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Ensemble Learning Based Analysis Correlating Graphology to Big Five Personality Model

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Abstract — *Graphology and the Big five personality model are two different streams for predicting an individual's personality. Though their mechanisms are different, both culminate in the same goal of personality assessment. Big Five is the standardized model and uses the responses of 44 item questionnaire to categorize the personality of the individual in terms of scores for five traits of openness, conscientiousness, extraversion, agreeableness and neuroticism. Graphology is not standardized, and it uses handwriting traits to predict certain personality traits. This research work extends graphological concepts to fit into the big five model personality classifications through the convergence of image processing and machine learning. A clustering-based analysis is made to correlate the graphological features and big five personality observations. From the analysis, an ensemble learning classifier model is built for big five personality traits prediction from graphological features.*

Keywords — *Machine Learning, Clustering, Graphology, Handwriting Traits, Big Five Personality***.**

I. INTRODUCTION

Graphology and the Big five model are two different streams for the prediction of personality. Graphology uses various handwriting characteristics like strokes, margin, line spacing and word spacing etc., to predict the personality of the individual. The big five model uses 44 item questionnaires to assess personality in five dimensions. Compared to Graphology, the big five models are standardized and comprehensive. It fits the personality of the individual into five categories of openness, conscientiousness, extraversion, agreeableness and neuroticism[1]. The characteristics of an open personality are creating, exploring new things, open to facing new challenges. The characteristics of a Conscientiousness personality are time conscious, planning ahead, attention to detail. The characteristics of Extraversion personality are socially active, free going to friends and acquaintances, enjoys conversations with new people. The characteristics of agreeableness are lovable, caring for others, empathetic and being ready to help others. The characteristics of neuroticism are mostly stressed, experiencing rapid mood shifts, most of the time feeling anxious. Graphology does not have any standards, and it does not fit the individual to a definite trait. The association of graphology features to personality traits is immense, and it lacks simplicity compared to the Big five personality model. But the reliability of the big five models depends on the genuineness of the respondent in answering the questionnaire and his mood swing. Graphology is resistant to these problems [2]. There is an increasing need for personality assessment in many applications like recruitment, personality training, criminology etc. Due to reliability concerns in the questionnaire-based model, non-intrusive means of personality assessment has gained importance. Graphology is a non-intrusive means for personality assessment. But its personality vocabulary is huge, and it needs to be reduced for better personality assessment of an individual. An attempt is made to fit the personality vocabulary of graphology to the big five personality classes. As part of this attempt, a clustering analysis based correlation is established between the graphology features and big five personality traits. Various features extracted from the handwritten document images are correlated to each of the big five personality classes in terms of various clustering effectiveness indicators. The best sets of features with a higher correlation to the big five personality classes are selected. Features in both categories of conventional and deep learning are explored in this work. The scores for each of the big five personality classes are found applying the fuzzy Gaussian model. The validity of the model is tested against various handwritten documents and cross-verification of results with big five questionnaire tests. Following are the important contributions of this work

1. Extraction of various conventional and deep learning features from handwritten documents
2. A fuzzy correlation model relating the features to scores for each of the big five personality traits.
3. Validation of proposed fuzzy correlation model with big five test results.

II. LITERATURE SURVEY

B Fallah et al. [3]used handwriting characteristics to predict personality. Experimentation was conducted using the MMPI dataset. Authors extracted text-independent features like margin, character sizes, line spaces, word spaces, word tilts and vertical ratio of characters. The neural network was trained to classify the features to MMPI personality scale score. The solution was able to achieve about 70% accuracy in the classification of MMPI scales. But MMPI scale is limited and outdated for personality assessment. Mekhaznia et al. [4] detected personality from handwritten documents. The neural network was trained to classify the extracted textural features into two personality classes. But accuracy is limited, and the work classified only two personalities. Mutalib et al. [5] extracted the pattern of t from the handwritten document and classified the personality using a neural network. The work classified three different personalities of optimistic, balanced and pessimistic. The classified personalities were limited compared to the big five personality classification. Gavrilescu et al. [6] classified personality based on the t character pattern. Template matching of the t character pattern is done to classify two different personalities. The approach classifies only limited personality, and also, the computational complexity is high. Mishra et al. [7] classified the personality by extracting line direction and spacing between lines in handwritten documents. The personality classification accuracy is low due to a reduced set of features. Asra et al. [8] used SVM for personality classification. The classification was done using zonal features extracted from characters. Champa et al. [9] extracted features of baseline, the pressure of the pen and the "t" pattern from handwritten documents and classified it to the personality of the individual using a neural network. The solution classified three different levels of self-esteem. Rahiman et al. [10] extracted features of the pressure of the pen, inclination of baseline and letters and size of writing from handwritten documents and classified it using rule matching to personality traits. But the personality vocabulary is huge and lacks comprehension. Fisher et al. [11] analyzed the handwriting features to predict if an individual has the potential to commit violent crimes. Three features of incline, shape and form are used for classifying the criminal tendency. The handwritten documents from criminals are used for this study. Prasad et al. [12] extracted six different features from handwritten documents. SVM classifier is used to classify the six features of personality. Features of baseline, letter size, the inclination of letters, pressure of the pen, spacing between word and letter are extracted. The features were classified into 16 different personalities. Grewal et al. [13]usedANN for personality prediction from features of the inclination angle of baseline and letters, pen pressure, the pattern of 'i' and 'f'.The features were classified into more than 50 different personalities. Coll et al. [14]used handwriting analysis to measure applicant aptitude during recruitment. Features like letter size, shape, slant, line angle are extracted from the handwritten document and classified using an artificial neural network. The ground truth for desirable aptitude is established based on past experience. The neural network is trained using these ground truth images. Mukherjee et al. [15]predicted personality from the inclination of letters and spaces between letters. But the approach lacked testing against real datasets. Joshi et al. [16] extracted features of inclination of alphabets and page margins to classify the personality. KNN classifier is used for classification. The personality vocabulary was huge, and the approach lacked testing against real datasets. Kacker et al. [17] extracted features of margins, baseline, letter size and zones from the handwritten document and classified them using rule-based matching to the personality of the individual. But the personality trait classes were more than 20 in this solution. Mutalib et al. [18] used handwriting analysis to assess the emotion control of an individual. The baseline features extracted from the handwritten document is classified using fuzzy logic to four levels of emotion control. Wijaya et al. [19] extracted margin features and classified it 15 different personalities using an SVM classifier. Chitlangia et al. [20] extracted the histogram of gradient (HoG) featured from the handwritten documents and classified it into five different non-standardpersonality traits. Multi-class SVM was used for classification. Different from extracting individual features, HoG is extracted from the entire document image and used for personality classification in this work. But the solution works only for documents with a single line. Pratiwi et al. [21] extracted features of baseline, slant, font size and breaks from the handwritten document and classified it into nine different personalities of the Enneagram scale. Correlation analysis is done between graphology and psychology using this work. Majumder et al. [22] extracted style based attributes from documents to classify big five personalities using a deep learning classifier. But classifying personality based on word semantics has higher false positives. Lokhande et al. [23] extracted letter features of underscores, dots, curves, strokes and connections from hand signatures to classify big five personality classes. Rule-based matching is done to classify personality. But the difference from the big model this work could not provide the score for the personalities. Hashemi et al. [24] extracted features of space between lines, page margins, the inclination of words and letters, letter size, sharpness in the corner from Farsi documents. The features are then classified into personalities using rule-based matching. The personality classes are high, and it is not comprehensive in this work.

