International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 13, No.1 (Jan-2023)

http://dx.doi.org/10.12785/ijcds/130119

Hybrid Intelligent Technique with Deep Learning to Classify Personality Traits

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Received 29 Jan. 2022, Revised 7 Sep. 2022, Accepted 15 Dec. 2022, Published 31 Jan. 2023

Abstract: The importance of personality traits in education, employment, and disease detection has prompted several studies to construct intelligent systems that can identify any individual's personality traits based on their signature, face, handwriting, etc. As is well known, signatures play a significant legal role in document authentication. Thus, graphology shows that the study of the signature features aids in the prediction of personality traits.This paper examines two models to categorize an individual's personality traits into five groups using the big five-factor.Much preprocessing is applied to data training and testing.The analysis of images is based on 6646 images in total and then split into 5315 for training and 1331 for testing.The first model is a designed convolution neural network(CNN) with five main layers and initializing hyperparameters in a good manner. The second method involves combining deep learning with fuzzy learning (FD5NN) to overcome data determinism and ambiguity.The results showed that both models produced good results. The designed CNN and hybrid FD5NN had accuracy rates of 0.93% and 0.97%, respectively. We conclude that whether deep learning is used alone or in hybridization with other representations, we will get the best results in extracting and classifying features from image signatures.

Keywords: Personality Traits, Deep Learning, Fuzzy Learning, CNN, Signature.

1. Introduction

The subject of personality occupies an important place in modern psychology, which is a natural product of two important branches of psychology, namely experimental psychology, and clinical psychology. The subject of personality study is no longer a recent topic. Ancient humans may have thought a lot about how to predict the behavior of other people, but there wasn't a clear scientific trend in explaining behavior at the time [1].Personality is presented from the point of view of psychologists as including dispositions, characteristics, temperament, motivation, emotional attitudes, and intelligence as a general predisposition to be included in these factors. Allport was one of the most prominent scientists who dealt with the study of personality based on the theory of traits, which deduced most of its hypotheses from field observations of normal individuals. Allport points out that personality is an integrated organization of the work of the body and mind in a unit that is not only a psychological construct or the construction of an abstract body [2].

Most of the studies that dealt with personality focused on the following question: what are the basic components (factors) that personality includes? Many answers were given to this question, and the views of personality psychologists differed in terms of the number of factors through which any personality can be described. Several personalities tests have been developed, but the Big Five Factor [3],and the MBTI (Myers-Briggs Type Indicator) [4]are the most important.

The Big Five Factors is a comprehensive and accurate classification to describe the human personality that has been proven by the scientific evidence of experimental research. As illustrated in Table I, this model aims to group personality traits into five main dimensions that are considered especially significant in life: Neuroticism (N), Extraversion (E), Conscientiousness (C), Agreeableness (A), and Openness (O) are the five personality traits (OCEAN) [5].

Recently, the detection of personality traits has become wide and varied. Many researchers in the area of artificial intelligence have been interested in the automatic prediction of personality traits through handwriting, signature, questionnaire responses, and facial expressions, in addition to the tweets they publish on social media and other platforms [6], [7]. The study of reading one's character via handwriting is called graphology. By looking at someone's handwriting and signature, graphologists can figure out who they are and what kind of person they are by looking at their personality [8].Today, personality trait analysis is one

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TABLE I. Big Five Factors

Big Five	Traits Representation
Neuroticism	Anxiety, anger, hostility, depression, consciousness self, impulsiveness,vulnerability,and stress
Extraversion	Warmth, gregariousness, assertiveness, activity, excitement ,and seeking
Openness	fantasy, aesthetics, feeling, ideas,and values
Agreeableness	trust, straight forwardness, modesty,and compliance
Conscientiousness	competence, dutifulness, discipline-self,and deliberation

of the most important things that international businesses need to hire someone who has a lot of skills and abilities. It can be used in forensic verification to identify some criminal evidence. Also ,it can be used in education to figure out a student's intellectual level, social characteristics, and physical or mental health [9].

In a biometric system, a person's physical components such as(fingerprints, face, and iris) or their behavior such as(voice, signature, and stride) may be used to identify them [10], [11].In the community, signatures are the most extensively used and recognized biometric technology due to its simplicity of use and reliability [12], [13].Signature is a projection approach for body language that summarizes a person's personality in several areas, such as their ability to interact socially, their accomplishments, their way of thinking, and their work habits. According to graphology theory, graphologists analyze handwriting and signatures to determine the writer's personality traits, characteristics, attitudes, feelings, and postures [14].

The signature comprises several characteristics that differentiate each individual. For example, if the signature size is too large, it implies the writer wants to get attention and take the initiative. If the signature is too small, it means the person is timid and has a high level of concentration. In general, if the owner has a signature that is about the same size as the average one, he is social and has a balanced and adaptable approach to life [6].Furthermore, there are many other features, such as dots on letters, curved starts, single lines or single underscores, and double lines, etc.Table II shows features with their personality traits [15].

Advances in machine learning and deep learning, as well as advances in pattern recognition and image processing, have led to the automated identification of personality traits using signatures. Several studies have been conducted in the field of artificial intelligence on the analysis of personality traits using signatures and have obtained positive results based on the features in the signature. This has led to the development of highly useful automated systems that save time and effort while compensating psychologists who may get sick or age over time.The contributions of this study can be summarized in to:

1) Development of two methods to classify the personality traits of an individual by using their signatures. The first technique was inspired by [16]and included a hybridization of fuzzy learning and deep learning (FD5NN) using joint learning instead of sequential learning. The second method is to build a convolutional neural network (CNN) that has five layers with different filters and a dropout layer.

2) Another significant contribution is that we have collected a dataset and classified them into the five major classes using a dictionary culled from several resources in addition to consulting an expert in personality science.

3) It contributes to the knowledge base and assists the person who knows how to classify human signatures.

4) This is the first study involving a hybrid system for personality traits classification. A comparison was made between the two proposed methods and with other traditional and pretrained methods using a variety of metrics as well as statistical test.

The rest of work organized as follow: Section 2 will discuss Literature Review, Section 3 and 4 will present Structure of Models, Section 5 will discuss Methodology, Section 6 will present Experimental Setups, Section 7 will present Results and Discussion. Finally, Section 8 will present Results Analysis using Statistical Tests followed by Section 9, which is Conclusion.

