavelet Filter Coefficients

The Daubechies D4 (db4) wavelet employs two sets of filter coefficients: scaling (low-pass) coefficients and wavelet (high-pass) coefficients. The high-pass filter coefficients are derived from the scaling coefficients using the following relationships:

The wavelet function coefficient values are:

$$1]\ g0 = h3 \qquad 2]\ g1 = -h2 \qquad 3]\ g2 = h1 \qquad 4]\ g3 = -h0. \tag{1}$$

These equations establish the complementary relationship between the analysis filters. The alternating sign pattern ensures orthogonality between the low-pass and high-pass filters, allowing the signal to be decomposed and reconstructed without introducing significant distortion.

Scaling Function

The approximation coefficients are computed using the Daubechies D4 s scaling function as:

$$\begin{gathered}\alpha_i = h_0 s_{2i} + h_1 s_{2i+1} + h_2 s_{2i+2} + h_3 s_{2i+3} \\ \alpha[i] = h_0 s[2i] + h_1 s[2i+1] + h_2 s[2i+2] + h_3 s[2i+3]\end{gathered} \tag{2}$$

where $s[i]$denotes the input signal samples and h_0, h_1, h_2,and $h_3$represent the scaling filter coefficients. This operation performs a weighted average of four neighboring samples while simultaneously reducing the sampling rate by a factor of two. The resulting approximation coefficients preserve the low-frequency characteristics that represent the overall structure of the signal.

Wavelet Function

The detail coefficients are obtained using the Daubechies D4 wavelet function expressed as:

$$\begin{gathered}c_i = g_0 s_{2i} + g_1 s_{2i+1} + g_2 s_{2i+2} + g_3 s_{2i+3} \\ c[i] = g_0 s[2i] + g_1 s[2i+1] + g_2 s[2i+2] + g_3 s[2i+3]\end{gathered} \tag{3}$$

where g_0, g_1, g_2,and $g_3$denote the wavelet filter coefficients. Unlike the scaling function, this operation emphasizes rapid changes within the signal and extracts the high-frequency information corresponding to edges, fine textures, and local variations. These detail coefficients provide valuable discriminative features for subsequent analysis.The "db4" wavelet is used for the purpose of decomposition in this investigation. The db4 wavelet is well-known for its orthogonally and smoothing capabilities and it is also useful for determining whether or not handwriting drawings have undergone any alterations. There are five separate handwriting image sub bands that are produced as a consequence of the multi-resolution analysis being deconstructed using the "db4" algorithm for four levels of decomposition. The fundamental objective of the technique that has been described is to partition the handwritten graphics that were originally created into a number of frequency bands. In the following, we will discuss the characteristics that were obtained using frequency decomposition.

Significance of the db4 Wavelet:

The Daubechies D4 wavelet is selected because of its excellent localization properties in both the spatial and frequency domains. Its orthogonal structure minimizes information redundancy while preserving important image characteristics during decomposition. By repeatedly applying the scaling and wavelet functions, the input image is separated into multiple frequency sub-bands that capture both global and local information. This multiresolution representation improves the extraction of meaningful handwriting features, making the db4 wavelet particularly suitable for personality recognition and handwriting analysis using deep learning techniques.

Architecture of Proposed Model

Fig 2 illustrates the architecture of the proposed handwriting analysis system. Initially, the input handwriting image is acquired and subjected to a filtering process to remove noise and improve image quality. The enhanced image is then processed through handwriting segmentation, where the handwritten content is separated into meaningful regions for detailed analysis. Subsequently, relevant characteristics such as texture, stroke patterns, and structural information are obtained during the feature extraction stage. These extracted features are provided as input to the Modified Backpropagation Neural Network (Modified-BPNN), which learns the underlying handwriting patterns and performs classification. Finally, the trained model generates the predicted class, representing the identified personality or behavioral category based on the handwriting characteristics.