TABLE I

SURVEY SUMMARY

Solution	Features	Personality classes	Problem
B Fallah et al. (2016)	Margin, Character Sizes, Line Spaces, Word Spaces, Word Tilts and Vertical Ratio of Characters	MMPI personality score	MMPI scale is limited and outdated for personality assessment
Mekhaznia et al. (2021)	Textural Features	2 personality class	Accuracy less than 70%
Mutalib et al. (2007)	T Pattern	Three personalities of optimistic, balanced and pessimistic	Scope of personality is limited
Gavrilescu et al. (2018)	T Pattern	Two personalities	Scope of personality is limited
Mishra et al. (2017)	Line Direction, Spacing Between Lines	More than 20 personalities	Limited accuracy
Asra et al. (2018)	Zonal Features of Characters	More than 20 personalities	Limited accuracy
Champa et al. (2010)	'T' Pattern, Pressure of Pen	Three different levels of self-esteem.	Scope of personality is limited
Rahiman et al. (2013)	Inclination Of Baseline, Letters and Pressure of Pen	More than 20 personalities	Personality vocabulary is huge and lacks comprehension
Fisher et al. (2012)	Incline, Shape and Form	Criminal tendency	The limited scope of personality
Prasad et al. (2010)	Baseline, Letter Size, Slant Of Letters, Pen Pressure, Word Spacing And Letter Spacing	16 different personalities	Personality vocabulary is huge and lacks comprehension
Grewal et al. (2012)	Base Line, Inclination of Letter, Pressure of Pin, 'I' And 'F' Pattern	50 different personalities	Personality vocabulary is huge and lacks comprehension
Coll et al. (2009)	Letter Size, Shape, Slant, Line Angle	20 different personalities	Personality vocabulary is huge and lacks comprehension
Mukherjee et al. (2016)	Letter Size, Spacing, Skew Angle, Slant Angle, Pressure and Signature	20 different personalities	Not tested against real datasets
Joshi et al. (2015)	Baselines, Inclination of Slants, Page Margins	More than 20 different personalities	Not tested against real datasets
Kacker et al. (2012)	Margins, Baseline, Letter Size and Zones	More than 20 different personalities	Personality vocabulary is huge and lacks comprehension
Mutalib et al. (2008)	Base Line Features	Four levels of emotion control	Limited scope
Wijaya et al. (2018)	Margin Features	15 personalities	Personality vocabulary is huge and lacks comprehension
Chitlangia et al. (2019)	Hog Features	Energetic, Extrovert, Introvert, Sloppy and Optimistic	Works only for document line
Pratiwi et al. (2016)	Baseline, Slant, Font Size and Breaks	Nine different personalities of Enneagram scale	Limited scope
Majumder et al. (2017)	Stylistic Features and Per Word Semantic Features	Big five personality	Higher false positives
Lokhande et al. (2017)	Signature-based features.	Big five personality	Could not provide the score for each personality
Hashemi et al. (2015)	Inclination Of Lines and Letters, Letter Size	More than 20 personalities	The personality classes are high, and it is not comprehensive in this work