2. Literature Review

In the literature review, the methods of feature extraction and classification of personality traits were divided into two directions. The first direction includes previous studies that tend to use structural methods to extract features and categorize them using one of the machine learning methods. As for the second trend, some papers preferred deep learning, which made great strides in extracting features and improving speed. They also expanded the data by means of transfer learning and augmentation techniques. One of the structural methods suggested by [8] and preferred ANN to classify signature images into four pairs "Introvert/ Extrovert, Intuitive/sensing, Thinking/ Feeling and Judging/ Perceiving" and used structural methods to extract five features. The work achieved an accuracy of 78% due to the lack of features and data set.In study [17] the researchers applied ANN and structural identification algorithm to predict personality traits. It achieved accuracy between 92%-100% because it applied more structural features and more data images which is 60 responds.Harris et al. [18] analyzed pressure and speed features to obtain 87.5% accuracy. It applied offline and online classification signature systems

TABLE II. Signature features and their Interpretation

NO.	Features	Type	Personality
1	Curve start	Curved backwards	Comfortable in the past.
		Curved Sharply	To establish a sharp mind.
2	End streak	Increase	open, foresight, wishes in the future, self-assured.
		Down	Lacking motivation, having a pessimistic outlook, lacking self-assurance, and being easily discouraged.
3	Middle streaks	Middle streaks	Possessive.
4	Underline	Underline	You have a unique concept in mind, but you'll need help deciding what to do next.
5	Size	Large	Ambitious and Rebellious.
		Small	Concentration and attention to detail are critical for them.
		Medium	Traditional and Realistic.
6	Shell	Shell	Excessive fear, introversion, and apathy are approximate, unsociable, and dislike collaboration.
7	Extreme margin	Tends to top side	Respect yourself and reflect your own happiness.
		Tends to bottom side	Depression, shyness, and a sense of alienation.
		Tends to right side	Careless, inattentive.
		Tends to left side	Dread of failure, fear of others, insecurity, and pessimism.
8	Dot Structure	Dot	Stable establishment engenders skepticism, and it is not always easy to maintain faith.
9	Separate	Separate	The past hasn't been as pleasant as it used to be.
10	Streaks disconnected	Streaks disconnected	A lot of people have limited desires and don't take risks. They also get discouraged and hesitate to make decisions.
11	Baseline	Straight angle	Reasonable, logical, and balanced.
		Negative angle	Pessimism and skepticism.
		Positive angle	creativity and Optimism.
12	Slant	Vertical	Balanced and thoughtful.
		Left	Introverted, reminisces about the past.
		Right	Future-oriented.
		Varying	Unpredictability.

using KNN and used 40 responses as a data set.Another good work [19] that proposed many machine learning algorithms (JRIP, Random Forest, and KNN) to predict the happy, sad, and stressed emotional states of people based on their online bio-metric handwriting and signatures. 134 participants were used to reach the best accuracy.

In second direction some researchers used deep learning like the work in [20] applied a convolution neural network to predict five personality traits using handwritten characters. Three convolution layers were used as feature extraction, then flattened images were passed to two fully connected layers, which in turn classified images into five personality traits. Another distinguished study [21] produced three different configurations of CNN to classify personality traits using signatures. It applied transfer learning (AlexNet) to overcome the lack of data and benefit from the knowledge gained from pre-trained models, so the paper proved the possibility of using deep learning to classify personality with a high efficiency of more than 98%. It turns out that using deep learning to look for features led to better results and less work than using structural methods.

On the other hand, we know that the machine learning community is constantly on the lookout for efficient representations of the current world. The generation of massive volumes of data is beneficial in many aspects of life, but it has put constraints on machine learning algorithms due to the ambiguity and noise inherent in big data, making it harder to anticipate. Fuzzy learning (FL) [22], [23] has been developed to deal with the uncertainties in raw data.

The fuzzy system [24], [25], [26] is a very effective method for simulating human thought and perception. It uses multivalued sets instead of binary propositions. Fuzzy logic uses linguistic information to model qualitative aspects of human knowledge and thinking without the use of precise quantitative analysis. From language input to linguistic output, fuzzy systems store rules and estimate sampled functions. The human brain is regarded as being successful not just through precise cognition but also through fuzzy conceptions, fuzzy reasoning, and fuzzy judgment.

In the field of machine learning, there have also been big changes in the development of neural networks [27]. Neural networks can process information in a hierarchical and sequential way to remove noise as the information moves from layer to layer. So, it mimics the way the human brain thinks and learns from training to figure out important features from the data itself. In the field of binary or multiple classification, many studies have been conducted on fuzzy neural networks (FNNs), which integrate fuzzy thinking with neural networks to process fuzzy inputs [28], [29], [30], as well as to learn from the environment and exploit parallel structure in high-speed neural networks.

Ghosh et al. [31] applied membership function π to the fuzzification process to expand the number of used features depending on the number of labels, but this led to increasing the time in the training and testing data and the dimensions of the problem, which is a major problem in the performance of the system.While in 2014 Ghosh et al. presented distinguished work [32] that suggested a fuzzy classification model (NF) based on a bell-shaped membership function. The fuzzified matrix constructed from the input characteristics was paired with a degree of class membership. The class labels assigned a numerical number to the degree of belongingness to each class. Then the paper used MLP-Backpropagation Algorithms for classification and achieved 98.4% accuracy.While S. Zhou et al. [33] used fuzzy deep belief network (FDBN) semi-supervised learning to train the data, this is done by transforming the data into a latent space and then fuzzifying the data in the last layer (output), which is responsible for the classification process. R. Zhang et al. [34] used Fuzzy Granulation and Continuous-valued Deep Belief Networks in sequential learning to estimate exchange rate fluctuation ranges. This analysis uses the daily EUR/USD and GBP/USD exchange rates. Researchers in work [35] proposed using sequential learning instead of a joint learning framework for classifying images. The pre-trained ResNet50 network is used for feature extraction, and the Brain Storm Optimization algorithm (BSO) is used to extract an ideal rule base. Finally, the classification of the images was done using a fuzzy rule-based classifier. The proposed method was applied to the Caltechld data set, and it achieved an accuracy of 86%.