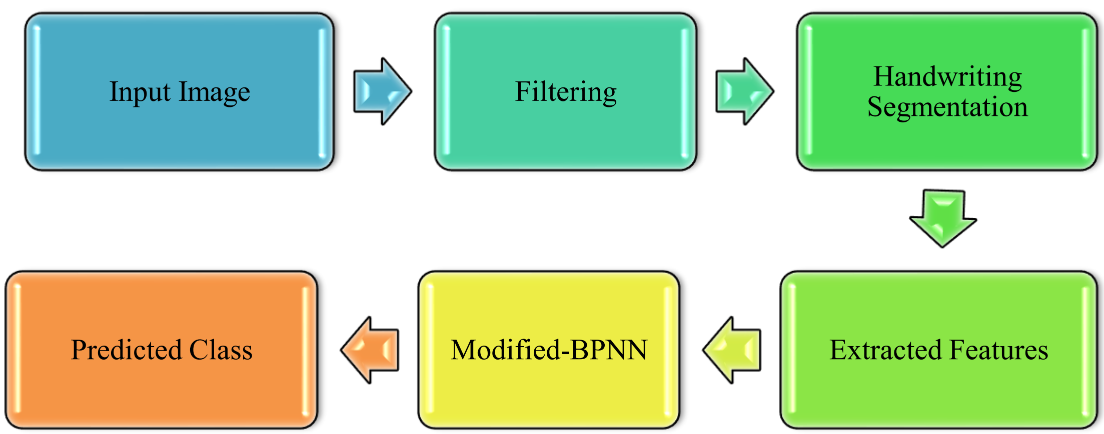

Fig 2: Architecture of Proposed Model

Modified Backpropogation Neural Network (MBNN):

Modified Backpropogation Neural Network (MBNN) belongs to the feed forward neural network class and is a kind of supervised neural forward feed network. The generalized neural regression network (MBNN) was developed to characterize and regulate nonlinear systems. This network incorporates one-pass learning and uses neural networks. The MBNN's ability to "learn" from data in a single pass and enable generalization from stored instances is one of its benefits. Additionally, it shows that using MBNN is advantageous because it can converge on the data's basic function using a small number of trainings. There are four levels: The input, the pattern, the summation and the output one. There are simple distribution neurons that are the inputs neurons of the input layer. These neurons are responsible for transmitting all of the measurement variable x to all of the neurons in the pattern.

Fig 2 illustrates the architecture of the proposed Modified Backpropagation Neural Network (Modified-BPNN) employed for handwriting-based personality classification. The network consists of four major components: the input layer, pattern (hidden) layer, summation unit, and output layer. The extracted handwriting features are processed through these layers to predict the appropriate personality class.

1. Input Layer

The input layer receives the feature vector generated during the feature extraction stage. In the illustrated architecture, the network accepts 296 input features, represented as $x_1, x_2, x_3, \dots, x_{296}$. These features describe various handwriting characteristics, including stroke properties, geometric attributes, texture descriptors, and frequency-domain information obtained using the Discrete Wavelet Transform (DWT). Each input neuron corresponds to one normalized feature and forwards its value to the hidden layer without performing any computation.

2. Pattern (Hidden) Layer

The hidden layer, referred to as the pattern layer, performs nonlinear mapping between the input features and the output classes. Every neuron in this layer receives weighted inputs from all neurons in the input layer, making it a fully connected architecture. Each neuron computes a weighted sum of its inputs, adds a bias term, and applies a nonlinear activation function to capture complex relationships among handwriting features. The hidden layer learns representative patterns that distinguish different handwriting styles and enhances the network's ability to model nonlinear data distributions.

The output of each hidden neuron can be expressed as

$$H_j = f\left(\sum_{i=1}^{296} w_{ij}\, x_i + b_j\right) \tag{4}$$

where:

- x_i denotes the i^{th} input feature,
- w_{ij} represents the connection weight,
- b_j is the bias associated with the hidden neuron,
- $f(\cdot)$ is the activation function.

3. Summation Unit

The outputs generated by all hidden neurons are transmitted to the summation unit. This unit combines the weighted contributions from the hidden layer to produce an aggregated decision value. The summation process integrates the learned feature representations and computes the final activation before classification.

Mathematically,

$$Z = \sum_{j=1}^{M} v_j\, H_j + b_o \tag{5}$$

where:

- H_j represents the output of the j^{th} hidden neuron,
- v_j denotes the output weight,
- b_o is the output bias,
- M is the total number of hidden neurons.

4. Output Layer

The aggregated value obtained from the summation unit is processed by the output neuron to generate the predicted class $\hat{s}(k)$. The output neuron applies an activation function to transform the computed value into the final classification result. During training, the predicted output is compared with the target class, and the prediction error is propagated backward through the network to update the connection weights. This iterative optimization enables the Modified-BPNN to minimize classification error and improve prediction accuracy.