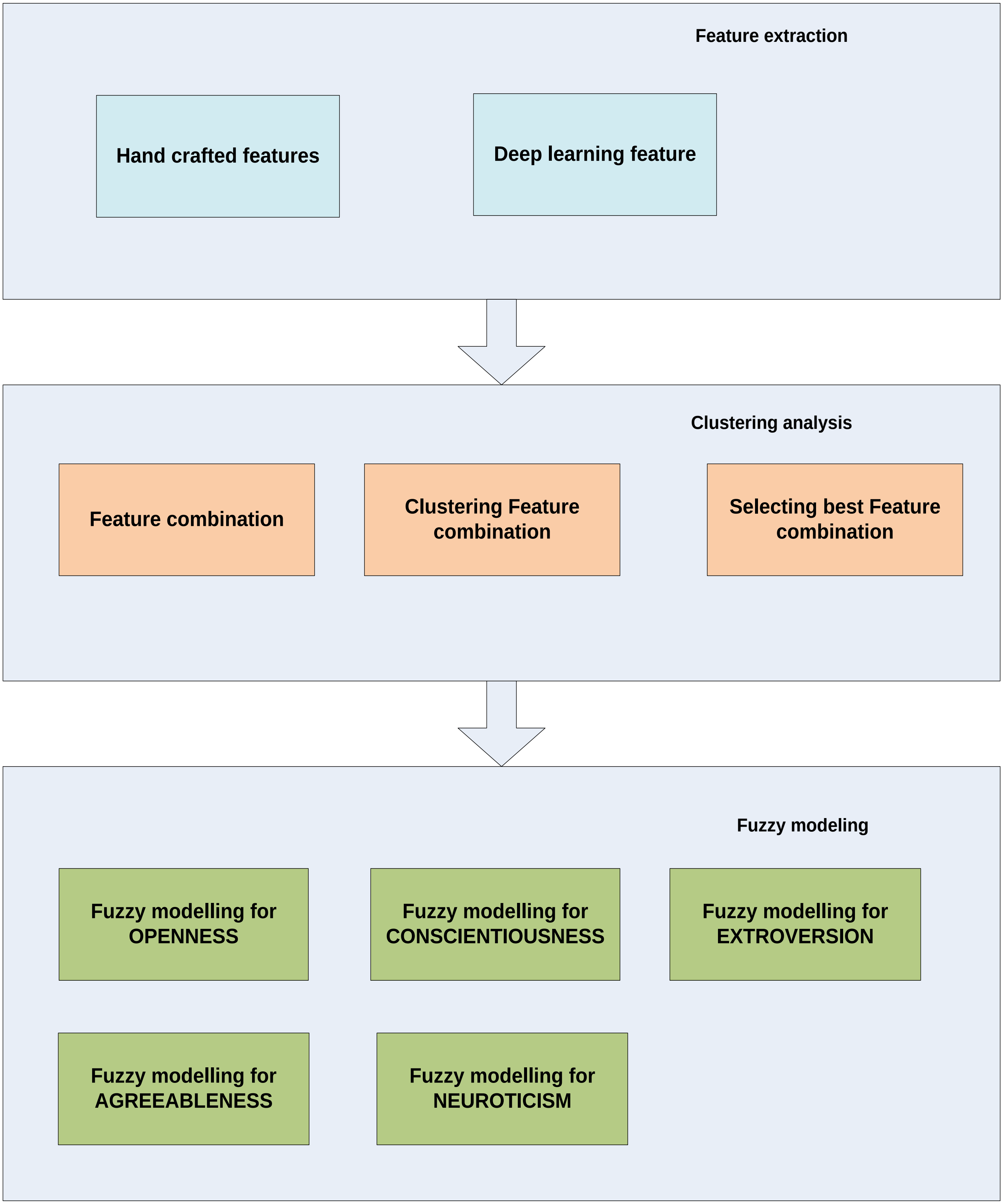

Fig.1. Proposed Ensemble Architecture

III. LITERATURE GAP

The summary of the survey is presented in Table I.

As seen from Table I, there are very works relating graphology

features to the big five personality classes. In most works on graphology based personality assessment, the numbers of personality classes are very high, and it is difficult to comprehend. In the very few works on graphology based big five personality assessment, there are the following problems:

1. Features are handcrafted, and there is no uniform normalization at the feature level. Due to this, personality assessment is a scaled variant.
2. In the big five models, an individual is assigned to all the big five personalities on different scales. But the existing works classify only the dominating personality and does not apply scoring to each personality trait.

The solution proposed in this work address these two problems.

IV. PERSONALITY PREDICTION

The proposed ensemble learning-based analysis correlating graphology to big five personalities involves following three important functionalities

1. Feature extraction
2. Clustering analysis
3. Fuzzy modelling

The functional components of the proposed solution are given in Figure 1. Various features are extracted from handwritten documents. Both handcrafted features used in earlier works and a novel deep learning feature are extracted from the handwritten document. Clustering analysis is conducted to select the best set of features correlating to the big five personalities. For different combinations of features, a clustering score based on three parameters of cohesion, separation and silhouette coefficient is calculated. The feature combined with the highest score is selected as a highly relevant feature for the personality clash. A fuzzy model has created an ensemble of the relevant features to predict big five personality scores for each of the personality classes in the range of 1 to 5, as given in Figure 2.

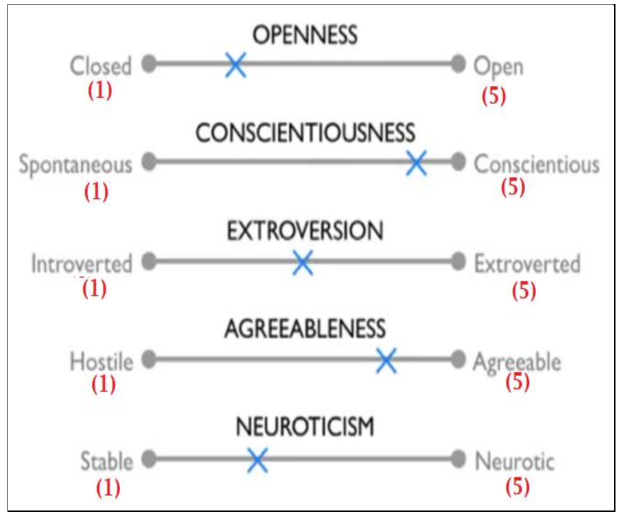

Fig.2. Big five personality output

Each of the three important functionalities is detailed below

A. Feature extraction

Both handcrafted and deep learning features are extracted in this work. The handcrafted features are normalized from exact values to categorical variables. This normalization is done to add scale invariance to the features irrespective of the input document size. The camera properties, resolution and distance of the document are considered in segmenting the pixel of the image [25]. The handcrafted features and their normalized categorical ranges are given in Table 2. In addition to the handcrafted feature, a novel deep learning feature is also extracted at the document level from the handwritten document image. Fisher vector-based Convolutional neural network (FV-CNN) is used for deep feature extraction from the handwritten image. The architecture of the FV-CNN is given in Figure 3.

Different from typical CNN [26], where features are extracted from the last pooling layers, the Fisher vector method extracts features from each of the convolutional filter responses. Compared to a typical convolutional filter response, FV-CNN features are very efficient in describing the input image. An additional advantage of FV-CNN is that rescaling of the input image is not needed.

TABLE IIHAND CRAFTED FEATURES

Features	**Significance**	**Normalized Values**
Baseline (F1)	It is also called the line of reality. A baseline is like a path that he/she follows to reach his destination or goal. A moody person will take more time to reach his goal than a person who is more stable.	Level [BL] Ascending[BA] Descending[BD] Varied[BV] Convex[BCV] Concave[BCC]
Margin (F2)	The top margin is an indication of taste and convention. The bottom margin of the page is an indication of indecision, laziness, sentimentality.	Even margin all around[ME] Too wide margin all around[MAW] Overly wide left margin[MLW] Overly wide right margin[MRW] Left margin narrowing as it descends[MLDN] Left margin widening as it descends[MLDW] Narrow left margin[MLN] Wide upper margin[MTW] Narrow upper margin[MTN] Wide lower margin[MDW] Narrow lower margin[MDN] No margins at all[MNO]
Space between lines (F3)	Spacing between lines is an indication of the planning and organizing ability of an individual.	Even[LE] Narrow[LN] Wide[LW] Very wide[LVW] Tangled[LT] Varied[LV]
Space between words (F4)	The spacing between words tells more about the distance the writer puts between himself and others in a social environment	Narrow[WN] Wide[WW] Even[WE] Uneven[WUE] Very wide[WVW]
The slant of character (F5)	Ability to express opinions, confidence in convictions	Right slant (RS) Left slant (LS) Vertical (VS)
Zonal presence of a character (F6)	Indication on openness to experience	High (H) Medium (M) Low (L)
Connectivity of letter (F7)	The individual is logical or imaginative, or impulsive	Connected (C) Disconnected(DC)