3. Convolution Neural Network (CNN)

The Convolution Neural Network is a kind of deep learning technique that is commonly used in object recognition and image classification [36]. CNN receives the image as input and feeds it to neurons, which extract and train features such as weights and biases. CNN is overcome the problem of overfitting that prevails on classical neural networks due to the lack of scaling of the input images. The calculation time and complexity increase when thousands of images are input into classical neural network, thus it is preferable to use CNN to simplify the features and format the image. CNN consists of several sequential layers, the convolution layer, pooling layer, and the last one fully connected layer which is responsible for classification and output. These layers use a non-linear function to transform one activation block to another [37]. Figure 1 illustrates the basic CNN layers sequence.

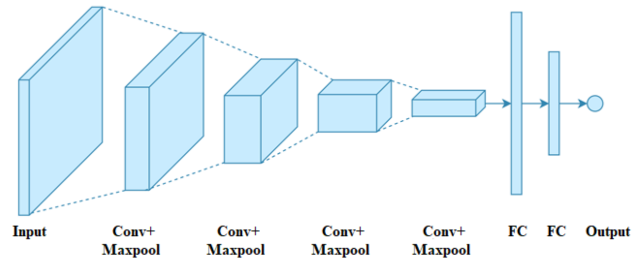

Figure 1. Basic Convolution Neural Network

Convolution is the first layer responsible for extracting features from an image, and it is a mathematical operation whose task is to maintain the relationship between pixels and to learn the features of the image. The number of shifted pixels over the input matrix is called stride(S). The filters shifted one pixel when S was set to 1, or shifted two pixels when S was 2, and so on. Sometimes the filter does not perfectly match the input image, so we have two options: First, the same padding fills the image with zeros from all sides, and it is proportional to the filter. Second, valid padding is to keep the valid part of the image and drop the rest. A pooling layer is used to reduce the number of parameters of a large image, and it can be called subsampling due to the decreasing dimensions of each map while keeping the essential information. The pooling process can be max, sum, or average [38]. The matrix was flattened into a vector to combine features and make a model, after that, the vector pass to the fully connected layer. Finally, an activation function like SoftMax or sigmoid can be used to categorize the outputs into one of the classes.

4. Fuzzy Logic

In Equation 1 A fuzzy set is a membership function mapped to the unit interval [0,1] [39], [40].

$$A : X \rightarrow [0, 1] \tag{1}$$

A membership grade might express an element's compatibility (x€X) with A representative elements [41]. If-then rules with fuzzy inputs take the form IF A leads to B, where A is a fuzzy set and B denotes either another fuzzy set or an input's function. To account for environmental ambiguity and imprecision, fuzzy rules are used to incorporate human-level decision making into a system. Fuzzy systems learn fuzzy membership functions automatically and construct fuzzy rules from a vast amount of training data. After linearly combining the fuzzy logic values in a defuzzifier, the final choice for particular specified jobs is formed [42]. Many previous studies have combined deep learning and fuzzy learning to overcome ambiguous data as well as to take advantage of both representations, but most of them used sequential combining instead of the joint combining that we applied in our work.

5. Methodology

Our study methodology starts with data acquisition (signature images), then moves on to data preprocessing, feature extraction, and classification. After parameterizing the input signature images, we extracted features and classified them using two models: hybrid deep learning with fuzzy learning and the proposed CNN model. Figure 2 depicts the workflow of the proposed methods.

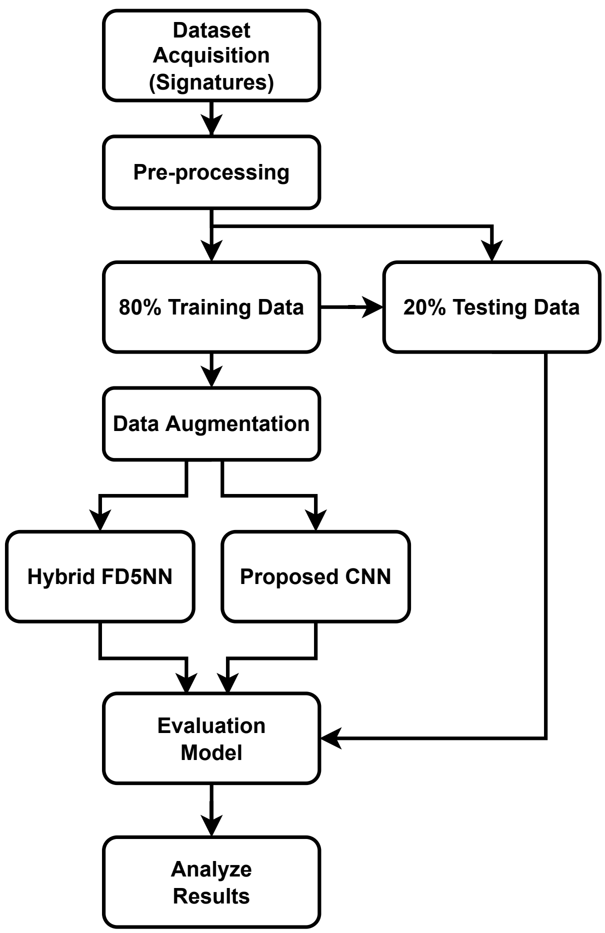

Figure 2. The workflow of the proposed methods

A. *Data set Acquisition*

The data set included signatures of faculty members of Mosul University, which were manually collected. The steps of data set acquisition are as follows:

1) A special form comprised of a number of rectangles on white paper was designed to collect the signature images. The average age of both sexes is between 24 and 65 years old.
2) The scanner (Canon Quick Menu version 2.8.5) was used as a medium to store photographs as digital images of the type.JPG file with a resolution of 600 dpi.
3) images are cropped with Adobe Photoshop and a photo editor.
4) According to the important features found in the signatures and shown by graphology, a dictionary was made from several resources [43], [44], [45], [46] in addition to consulting an expert in personality psychology to classify the signatures into five categories. Figure 3 illustrates this classification.