The output is represented as

$$\hat{s}(k) = f(Z) \quad (6)$$

where $\hat{s}(k)$ denotes the predicted personality class.

Working Principle

Initially, the extracted handwriting features are supplied to the input layer. These features are propagated through the hidden layer, where the network learns complex relationships among different handwriting characteristics. The summation unit combines the responses of the hidden neurons, and the output layer generates the final prediction. During training, the Modified-BPNN continuously updates its weights using an improved backpropagation learning mechanism until the prediction error reaches a minimum. This optimized learning process enables the classifier to recognize subtle handwriting variations and achieve reliable personality classification.

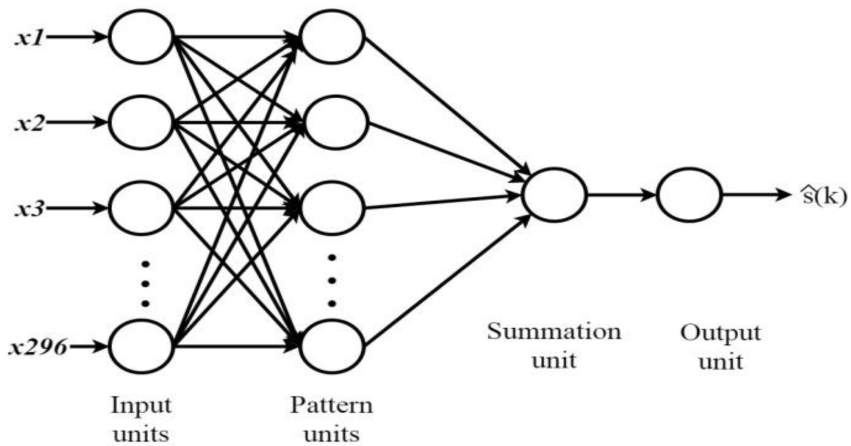

Fig:3 MBNN Architecture

ALGORITHM OF MODIFIED BPNN

Step 1: Initialize the weights to small random Values.

Step 2: Choose the pattern X dk and apply it the input layer Vok= X dk for all k

Step 3: Propagate the signal through the network Vmi = f (netmi)= f (∑j wmijVm-1j)

Step 4: Compute the deltas for the output layer δMi = f (netMi) (tdi- VMi)

Step 5: Compute the deltas for the preceding layer for m =M, M-1,2 δM-1i = f (netm-1i) ∑jwmij δmj)

Step 6: Update all the connections

Δwm u = ƞδmi Vm-1j w newij = w oldij + Δwij Modified BPN: wnewij = woldij + Δwij * α* L(w)

Step 7: Return to step 2 and iterate for the subsequent pattern.

Several characteristics are extracted from the picture once the preprocessing step has been completed. A neural network is used for class identification, and these recovered properties are used as the input feature vectors for the neural network. The MBNN training process involves concatenating all of the characteristics that have been acquired. A total of seven hundred samples from our database are used to train MBNN on these different features. The trained model is put through its paces in the assessment process.

The proposed Modified Backpropagation Neural Network (MBNN) comprises 15 input neurons, 20 hidden neurons, and a single output neuron. The input layer processes the extracted feature vector, the hidden layer learns the complex nonlinear relationships among the features, and the output layer generates the final classification result. To enhance the training process, it employs a normalized radial basis function. As a neural network architecture grounded in logistic regression, MBNN is widely applied across various domains such as predictive modeling, control systems, plant process simulation, and general function approximation tasks. As a result of the fact that MBNN is a type of feed forward back propagation neural networks that can be trained in a single run, it converges to the subjacent regression surface much more fast than other options. It has a well-deserved reputation for being able to quickly train it and resolve any and all regression problems. It does this by calculating the distance between a particular sample pattern and the patterns that are incorporated in the training set.

The Modified Backpropagation Neural Network (MBNN) consists of four hierarchical layers: input, pattern, summation, and output, as illustrated in Fig. 1(b). The input layer is responsible for receiving external signals, while the pattern layer maps the input data using the features learned from the training dataset. When convolutional operations are applied in MBNN designs, it is standard practice to align the number of hidden layer neurons with the number of unique input patterns in the training set [1], [2].