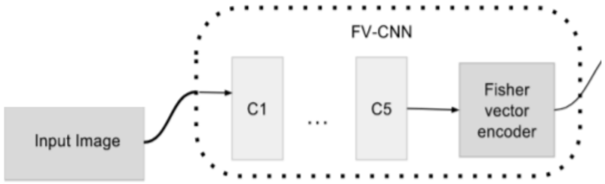

Fig.1. FV-CNN Architecture

Resnet 50 [27] is used as the CNN model in this work. Resnet or Residual Network was proposed by Microsoft researchers in 2015 to solve the vanishing gradient due to a higher number of layers in deep CNN. Resnet increases the feature learning ability using the skip connection strategy, thereby maximizing the effectiveness of the deep network. The gradient vanishing problem is solved due to skipping the connection in the Resnet. The configuration of Resnet-50 is given in Table III.

TABLE IIIRESNET-50 CONFIGURATION

Layer name	Output size	Type
Input	224*224*3	None
Convolution 1	112*112	7 × 7, 64, stride 2 3 × 3 max pool, stride
Convolution 2	56*56	$\begin{bmatrix} 1*1 & 64 \\ 3*3 & 64 \\ 1*1 & 256 \end{bmatrix} * 3$
Convolution 3	28*28	$\begin{bmatrix} 1*1 & 128 \\ 3*3 & 128 \\ 1*1 & 512 \end{bmatrix} * 4$
Convolution 4	14*14	$\begin{bmatrix} 1*1 & 256 \\ 3*3 & 256 \\ 1*1 & 1024 \end{bmatrix} * 6$
Convolution 5	7*7 1*1	$\begin{bmatrix} 1*1 & 512 \\ 3*3 & 512 \\ 1*1 & 2048 \end{bmatrix} * 3$ Avg pool,1000-d FC

Fisher vector uses a Gaussian mixture of local image descriptors with the use of nonlinear Hellinger's kernel and l2 normalization. At each convolutional layer, K different filter kernels of dimension M×N feature maps are used. The feature map is the local descriptor. The response of M×N local descriptors is then pooled to get the feature vector. The handwritten document image is given as input to FV-CNN based on Resnet-50 to convert into a feature vector of dimension 1*4096.

B. Clustering analysis

The aim of clustering analysis is to select the best set of features most relevant to the specific class of the big five personalities. The features are ensembled in different combinations. For each combination, clustering of handwritten documents is done for each personality on a different scale. The cluster for a feature combination is scored with a weighted fitness score based on three parameters of cohesion, separation and silhouette coefficient. The feature combined with the highest value for the fitness score for its cluster is the highly relevant feature for that particular personality class.

Cohesion is the measurement of the degree of similarity of items within the cluster. The higher value of cohesion demonstrates the good compactness of clustering. It is calculated in terms of the sum of squares of distances of each point in the cluster to the centroid of the cluster, as given below

$$Ch = \sum_i \sum_{x \epsilon C_i} (x - m_i)^2 \tag{1}$$

Separation is an indication of how well-separated a cluster is from other clusters. It is measured as

$$Sp = \sum_i |C_i| \, (m - m_i)^2 \tag{2}$$

Where $|C_i|$ is the size of the cluster i, and m is the centroid of the whole feature set. Higher the separation is an indicator of good clustering.

The silhouette analysis reveals the mean distance between clusters. It is calculated in terms of

$$sc = \begin{cases} 1 - \frac{a}{b}\ , \ if a < b \\ \frac{b}{a} - 1 \ if a \geq b \end{cases} \tag{3}$$

In equation (3), a and b are the average and minimum distance of points in one cluster to another cluster. SC value range from 0 to 1, and when it is towards 1, the clustering quality is good.

Clustering is done using K means clustering with K value as 5 (Each personality has a score from 1 to 5). The fitness score for the cluster is calculated as

$$F_c = w_1 \times Ch + \ w_2 \times Sp + \ w_3 \times sc \tag{4}$$

Where $w_1, w_2 and w_3$ are the preference weights for $Ch, Spandsc$. It is allocated in such a way that

$$w_1 + w_2 + \ w_3 = 1$$

Say there is the total of $n$features extracted from the handwritten document. The features can be combined in $2^n - 1$ combination. For each of the 2^n combinations, F_c Is calculated. The combination with maximum value for F_c Is selected as the relevant set of features for the personality class. This process is repeated for all five personality classes, and the relevant features for each personality are determined.

C. Fuzzy modelling

In the earlier section, a relevant set of features are identified for each personality, but the association between the features to the score for each personality must be determined. This is determined using the fuzzy model. A training dataset is created with feature combination and score of personality.

Clustering is done using Fuzzy C Means clustering with number of clusters as P. The cluster centre is given as

$$D = \{ D_{e,q} , e = 1,2 \ldots 5 and q = 1,2,3\}$$

Where $D_{e,q}$ It is the qth feature of the eth cluster.

The closeness of the q[th] feature of the r[th] data f r,q with q[th] feature of eth cluster is defined using Gaussian function [28] as

$$G(f_{r,q}, D_{e,q}, \sigma_{e,q}) = e^{\frac{(f_{r,q}-D_{e,q})^2}{\sigma_{e,p}{}^2}} \qquad (5)$$

Where

$$\sigma_{e,q} = \frac{1}{N_e}\sum_{r=1}^{N_e}(f_{r,q} - D_{e,q})^2$$

Features closeness to cluster in terms of Gaussian function is given as

$$\Psi_{r,e} = \prod_{q=1}^{P} G(f_{r,q}, D_{e,q}, \sigma_{e,q}) \qquad (6)$$

Using linear regression, the output label is given as

$$\Phi_{r,e} = W_{e,0} + \sum_{q=1}^{P} W_{e,q,f_{r,q}} \qquad (7)$$

Where W is the regression coefficient, the final cluster label is found as weighted membership of the link.