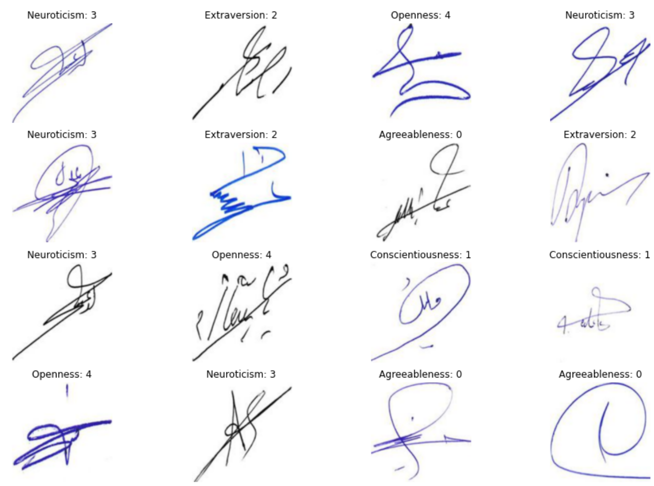

Figure 3. The classification of signatures according to the Big Five Factor

5) The data set that was used has 6646 signatures with 200 respondents who will write more than 33 signatures in different positions.

B. *Image Pre-processing*

Data preprocessing is an essential step for identifying important features in signature images and also ensures that the data is well prepared for certain types of analysis. Figure 4 shows many processes were applied to digital images:

1) Resize Image: Cutting images using Photoshop and photo editors are produced in different sizes, so we need to uniform the pixel size using a resize process with dimensions of 200 width and 200 heights.
2) Image Transform: OpenCV library was used for reading images and display them as blue hue (BGR), therefore, we need to convert images from BGR to RGB colour-space and show them by matplotlib library.
3) Edge detection: Canny method [47]was used to highlight the important edges of the object (signature) and analyse it accurately.
4) Bounding Box: It is one of the most important annotation techniques for digital images. It is an abstract rectangle used to discover the object and also, it is a reference point drawn over the images.
5) Cropping Image: The process of removing redundant white areas and unimportant edges in the image to

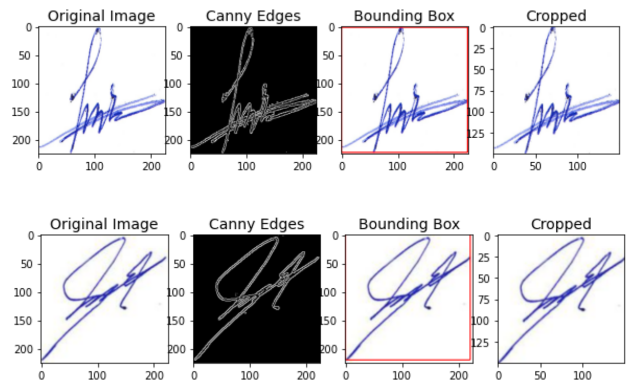

Figure 4. Image Pre-processing steps

determine the edges rich with necessary features.

6) Splitting Digital Images: the signature images were randomly distributed among 80% training and 20% testing. The data set consists of 6646 total images split into 5315 images for training and 1331 images for testing.

7) Data Augmentation

Numerous studies have proved that as the quantity of training data increases, the efficiency of deep learning algorithms will improve. There are many techniques for increasing data, including data augmentation. It is used to overcome data imbalance and scarcity. Several operations were used to increase data, for example: rotation with range (25), zoom with range (0.1), width shift with range (0.1), height shift with range (0.1), shear with range (0.2) and horizontal flip.

C. Feature Extraction and Classification

In this section, feature extraction and classification were performed on two different deep learning models, and they are as follows:

1) **Hybrid Deep Learning and Fuzzy Learning (FD5NN)**

In this model, dense neural network is combined with fuzzy logic system, and the model is called hybrid (FD5NN). In order to benefit the features of both representations, the input layer of FD5NN follows two paths: the first path is passed to the fuzzy logic representation, and the second path is passed to the deep neural network simultaneously. In general, the hybrid system FD5NN consists of four main learning components, as shown in the Figure 5. The first part is applied fuzzy representation; the second part includes the application of a deep neural network, which consists of five layers; and the third part is the combination of two representations. Finally, the feature extraction of both representations was transferred to the last part, which is responsible for the process of classifying images of signatures into five main categories according to the Big Five factor.

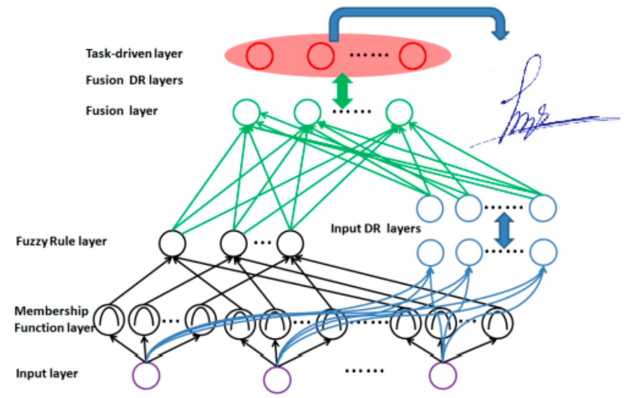

Figure 5. Main Parts of Hybrid FD5NN

The Hybrid FD5NN algorithm can be summarized in the following steps:

- In part1 each node in the input layer will be associated with more than one fuzzy membership function simultaneously. In this part the Gaussian membership function was used according to works [48], [49] to determine the degree of association of each node in the fuzzy sets.
- In the membership function layer, the node will be called i^{th} fuzzy neuron $\mathrm{u}_i(.) : R \rightarrow [0, 1]$ which converts the k^{th} of input to fuzzy degrees according to the following Gaussian Equation 2:

$$\text{output}_i^{(l)} = u_i\left(\mathrm{a}_k^{(l)}\right) = \frac{e^{-(\mathrm{a}_k^{(l)}-\mu_i)^2}}{\sigma_i^2}, \quad \forall_i \qquad (2)$$

µ and σ are coefficients of the Gaussian membership function, which denote mean and standard deviation, respectively.

- Fuzzy rule layer: all the outputs of the membership functions are joined together to get fuzzy degrees through the multiplication process (AND), the equation 3 shows that:

$$\text{output}_i^{(l)} = \prod_j \mathrm{o}_j^{(l-1)}, \quad \forall_j \epsilon \Omega_i \qquad (3)$$

where Ω_i is the collection of nodes on the previous layer or $(\mathrm{l}\text{-}1)^{th}$ layer that connect to i.