The summation layer subsequently integrates the outputs from the pattern layer and performs multiplication operations to compute the input to the final output layer [3]. This is done with the appropriate interconnection weights. On the basis of the input dataset that was used, the output layer nodes provide the outcomes that are wanted. The MBNN will estimate the value of M in a much shorter amount of time than the propagation time for each and every collection of N inputs. The time it takes for an input to be sent over a network is referred to as the network's propagation time. M is defined as the estimated values of the desired signals (k), denoted by the symbolˆ(k). A representation of the values of the input feature vectors from the input nodes is denoted by the letter N, as illustrated in Figure 1b. This is how the MBNN algorithm determines the estimated M (N) (also known as sˆ(k)).

$$M(N) = \frac{\sum_{i=1}^{n} M_i \exp\left(\frac{-D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^{n} \exp\left(\frac{-D_i^2}{2\sigma^2}\right)} \tag{7}$$

$$D_i^2 = (N - N_i)^T.(N - N_i) \tag{8}$$

In the context of MBNN (Memory-Based Neural Networks), the smoothing factor is denoted by the symbol σ, and the number of input data samples is represented by *n*. Choosing an appropriate value for σ is crucial. A higher σ enhances the model's ability to generalize, while a lower σ reduces this capability. In essence, as σ increases, the function approximation becomes smoother; conversely, a smaller σ leads to a less smooth approximation. The estimation of M(N) involves calculating a weighted sum of all observed values *Mi*, where each value is weighted based on its exponential decay relative to its Euclidean distance from *N*. This approach provides a means to determine M(N) by emphasizing values closer to *N* more heavily. In this study, the input to the MBNN consists of features extracted from images. These features form the input vectors, labeled from x_1 to x_m, and serve as the foundation for the network's processing.

4. EXPERIEMENTS AND RESULTS

To evaluate the reliability of the proposed system, we adopted, an established and widely recognized state-of-the-art methods as benchmarks. These methods were implemented and tested under identical conditions, utilizing the same dataset and following the same training and evaluation protocols.

$$\text{Accuracy}= \frac{\text{True Positive images+True Nagative Images}}{\text{Positive images +Negative Images}} \tag{9}$$

$$\text{Sensitivity}= \frac{\text{True Positive images}}{\text{Positive images}} \tag{10}$$

$$\text{Specificity}= \frac{\text{True Nagative Images}}{\text{True Negative Images+False Positive images}} \tag{11}$$

$$\text{Precision}= \frac{\text{True Positive images}}{\text{True Positive images+False Positive images}} \tag{12}$$

For the purpose of this investigation, handwriting and signature image samples from a variety of individuals were scanned digitally. The training data consisted of 25 different authors, while the testing data consisted of 100 different writers. The samples were written on paper that was A4 in size and did not have any lines.