$$\bar{N}(r) = \sum_{e=1}^{P} \Psi_{r,e}\Phi_{r,e} \qquad (8)$$

The error of fitting is calculated between $\bar{N}(r)$and $N(r)$ as given below

$$E = \sum_{r=1}^{N} ||\bar{N}(r) - N(r)||^2 \qquad (9)$$

The Gaussian parameters $D_{e,q}, \sigma_{e,q}$ and the regression coefficients $W_{e,p}$ are optimized with decent gradient method as below

$$D_{e,q}(t+1) = D_{e,q}(t) + \eta_C \frac{\partial E}{\partial D_{e,q}} \qquad (10)$$

$$\sigma_{e,q}(t+1) = \sigma_{e,q}(t) + \eta_\sigma \frac{\partial E}{\partial \sigma_{e,q}} \qquad (11)$$

$$W_{e,q}(t+1) = W_{e,q}(t) + \eta_W \frac{\partial E}{\partial W_{e,q}} \qquad (12)$$

The iteration is given as t, and learning parameters are $\eta_C, \eta_\sigma, \eta_W$. Fuzzy Gaussian membership functions are obtained for each of the classes correlating features to the scores. Once these functions are obtained for all Big five personalities, these functions are invoked for any new input features to get the personality score for each of the big five personalities.

V. RESULTS

A total of 200 handwritten images were collected from graphologists. Big five psychometric tests were also conducted on the 200 participants [29].

Each of the images was tagged with the score for each of the big five personality classes based on the results of the big five psychometric test results. Both handcrafted features (7 features, F1-F7) and deep learning features (F8) are extracted from each of the handwritten images. The total number of feature combinations for 8 features is 255. Each of 255 combinations is explored for five different personalities. The best feature set combination for each of the five personalities is given in Table IV.

TABLE IVBEST FEATURES

Personality type	Feature combination
Openness	F4 + F5 + F8
Conscientiousness	F3+F6+F7+F8
Extraversion	F4 + F7 + F8
Agreeableness	F1+F2+ F3 + F8
Neuroticism	F2+F5+F6+ F7 + F8

The results show that not all graphological features are needed for scoring all personalities, and there exists a subset of graphological feature mapping to big five personalities.

The difference in fitness scores for each of the big five personalities for each of the five scoring levels is shown in the box-whisker plot Figure 4 – Figure 8. The plot shows a clear separation between the scores (five scores given as group 1 to group 5) for all the big five personalities with the best set of feature combinations.

The accuracy measurement is done for each of the five personality types. The performance is compared against personality detection approaches proposed by Lokhande et al. [23] and by Gavrilescu et al. [6]. These works were selected for comparison, as they were the most recent work on big five personality classification from handwritten documents.

The personality prediction accuracy for each of the five personality traits is measured and given in Table 5.

TABLE V ACCURACY

Personality type	Lokhande et al (2017)	Gavrilescu et al (2018)	Proposed
Openness	78.9	88.3	89.1
Conscientiousness	76.4	80	83
Extraversion	79	87.4	89.2
Agreeableness	80	80	82
Neuroticism	77.6	85.3	88.6
Average	**78.38**	**84.2**	**86.38**

The average accuracy in the proposed solution is 2.18% higher compared to Gavrilescu et al. and 8% higher compared to Lokhande et al. Use of both handcrafted features and deep learning features with efficient feature selection has increased the average accuracy in the proposed solution. The average accuracy is higher for Openness, Extraversion and Neuroticism personalities. But it is at least 6% lower for Conscientiousness and Agreeableness personality. Integrating even more character features like 's', 'm','l' patterns can reduce this difference inaccuracy.
Sensitivity is measured for all the five big five personality traits and given in Table VI.

TABLE VISENSITIVITY

Personality type	Lokhande et al. (2017)	Gavrilescu et al. (2018)	Proposed
Openness	75.7	85.9	88.4
Conscientiousness	74.2	78	82.5
Extraversion	76	83.4	87.9
Agreeableness	79	78	81.2
Neuroticism	75.2	82.5	87.5
Average	**76.02**	**81.56**	**85.5**

The average sensitivity in the proposed solution is 4.6% higher compared to Gavrilescu et al. and 9.48% higher compared to Lokhande et al. The sensitivity is higher in the proposed solution due to the higher statistical correlation of features to the big five personality classes. Though the sensitivity is higher in the proposed solution, it could sill be improved by adding more features with higher statistical correlation to the big five personality classes. Like inaccuracy, the sensitivity for classes openness, extraversion and neuroticism are higher compared to Conscientiousness and Agreeableness.
Specificity is measured for all the five big five personality traits and given in Table VII.

TABLE VIISPECIFICITY

Personality type	Lokhande et al (2017)	Gavrilescu et al (2018)	Proposed
Openness	76.7	86.1	89.4
Conscientiousness	75.3	78.5	83.5
Extraversion	77	83.9	88.9
Agreeableness	78.5	78.56	83.4
Neuroticism	76.4	82.6	88.3
Average	**76.78**	**81.93**	**86.7**

The average specificity in the proposed solution is 4.77% higher compared to Gavrilescu et al. and 9.92% higher compared to Fallah et al. The specificity is higher in the proposed solution due to the selection of proper features combined with a higher correlation to personality classes. But still, the specificity value is only 86.7% in the proposed solution, and this could be improved further by the integration of even more document and character level features.
In summary, the proposed solution performed better in terms of accuracy, sensitivity and specificity compared to existing works. This is due to an ensemble of both handcrafted and deep features with the most relevant feature selection based on clustering analysis.