- In Part2 the input layer connected to the five sequential dense neural network layers to provide a high-level representation of the input layer. Equation 4 illustrated that with activation function sigmoid to compute weights and bias.

$$\text{output}_i^{(l)} = \frac{1}{1+e^{-\mathrm{a}_i^{(l)}}}, \mathrm{a}_i^{(l)} = \mathrm{w}_i^{(l)} o^{(l-1)} + \mathrm{b}_i^{(l)} \quad (4)$$

$\frac{1}{1+e^{-a_i^{(l)}}}$ is the sigmoid activation function, $w_i^{(l)}$ the weight parameter of node i on the l^{th} layer,$o^{(l-1)}$ is the output of the previous layer, and $b_i^{(l)}$ the bias parameter of node i on the l^{th} layer.

- The Fusion Part (Part3): This part responsible of merging the fuzzy rule layer with the last dense neural network layer, because it is preferable to extract multiple features from several aspects and to obtain a high-level representation with low noise and uncertainty and this called multi-modal learning [50], The equations 5, 6 for this layer are listed below.

$$\text{output}_i^{(l)} = \frac{1}{1+e^{-a_i^{(l)}}} \tag{5}$$

$$a_i^{(l)} = (w_d)_i^l (o_d)^{(l-1)} + (w_f)_i^l (o_f)^{(l-1)} + b_i^{(l)} \tag{6}$$

Where o_d and o_f represent output of dense layers and fuzzy layer respectively. w_d is weight of dense layers and w_f is weight of fuzzy layer. After combining the two representations, the fused information is converted into multiple and fully connected layers, as in Equation 4. The output of combination the neural representation with the fuzzy representation does not have degrees of fuzziness.

- Task-driven layer (Part4): Is also known as the classification layer, and its task is to classify the fused data into the category it belongs to. The SoftMax function was used to classify five types of personality traits according to the Big Five factor through the following equation 7

$$\hat{y}_{ic} = p(y_i|f_i) = \frac{e^{w_c \pi_\Theta(f_i)+b_c}}{\sum_c e^{w_c \pi_\Theta(f_i)+b_c}} \tag{7}$$

f_i represent i^{th} input and y_i represent its label. c^{th} is the classes of personality traits and b_c, w_c represents the bias and regression coefficient respectively. $\pi\Theta(f_i)$ refers to the FDNN's feed-forward translation from the input layer to the final task-driven layer. $\hat{y}_i = [\hat{y}_{i1}, \hat{y}_{i2}, ...\hat{y}_{ik}]$ the neural network's anticipated labels with k classes.

- Mean Square-Loss is utilized according to [16] in regression jobs where the goal is to minimize the predicted value of a function on our training data, commonly known as the ”loss function” Equation 8 shows that.Also, the categorical cross entropy function can be used for multi-classification and get good results.

$$c = \frac{1}{m}\sum_{i}^{m} \|y_i - \hat{y}_i\|_2^2 \tag{8}$$

In the hybrid model FD5NN, the nodes of the input layer are connected to nodes of the fuzzy membership function layer, and at the same time the input layer is connected to the dense layer. After that, the output of the fuzzy membership function layer is passed to the fuzzy rule layer and the multiplication operation (AND) is performed to find the output of the fuzzy part, look Figure 6. As for the deep network part, after connecting the input layer with the first dense layer, the output passed on to the rest of the other dense layers which using the sigmoid activation function to find the best features, which are between [0,1]. To obtain multiple advantages from different representations, like reduce uncertainty and increase accuracy and performance, the outputs of both representations are combined in the fusion layer. Finally, the output of the fusion layer is passed to the task driven layer which responsible for the classification process into five categories of personality traits using the SoftMax activation function, the use of the Adam optimizer and the error function Mean Square Error.

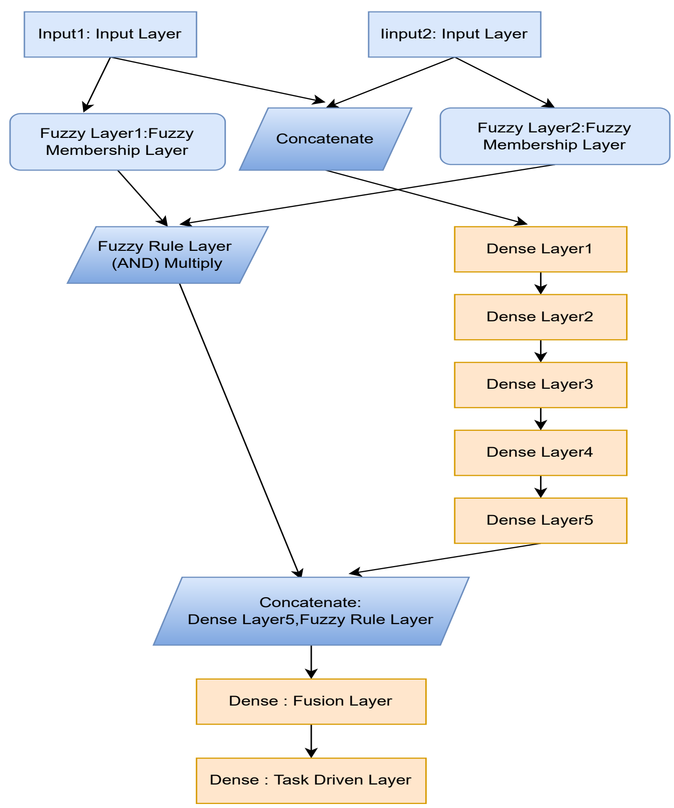

Figure 6. Flow chart of Hybrid FD5NN System

2) **Designed Convolution Neural Network (CNN)**
Designed CNN consists of five convolution layers (a feature map) and variable filters (batch size multiplied by a certain amount) used to build a convolution neural network, Figure 7 shows the

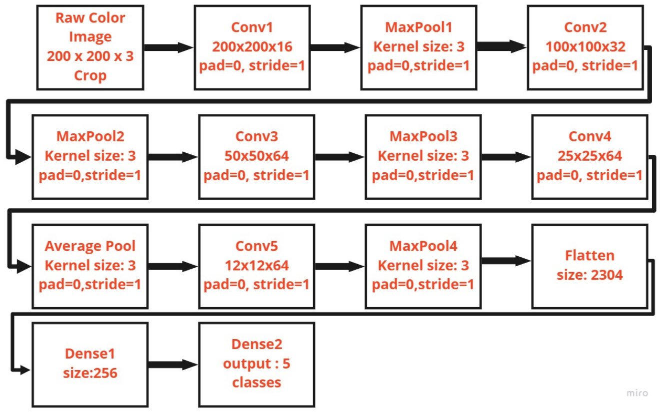

Figure 7. The configuration of proposed CNN

configuration of designed CNN. The same padding and ReLU activation function were employed to prevent image reduction. To ensure that the most significant features were captured, a Max Pooling layer was added after each convolutional layer except the conv4 block, which employed average pooling. To prevent overfitting, the network is flattened and then a dropout layer with a value of 0.5 is added, followed by two fully connected layers that are responsible for classifying the data into five categories using the SoftMax activation function.Figure 8 shows the Algorithm of proposed CNN.