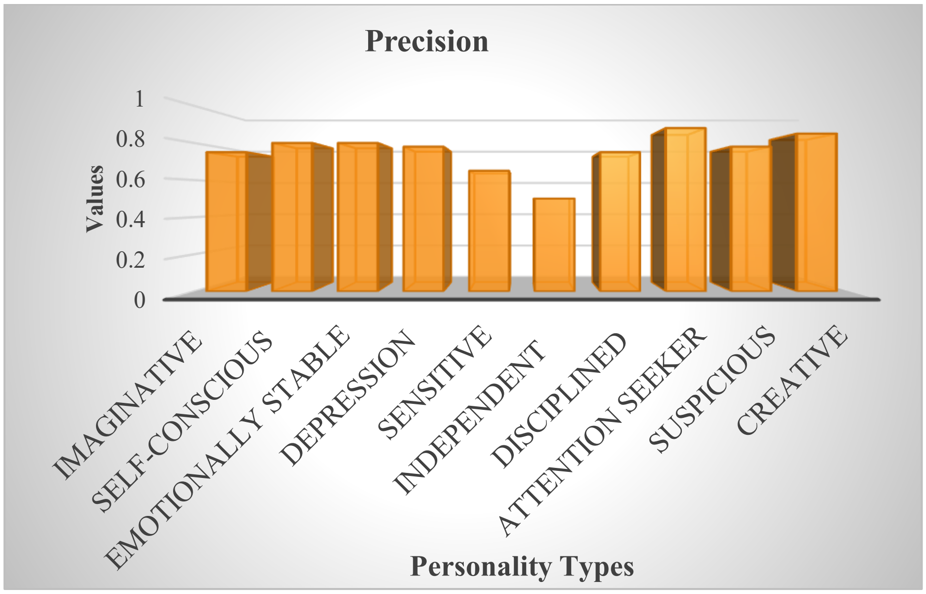

Fig 4: Precision Comparison of Personality Types

Fig. 4 illustrates the precision achieved by the proposed Modified Backpropagation Neural Network (Modified-BPNN) for different personality classes. The horizontal (x) axis represents the personality categories, while the vertical (y) axis indicates the corresponding precision values. The results demonstrate that the proposed model achieves consistently high precision across most personality traits, indicating its capability to correctly identify positive instances with minimal false-positive predictions. Among the evaluated classes, the Attention Seeker personality exhibits the highest precision, suggesting that the extracted handwriting features for this category are highly distinctive and effectively learned by the classifier. Comparatively lower precision values are observed for the Independent and Sensitive classes, indicating a greater similarity between these handwriting patterns and those of other personality categories. Overall, the precision results confirm the robustness of the proposed framework in accurately distinguishing multiple personality traits based on handwriting characteristics.

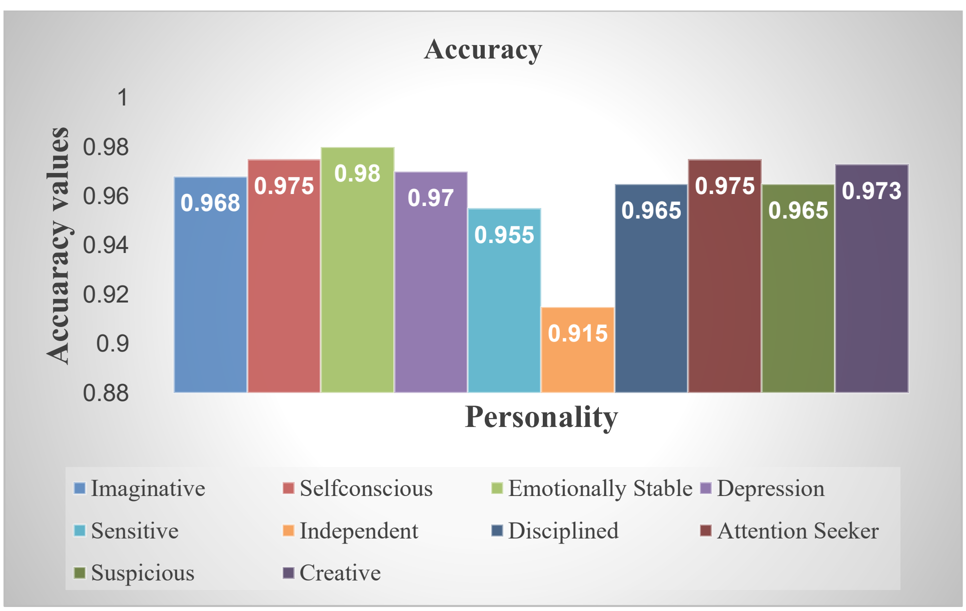

Fig 5: Accuracy Comparison of Personality Types

Fig. 5 presents the classification accuracy obtained for the various personality classes using the proposed Modified-BPNN model. The recorded accuracy values range from 91.5% to 98.0%, demonstrating the effectiveness of the proposed approach. The highest classification accuracy of 98.0% is achieved for the Emotionally Stable personality trait, while most of the remaining classes exhibit accuracies above 96%, reflecting the strong generalization capability of the classifier. The lowest accuracy of 91.5% indicates that this personality category shares certain handwriting characteristics with other classes, making its classification relatively more challenging. Despite this variation, the consistently high accuracy across all personality traits confirms that the combination of preprocessing, feature extraction, and the Modified-BPNN classifier successfully captures the discriminative characteristics of handwritten samples. These findings demonstrate the suitability of the proposed framework for reliable handwriting-based personality prediction.