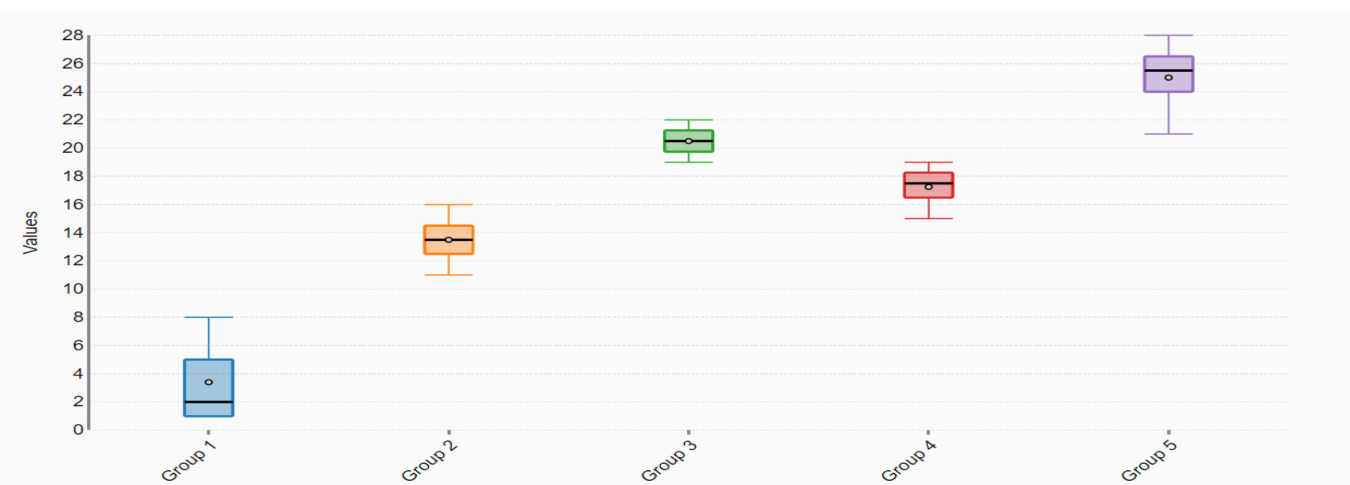

Fig.4.Fitness score for Openness

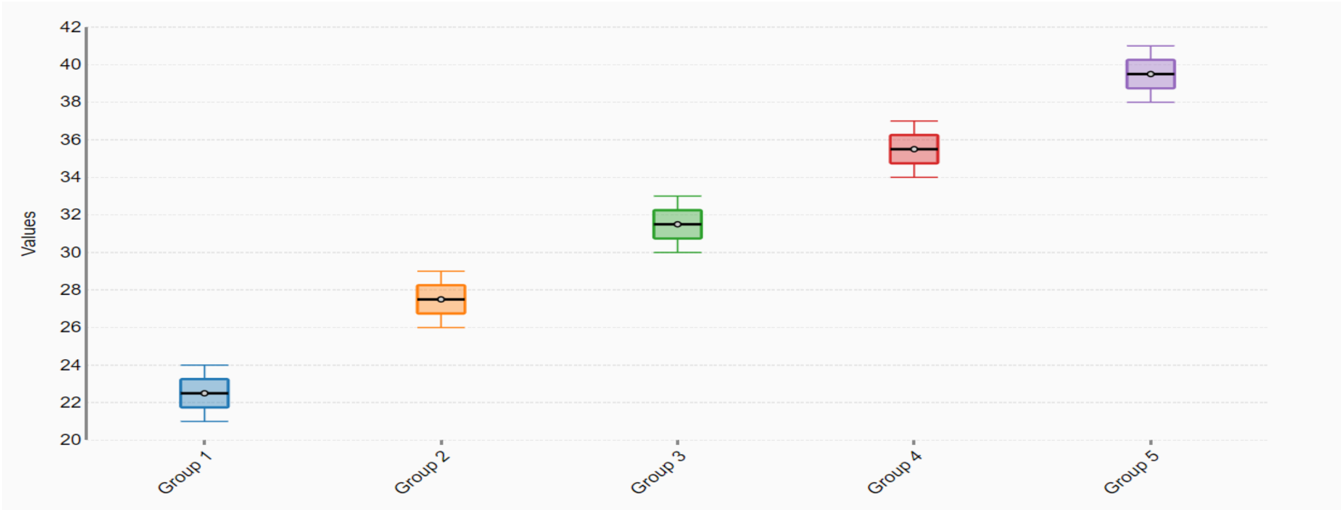

Fig.5. Fitness score for Conscientiousness

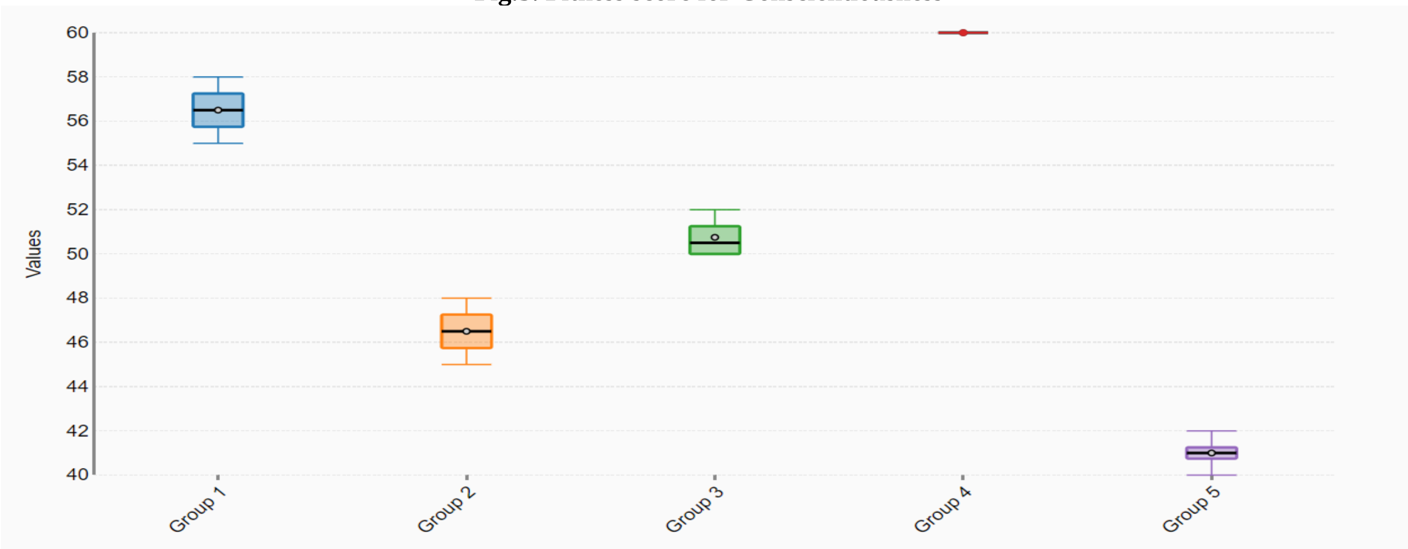

Fig.6. Fitness score for extraversion

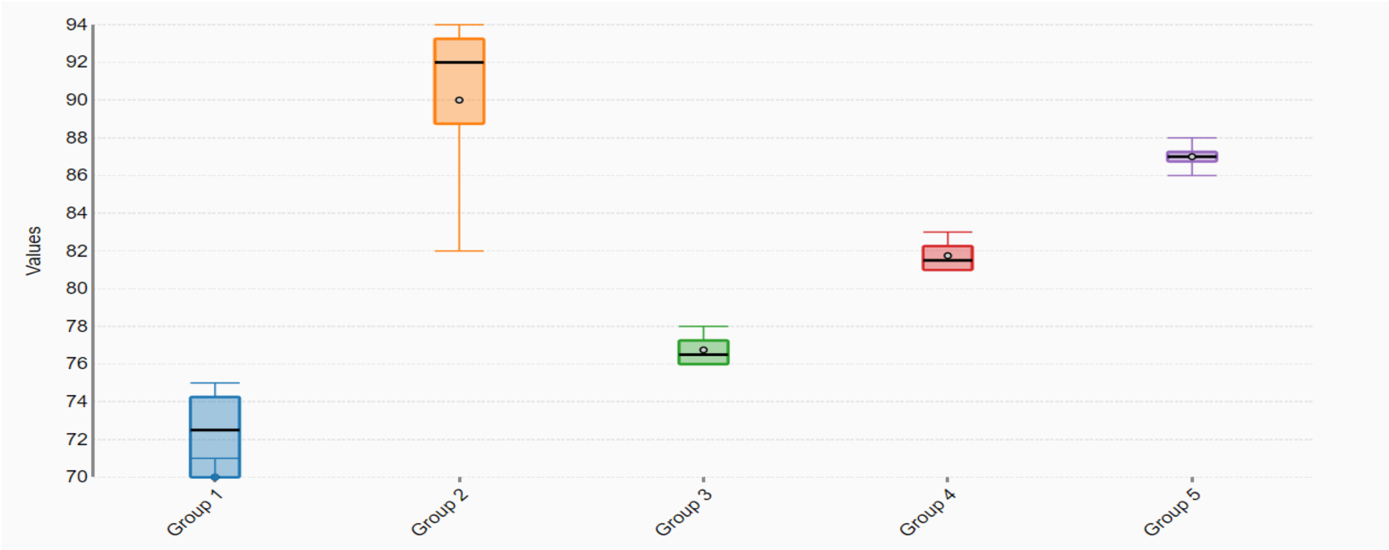

Fig.7. Fitness score for Agreeableness

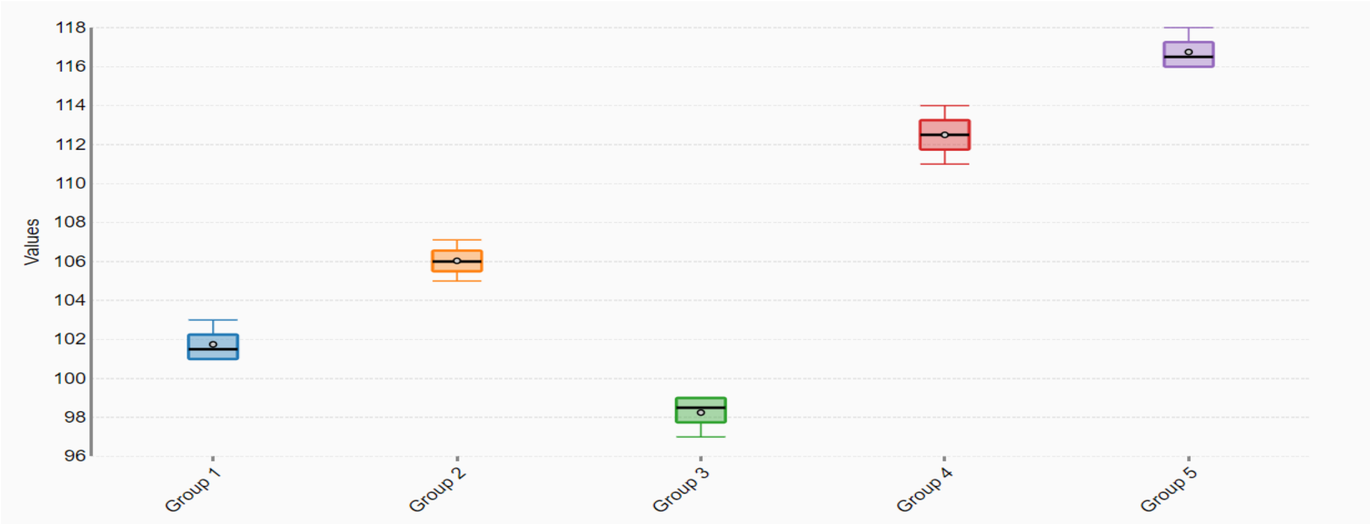

Fig.8.Fitness score for Neuroticism

The mean square error (MSE) between the personality score provided by the proposed fuzzy model and the actual score given by the big five psychometric models is measured for all five personalities, and the result is given in Table VIII.

TABLE VIII MEAN SQUARE ERROR BETWEEN THE PERSONALITY SCORE PROPOSED FUZZY MODEL AND THE ACTUAL SCORED FEATURES

Personality type	Proposed
Openness	0.256
Conscientiousness	0.450
Extraversion	0.248
Agreeableness	0.490
Neuroticism	0.264
Average	**0.341**

The MSE difference between the predicted score and actual score is less in the proposed solution demonstrating the effectiveness of the proposed fuzzy model on a relevant set of features. Also, the MSE is very less for Openness personality compared to others. The lower MSE signifies the suitability of the proposed fuzzy scoring model for the big five personality scale.

The overlap in misclassification between personality classes is measured in the proposed solution, and the result is given in Table IX.

IX MISCLASSIFICATION BETWEEN CLASSES

Personality type	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Openness	X	1%	1%	1%	1%
Conscientiousness	1%	X	3%	3%	3%
Extraversion	1%	1.5%	X	1%	1%
Agreeableness	1%	3%	1%	X	2%
Neuroticism	1%	3%	1%	2%	X

From the results, it can be seen misclassification is higher for the combination of Conscientiousness and Neuroticism compared to other classes. Thus, the selection of more features to separate Conscientiousness and Neuroticism classes is the missing link in the proposed solution to improve the classification performance.

VI. CONCLUSION

This work proposed a big five personality prediction system from handwritten documents. Both handcrafted and deep learning features were extracted from the handwritten document. The most relevant features for each personality class are found using clustering analysis. The fuzzy model was proposed to classify the personality to a very fine-grained level of scores for each personality. The proposed solution achieved an average accuracy of 86.38% in personality prediction with 2.18% higher accuracy compared to the state of the existing artworks.