Proposed CNN Algorithm

1. Initialize hyperparameters : filters number=32, width image=200, height image=200, and epochs number (N)=100.
2. For i=1…….. N do
   a. Apply five Convolutional blocks with ReLU,the same padding, and different batch sizes (16,32,64,64,64).Apply max and average pooling.
   b. Apply Flatten Layer.
   c. Apply Dropout Layer.
   d. Apply Fully Connected Layer1 with ReLU and 256 units.
   e. Apply Fully Connected Layer2 with five units and SoftMax activation function.
3. Compile the model using Adam as optimization, sparse categorical cross-entropy as loss function and accuracy as a metric.
4. Fitting model and save it.

Figure 8. Pseudo code of proposed CNN

6. Experimental Setups

This section configures the important parameters to run the training and testing processes on the data set. The two proposed models were applied to the Spyder environment using the Keras and TensorFlow libraries. The data-training process in hybrid FD5NN consists of two phases:

- Initialization of parameters.
- Fine tuning of parameters.

Initializing parameters is an essential process in both representations, especially deep learning, to make it convergence to the local minimum with high performance. Weights are configured in the five deep learning layers in addition to the fusion and the classification layer according to the uniform random distribution in Equation 9 [51].

$$w_i^{(l)} \sim \cup\left[-\frac{1}{\sqrt{n^{(l-1)}}}, \frac{1}{\sqrt{n^{(l-1)}}}\right] \tag{9}$$

Where stands for a uniform distribution and all values have an equal probability, $n^{(l-1)}$ means the number of nodes in the layer (l-1)th.

In the fuzzy part, all the weights between the two layers of the fuzzy membership function and the fuzzy rule are initialized with a value of 1. the value of means is random value, and standard deviation is 1[51]. After trial and error, the important hyperparameters in both proposed models, FD5NN and designed CNN, are summarized in Table IV.

TABLE III. Initialization of Hyperparameters

Hyperparameters	Values
Learning rate	0.001
Batch size	16
No. of Nodes in the membership function	256 nodes
No. of Nodes in the deep part	150 nodes
Filter kernel size	3
Max pooling kernel size	2
Activation functions	ReLU, SoftMax
Dropout	0.5

In the fine tuning stage, the parameters are adjusted by using the backpropagation algorithm and the Adam optimizer, which is based on Equation 10. The BP algorithm calculates the gradient descent, reduces the error rate, and makes the model generalize for data that hasn't been seen before.

$$\frac{\partial C}{\partial \Theta^{(l)}} = \sum_n \left(\frac{\partial C_n}{\partial O_i^{(l)}}\right) \frac{\partial O_i^{(l)}}{\partial a_i^{(l)}} \frac{\partial a_i^{(l)}}{\partial \Theta^{(l)}} \tag{10}$$

C represents loss function that used in FD5NN model in equation 8.Θ reflects common parameters in FD5NN. The term $\left(\frac{\partial C_n}{\partial O_i^{(l)}}\right)$ represents Backpropagation, whereas the other two terms $\frac{\partial O_i^{(l)}}{\partial a_i^{(l)}}, \frac{\partial a_i^{(l)}}{\partial \Theta^{(l)}}$ represent the derivation of Backpropagation.The gradient of neurons in all parts except the fuzzy part can be calculated using Equations 2, 3, 4, 5, and 6. Whereas, in the fuzzy part, it can be calculated using Equation 4.

7. Results and Discussion

To categorize personality traits using signatures, the data set was trained and verified individually for each model. Figure 9 illustrates the accuracy and loss associated with training and validation processes.

When the training epochs increase in (a), (b) in Figure 9, the accuracy and loss curves become flat while the test data curve is fluctuating, so the ideal point for the hybrid model can be made at 80 cycles. The FD5NN is non-convex, and the converged point is predicted to be just a local optimum. (c), (d) in Figure 9. show that it is better to limit the number of cycles to 40 cycles to avoid overfitting and reach the optimum value.

From Table IV, we notice that the deep learning model achieved high accuracy and performance, whether it was trained alone or combined with another model. Moreover, the results showed that the hybrid FD5NN model is superior to the designed CNN model in accuracy and loss because it uses both fuzzy learning and deep learning to overcome the determinism and ambiguity of big data in addition to remove the noise data. The FD5NN model achieved about 0.97% in validation accuracy and 0.0949 in validation loss, overcoming the designed CNN model in both training and validation. It also took a shorter time in training than the designed CNN model.

To further demonstrate the acquired results and the changes in classification errors across five classes in two models, Tables V, VI display the confusion matrix and percentage error of classification (error probability). The confusion matrix shows how difficult it is for the two classifiers to choose between five different classes.

The probability of errors for both models was calculated using the following equation 11:

$$error\ rate = \frac{FP + FN}{TP + FN + FP + TN} \tag{11}$$

The TP, TN, FP, FN is denoted by true positive, true negative, false positive and false negative respectively. According to the confusion matrix analysis for personality trait classification, the average error rate achieved by the hybrid FD5NN system was (1.022%), which is better than the designed CNN (1.322%).

In Tables VII and VIII, we note that the precision metric of the FD5NN model is slightly better than that of the designed CNN model, which means that FD5NN succeeds in predicting more positive samples than the designed CNN model. As for other metrics such as precision, recall, F1-score, specificity, and NPV (negative predictive value), both models achieved good results. While for FNR (false negative rate) and FPR (false positive rate) metrics, the FD5NN model did a fairly good test compared to the designed CNN model because it has a lower false-negative or false-positive rate than the designed CNN model.

8. Results Analysis using Statistical Test

The Friedman test and Wilcoxon signed-rank test are used to determine the significance of the superiority of the hybrid FD5NN model and the designed CNN model over other traditional methods.