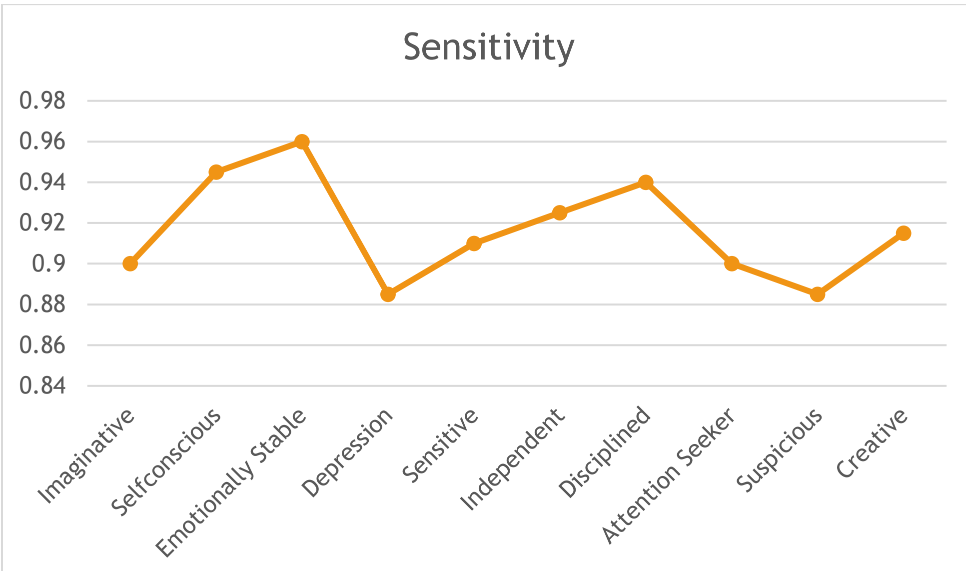

Fig 6: Sensitivity Comparison of Personality Types

Fig. 6 presents the sensitivity achieved by the proposed Modified Backpropagation Neural Network (Modified-BPNN) for different personality classes. The horizontal (x) axis represents the personality categories, while the vertical (y) axis denotes the corresponding sensitivity values. Sensitivity measures the ability of the classifier to correctly identify samples that truly belong to a particular personality class. The results indicate that the proposed model achieves consistently high sensitivity across most categories, demonstrating its effectiveness in reducing false-negative classifications. The Emotionally Stable personality class records the highest sensitivity, indicating that the classifier accurately recognizes the majority of samples belonging to this category. In contrast, comparatively lower sensitivity is observed for the Depression and Suspicious personality classes, suggesting that these handwriting patterns exhibit greater similarity with other categories. Nevertheless, the overall sensitivity values confirm that the proposed framework reliably detects personality traits from handwritten samples.