REFERENCES

[1] John, O. P., & Srivastava, S., The Big-Five trait taxonomy, History, measurement, and theoretical perspectives. In L. A. Pervin& O. P. John (Eds.), Handbook of personality, Theory and research, New York, Guilford Press, 2 (1999) 102–138.

[2] Lakshmi Durga, R Deepu, Handwriting Analysis Through Graphology, A Review, International Conference on Advances in Computing, Communications and Informatics (ICACCI), (2018)

[3] B Fallah, H Khotanlou, Identify human personality parameters based on handwriting using neural networks, in Artificial Intelligence and Robotics (IRAN OPEN). (2016)

[4] Mekhaznia, T., Djeddi, C., & Sarkar, S. (2021), Personality Traits Identification Through Handwriting Analysis, Pattern Recognition and Artificial Intelligence, 4th Mediterranean Conference, MedPRAI, Hammamet, Tunisia, Proceedings, 1322 (2020) 155–169. https,//doi.org/10.1007/978-3-030-71804-6_12

[5] Mutalib, S., Rahman, S.A., Yusoff, M., Mohamed, A Personality analysis based on letter 't' using backpropagation neural network, In Proceedings of the International Conference on Electrical Engineering and Informatics Institut Teknologi Bandung (2007).

[6] Gavrilescu, M., Vizireanu, N, Predicting the Big Five personality traits from handwriting, J Image Video Proc. 57 (2018).

[7] Mishra A, Forensic Graphology, Assessment of Personality. Forensic Res Criminol, Int J., 4(1) (2017) 9-12. DOI, 10.15406/frcij.2017.04.00097

[8] Asra, S., Shubhangi, D.C, Human behaviour recognition based on handwritten cursives by SVM classifier, In, International Conference on Electrical, Electronics, Communication Computer Technologies and Optimization Techniques, ICEECCOT (2017) (2018). 10.1109/ICEECCOT.2017.8284679

[9] H.N. Champa, K.R.AnandaKumar, Artificial Neural Network for Human Behavior Prediction through Handwriting Analysis, International Journal of Computer Applications (0975 - 8887) . 2(2) (2010).

[10] A. Rahiman, D. Varghese, M. Kumar, Handwritten Analysis Based Individualistic Traits Prediction, International Journal of Image Processing (TJIP), 7(2) (2013).

[11] J. Fisher, A. Maredia, A. Nixon, N. Williams, J. Leet, IdentifYing Personality Traits, and Especially Traits Resulting in Violent Behavior through Automatic Handwriting Analysis, Proceedings of StudentFaculty Research Day, CSIS, Pace University, (2012).

[12] Sh. Prasad, V. Kumar, A. Sapre, Handwriting Analysis based on Segmentation Method for Prediction of Human Personality using Support Vector Machine, International Journal of Computer Applications (0975 - 8887) . 8(12) (2010).

[13] Grewal, Prashar, Behavior Prediction Through Handwriting Analysis, IJCST (2012).

[14] Coll, R.; Fornes, A.; Llados, J, Graphological analysis of handwritten text documents for Human Resources Recruitment, ICDAR '09 (2009) 1081-1085.

[15] S. Mukherjee and I. De, Feature extraction from handwritten documents for personality analysis, International Conference on Computer, Electrical & Communication Engineering (ICCECE), (2016) 1-8.

[16] P. Joshi, Handwriting analysis for detection of personality traits using machine learning approach, International Journal of Computer Applications (0975 8887) . 130 (2015).

[17] R. Kacker and H. B. Maringanti, Personality analysis through handwriting, GSTF Journal on Computing (JoC), 2 (2012) 94–97.

[18] S. Mutalib, R. Ramli, S. A. Rahman, M. Yusoff and A. Mohamed, Towards emotional control recognition through handwriting using fuzzy inference, 2008 International Symposium on Information Technology, (2008) 1-5

[19] Wijaya, Waskitha& Tolle, Herman &Utaminingrum, Fitri., Personality Analysis through Handwriting Detection Using Android Based Mobile Device, Journal of Information Technology and Computer Science. 2 (2013). 10.25126/jitecs.20172237.

[20] Chitlangia, Aditya &Malathi, G., Handwriting Analysis based on Histogram of Oriented Gradient for Predicting Personality traits using SVM, Procedia Computer Science. 165 (2019) 384-390. 10.1016/j.procs.2020.01.034.

[21] Pratiwi D, Santoso GB, Saputri FH, Personality type assessment system by using enneagram-graphology techniques on digital handwriting, International Journal of Computer Applications 147(11) (2016).

[22] N. Majumder, S. Poria, A. Gelbukh and E. Cambria, Deep Learning-Based Document Modeling for Personality Detection from Text, in IEEE Intelligent Systems, 32(2) (2017) 74-79.

[23] Lokhande VR, Gawali BW, Analysis of signature for the prediction of personality traits, In Intelligent Systems and Information Management (ICISIM), 1st International Conference on. IEEE; (2017) 44–9.

[24] Hashemi S, Vaseghi B, Torgheh F, Graphology for Farsi handwriting using image processing techniques, IOSR J Electron CommunEng(IOSR-JECE) 10(3) (2015) 01–7.

[25] Deepu, R; Murali, S; Raju, Vikram, A Mathematical model for the determination of the distance of an object in a 2D image, Proceedings of the International Conference on Image Processing, Computer Vision, and Pattern Recognition (IPCV); Athens, Athens, The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp)(2013) 1-5.

[26] Lakshmi Durga Deepu R. Ensemble Deep Learning to Classify Specific Types of t and i Patterns in Graphology, Global Transitions Proceedings, (2021).

[27] K. He, X. Zhang, S. Ren and J. Sun, Deep Residual Learning for Image Recognition, 2016 IEEE Conference on Computer Vision and Pattern Recognition,(CVPR), (2016) 770-778

[28] Sitansu Kumar Das, Sanjoy Kumar Saha, Dipti Prasad Mukherjee Multiple Objects Segmentation with Fuzzy Rule-Base Trained Topology Adaptive Active Membrane, ICVGIP '10, Chennai, India Copyright 2010 ACM 978-1-4503-0060-5/10/12. (2010).

[29] https,//openpsychometrics.org/tests/IPIP-BFFM/