1) Friedman test

The Friedman test is a nonparametric statistical tool. It is also called the Two-way Analysis of Variance Using Ranks. It utilizes data rankings rather than actual values. The Friedman test is used to determine if two or more models exhibit significant differences [52]. Equation 12 gives its F statistic.

$$F = \frac{12N}{K(K+1)}\left[\sum_{j=1}^{k} \mathrm{R}_j^2 - \frac{K(K+1)^2}{4}\right] \tag{12}$$

N is the total number of predicted outcomes; k denotes the total number of comparable models; and R_j denotes the average rank-sum achieved in each prediction using each method, as defined by equation 13.

$$R_j = \frac{1}{N}\sum_{i=1}^{N} \mathrm{r}_i^j \tag{13}$$

r_i^j is the rank sum of the i^{th} predicting result and the j^{th} model, from 1 (smallest predicting error) to k (biggest predicting error) [52]. Table IX illustrates that with the F statistic in the rejection zone, one should reject the null hypothesis and accept the alternative hypothesis that the prediction errors of comparison models are different and not equal.

2) Wilcoxon signed-rank test

It is a nonparametric test and is used to determine the differences between two equal samples and to determine whether or not their population's mean ranks vary [53]. Wilcoxon is given by Equation 14 [52]:

$$W = min\{W^+, W^-\} \tag{14}$$

W^+,W^- are the sums of $I^+(di)$ and $I^-(di)$, respectively. di is the difference data between two data samples. $I^+(di)$ denoted a dummy counter with a value of one if di > zero and 0 otherwise. and $I^-(di)$ is a dummy counter with a value of one if di < zero and zero otherwise. If di equals 0, this record is deleted;

The Wilcoxon test in Table X showed that the classification of personality traits in the hybrid FD5NN model is lower compared to the following models [9], [21]: traditional deep neural network (DNN) with P-VALUE = 0.014 and z=-2.451, traditional

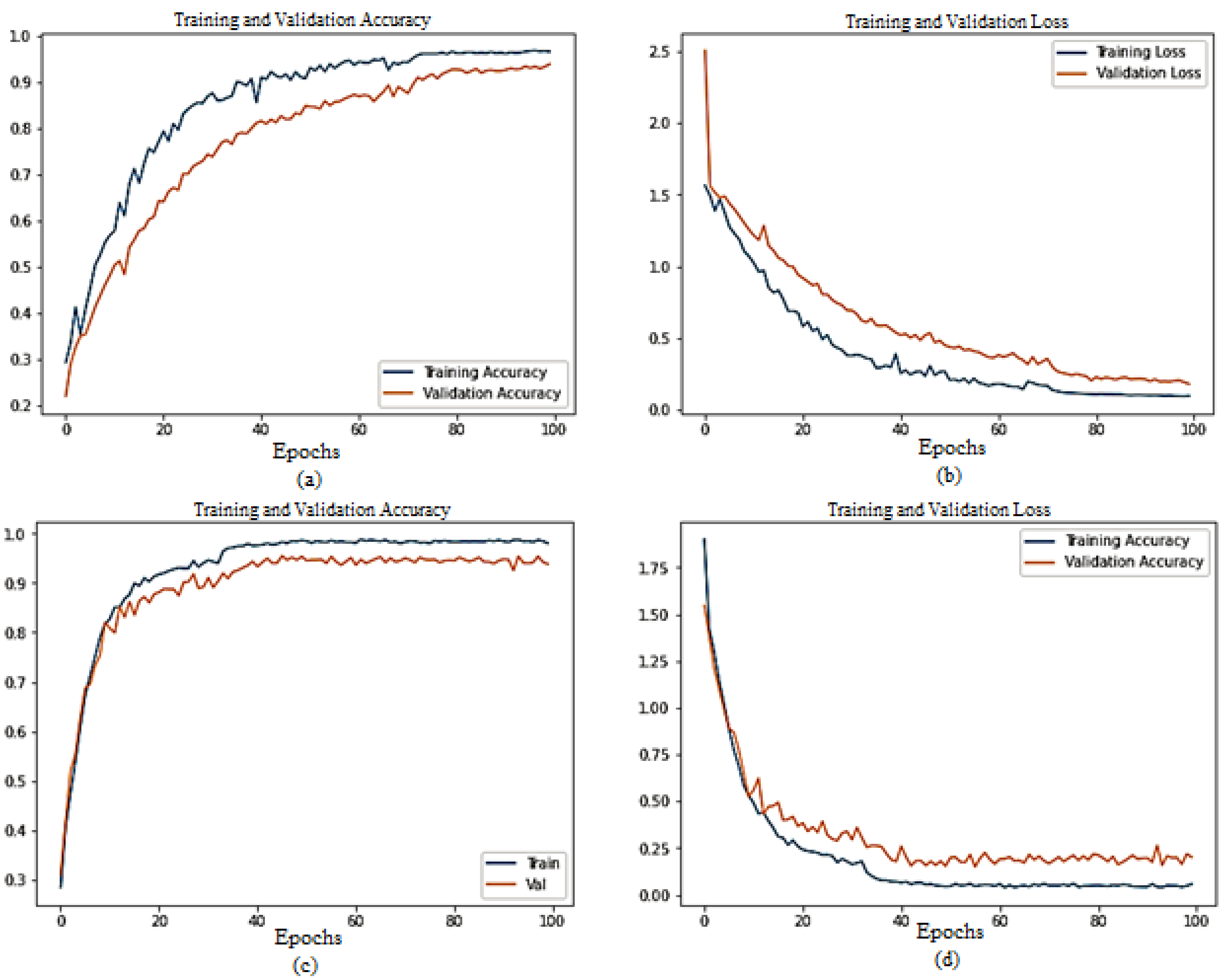

Figure 9. (a): show training and validation accuracy of FD5NN. (b): show training and validation loss of FD5NN. (c) show training and validation accuracy of designed CNN. (d) show training and validation loss of designed CNN.