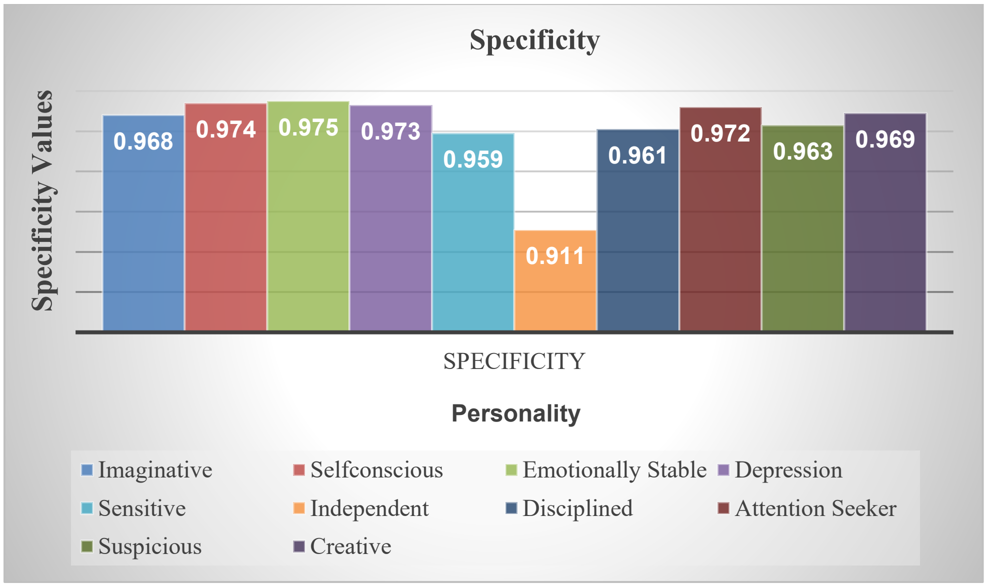

Fig 7: Specificity Comparison of Personality Types

Fig. 7 illustrates the specificity obtained for the various personality classes Specificity represents the capability of the classifier to correctly identify samples that do not belong to a particular personality class, thereby reducing false-positive predictions. As shown in the figure, the majority of the personality classes achieve specificity values greater than 0.95, indicating excellent discrimination between different handwriting patterns. The Emotionally Stable personality class exhibits the highest specificity, demonstrating that the proposed method effectively distinguishes this category from the remaining classes. A comparatively lower specificity value is observed for the Independent personality class, indicating a greater overlap between its handwriting characteristics and those of other personality traits. Overall, the specificity results demonstrate that the proposed classifier maintains strong discrimination capability and accurately separates different personality categories.

4. Comparison with other methods

The proposed model achieves an overall accuracy of 91%. It shows improved performance in detecting traits such as emotional stability and attention-seeking behaviour. The results indicate that MBPNN with multi-task learning outperforms traditional methods.

Method	Accuracy (%)
KNN	78
CNN	85
Existing BPNN	88
Proposed MBPNN (MTL)	**91**

The proposed method outperforms existing models due to improved feature learning and shared representation through multi-task learning. It is competitive, computationally efficient. The proposed MBPNN achieves a balanced trade-off between classification accuracy, computational efficiency, and implementation complexity. The DWT-based feature extraction preserves important structural information in handwriting, while the modified weight-update mechanism improves convergence during training.

Limitations:

Although the proposed model achieves high accuracy, the dataset size is relatively limited. Additionally, handwriting-based personality prediction may be influenced by external factors such as writing conditions. Future work will address these limitations using larger and more diverse datasets.

5. Conclusion:

Handwritten text is a kind of expressive conduct that sheds light on a person's personality characteristics. Handwriting is a unique behavioral characteristic that reflects an individual's writing habits, motor skills, and cognitive patterns. Since every person possesses a distinctive handwriting style, the analysis of handwritten samples can provide valuable insights into personality traits and behavioral tendencies. This study presented a handwriting-based personality prediction framework that integrates image preprocessing, feature extraction using the Discrete Wavelet Transform (DWT), and classification using a Modified Backpropagation Neural Network (Modified-BPNN). The proposed methodology effectively extracts discriminative handwriting features, including structural, statistical, and frequency-domain characteristics, which enhance the learning capability of the classifier.

The performance of the proposed model was evaluated using several standard classification metrics, including accuracy, precision, sensitivity, specificity, and the confusion matrix. Repeated experimental trials were conducted to verify the stability and consistency of the classification results. The obtained confusion matrix demonstrated that the majority of handwriting samples were correctly assigned to their respective personality classes, indicating the effectiveness of the proposed classification model. Furthermore, the high precision, sensitivity, and specificity values obtained across different personality categories confirm the robustness of the extracted feature set and the reliability of the Modified-BPNN classifier.

Experimental evaluation showed that the proposed framework achieved an overall classification accuracy of approximately 91%, demonstrating its capability to accurately distinguish personality traits from handwritten samples. The integration of DWT-based multiresolution feature extraction with the Modified-BPNN classifier significantly improved the discriminative power of the model while reducing the influence of noise and irrelevant information. The results indicate that the proposed approach provides a reliable and computationally efficient solution for handwriting-based personality assessment.

Overall, the proposed framework offers a robust and effective method for automated personality prediction using handwriting analysis. Its ability to extract meaningful handwriting features and achieve high classification performance makes it suitable for applications in behavioral analysis, psychological assessment, human resource screening, forensic document examination, and intelligent decision-support systems.

Future Scope

Future research may focus on increasing the size and diversity of the handwriting dataset to improve the generalization capability of the model. Additional deep learning architectures, such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, Vision Transformers (ViTs), and hybrid ensemble models, can be explored to further enhance classification performance. Moreover, incorporating multilingual handwriting samples, online handwriting dynamics, and multimodal behavioral features could improve the accuracy and applicability of personality prediction systems in real-world scenarios.

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