TABLE IV. show accuracy and loss of two Models

Model	Training loss	Training Accuracy	Validation loss	Validation Accuracy	Time in Minutes
FD5NN	0.00854	0.9912	0.0949	0.9669	274.32
designed CNN	0.0572	0.9803	0.2301	0.9391	385.42

TABLE V. Percentage Error in Confusion Matrix of FD5NN

			Predicted Class			
True Class	Agreeableness	Conscientiousness	Extraversion	Neuroticism	Openness	Error Probability
Agreeableness	260	0	0	1	3	0.53%
Conscientiousness	0	270	0	1	4	0.68%
Extraversion	1	1	253	3	7	1.20%
Neuroticism	0	2	1	268	2	0.90%
Openness	2	1	3	2	246	1.80%
Average						1.022 %

TABLE VI. Percentage Error in Confusion Matrix of designed CNN

	Predicted Class					
True Class	Agreeableness	Conscientiousness	Extraversion	Neuroticism	Openness	Error Probability
Agreeableness	254	1	1	1	2	0.83%
Conscientiousness	0	258	2	2	2	1.35%
Extraversion	1	2	271	0	6	1.35%
Neuroticism	2	4	0	240	4	0.98%
Openness	3	5	6	0	264	2.10%
Average						1.322 %

TABLE VII. Show Metrics of FD5NN

Classes	Precision	Recall	F1-score	Specificity	NPV	FNR	FPR	Support
Agreeableness	0.99	0.98	0.98	0.99	0.99	0.02	0.01	264
Conscientiousness	0.99	0.98	0.98	0.99	0.99	0.02	0.01	275
Extraversion	0.98	0.95	0.96	0.99	0.99	0.05	0.01	265
Neuroticism	0.97	0.98	0.97	0.99	0.99	0.02	0.01	273
Openness	0.95	0.97	0.95	0.99	0.99	0.03	0.01	254
macro avg	0.98	0.97	0.97					1331
weighted avg	0.98	0.97	0.97					1331

TABLE VIII. Show Metrics of designed CNN

Classes	Precision	Recall	F1-score	Specificity	NPV	FNR	FPR	Support
Agreeableness	0.98	0.98	0.98	0.99	0.99	0.02	0.01	264
Conscientiousness	0.96	0.98	0.97	0.98	0.99	0.02	0.02	275
Extraversion 0.97	0.97	0.97	0.99	0.99	0.03	0.01	265	
Neuroticism	0.99	0.96	0.97	0.99	0.99	0.04	0.01	273
Openness	0.95	0.95	0.95	0.98	0.98	0.05	0.02	254
macro avg	0.97	0.97	0.97					1331
weighted avg	0.97	0.97	0.97					1331

TABLE IX. Friedman Test of Two Proposed Models

First Dimension	Friedman Test
FD5NN-designed CNN	H0: e2=e3=e4=e5
FD5NN-DNN	F= 3.75
FD5NN-CNN	P-Value =< 0.01
FD5NN-ResNet50	Reject null hypothesis and
FD5NN-VGG16	accept alternative hypothesis
FD5NN-Inceptionv3	
FD5NN-AlexNet	
Second Dimension	**Friedman Test**
designed CNN -FD5NN	H0: e1=e2=e3=e4=e5
designed CNN -DNN	F= 3.75
designed CNN -CNN	P-Value =< 0.01
designed CNN -ResNet50	Reject null hypothesis and
designed CNN -VGG16	accept alternative hypothesis
designed CNN -Inceptionv3	
designed CNN -AlexNet	

convolution neural network (CNN) with P-VALUE = 0.07 and z=-2.701, ResNet50 with P-VALUE = 0.007 and z=-2.675, Inceptionv3 with P-VALUE = 0.019 and z=-2.352, finally AlexNet with P-VALUE = 0.05 and z=-2.812. As a result, we reject the null hypothesis and replace it with the alternative hypothesis, which states that using a hybrid FD5NN model, there are statistically significant differences in the classification of personality traits. But on the other hand, no statistical differences were observed with the VGG16 model, so retain null hypothesis. makecell

TABLE X. Wilcoxon test of designed CNN

Algorithm	Median	Z	P-Value	Null Hypothesis
designed CNN DNN	0.9450 0.8550	-2.814	0.05	Reject null hypothesis
designed CNN CNN	0.9450 0.6200	-2.701	0.007	Reject null hypothesis
designed CNN VGG16	0.9450 0.9200	-2.120	0.034	Reject null hypothesis
designed CNN ResNet50	0.9450 0.9900	-2.812	0.004	Reject null hypothesis
designed CNN Inceptionv3	0.9450 0.9650	-2.842	0.004	Reject null hypothesis
designed CNN AlexNet	0.9450 0.9400	-2.670	0.08	Reject null hypothesis

The Figure 10 revealed that the proposed strategies were effective. They outperformed deep learning and pretrained models (convolution neural network(CNN), dense neural network(DNN), AlexNet, VGG16, Inceptionv3), except for the pretrained ResNet50 model. We conclude that deep learning produces positive outcomes regardless of whether it is used alone or in combination with another representation to enhance its performance.

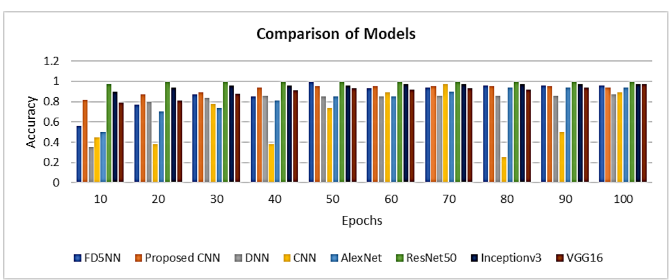

Figure 10. Comparison of Models

9. Conclusion

This work depicts the classification of personality traits of an individual based on two methods: designed CNN and hybrid FD5NN.CNN is designed to bring more features and perform classification with good accuracy.After many experiments,we optimized the hyperparameters of the CNN structure to get the best accuracy and lowest error. On the other hand, we applied a hybrid system that is something different from previous studies in the field of personality traits classification. The objective of the hybrid FD5NN is to control noise in images using deep learning as well as to process ambiguous data using fuzzy learning. The two proposed methods were compared with other previous methods. They were both trained on the same data set. The mathematical and statistical measurements showed that the two new methods did better than the old ones, except for some pre-trained methods. In future recommendations, the two methods can be applied to solve another problem, or it is possible to collect more signature data or use other information related to the individual called ”demographic information,” such as gender, age, education level, etc., to increase accuracy further.

Acknowledgment

We would like to express our gratitude to the University of Mosul faculty members, particularly the College of Computer Science and Mathematics, for giving us with their signatures.

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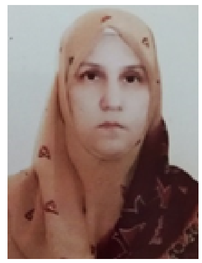

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