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Research paper

A Hybrid Framework for Personality Prediction based on Fuzzy Neural Networks and Deep Neural Networks

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Abstract

In general, humans are very complex organisms, and therefore, research on their various dimensions and aspects including personality has become an attractive subject of research works. With the advent of technology, the emergence of a new kind of communication in the context of social networks has also given a new form of social communication to the humans, and the recognition and categorization of people in this new space have become a hot topic of research that has been challenged by many researchers. In this paper, considering the Big Five personality characteristics of the individuals, first, a categorization of the related works is proposed, and then a hybrid framework based on the fuzzy neural networks (FNN) and the deep neural networks (DNN) is proposed, which improves the accuracy of personality recognition by combining different FNN-classifiers with DNN-classifier in a proposed two-stage decision fusion scheme. Finally, a simulation of the proposed approach is carried out. The suggested approach uses the structural features of a social networks analysis (SNA) along with a linguistic (LA) analysis feature extracted from the description of the activities of the individuals and comparison with the previous similar research works. The results obtained well-illustrate the performance improvement of the proposed framework up to 83.2% of the average accuracy of the personality dataset.

1. Introduction

Social networks, today, have formed one of the inseparable aspects of the human life, and the individuals, according to their activities in this complex space, experience different approaches [1]. The presence of human beings in social networks and various virtual groups has created a cyber-personality for them, and this personality can be categorized into different categories depending on the type of the user interactions that take place in this area [2]. Identifying and recognizing the personality of people in this new space could have different advantages from various viewpoints. For example, its usage in the recommender systems, customer relationship management, and novel e-commerce services could be referred to. Among the existing social networks, Facebook can be considered as one of the largest social networks, with its members accounting for about a quarter of the total population of the earth. Most Facebook users spend more than half an hour a day using it, mostly sharing their pictures and videos, and recording their feelings and opinions in terms of comment or status [1]. Therefore, a wide range of research topics can be carried out in different domains using the Facebook data.

Despite the growing applications that can be considered for personality recognition, analytically, recognizing the personality of the people according to the various activities that are performed on social networks is a challenging and attractive subject that has been considered in various research works today [4]. On the one hand, the extraction of the proper attributes for the analysis of the individuals' personality, and on the other hand, selection of an appropriate personality model are hot topics that affect the algorithms for recognizing and categorizing the personality of the individuals.

In this paper, we focus on the structural features of Social Networks Analysis (SNA) and Linguistic Analysis (LA) of descriptions that exist in the status attribute that is related to the user activities, and develop a hybrid framework for identifying and categorizing the individuals based on the Big Five model of personality. The proposed framework utilizes the Fuzzy Neural Networks (FNN) and Deep Neural Networks (DNN) along with the methodologies of feature extraction and fusion of classifiers. The rest of the paper is organized as what follows. Section 2 presents the related works, and a categorization of them is provided. Section 3 discusses the proposed hybrid framework. The results obtained and discussion are in Section 4. The paper is concluded in Section 5.

2. Related Works

The most similar previous research works with ours in personality prediction based on the Big Five personality model using social media could be found in [1-3]. The Big Five personality trait model consists of Openness (OPN), Conscientiousness (CON), Extraversion (EXT), Agreeableness (AGR), and Neuroticism (NEU) [2]. Using the user behavior features in the social media platforms and using four deep learning architectures include MLP, LSTM, CNN 1D, and LSTM combined with CNN 1D, found in [1]. Some researchers have used the text and time-related features in order to predict personality [5]. Some used Facebook to predict personality, and the others used Twitter [6, 7]. A comprehensive meta-analysis of the relations between personality and workplace deviance has been done in [8], and the validities of the Big Five domains with those of the HEXACO domains for predicting workplace deviance are compared. Intending to extract personality from the use of language, the authors in [9] have covered all aspects of this process in terms of the text normalization techniques, feature extraction, feature selection, data pre-processing, data sampling, and training predictive models to predict the personality types.

Relationships between the Big Five personality traits on the NEO personality inventory-revised and the g-residualized scores of the seven factors of the Cattell-Horn-Carroll (CHC) model on the Woodcock-Johnson-III have been studied in [10]. They showed that openness accounted for a significant variance in all the seven WJ-III IQ factors with the O-crystallized intelligence (Gc) relationship being the strongest, and all the other personality-IQ relationships being small. However, using the residualized scores to remove the common intellectual variance showed that openness related only to Gc, while extraversion related to both the processing speed and Gc.

Difference investigation in personality traits among violent, theft, and illegal drug use criminals comparing them with normal adults and the characteristics of personality traits of criminals was the purpose of the study in [11].

The importance examination of Big-Five personality in predicting the aspects of the self-concept (i.e. self-control, self-esteem, and self-feelings) was done in [12]. The two-step cluster analysis has yielded three personality types corresponding to the resilient, over-controlled, and under-controlled types, and had meaningfully distinguished the self-variables of interest. However, this type of approach has shown weaker predictions than continuous, and even has dichotomized the Big-Five traits.

The cyberbullying detection model based on user personality, determined by the Big Five and Dark Triad models was presented in [13]. This model aimed to recognize bullying patterns among Twitter communities, based on relationships between personality traits and cyberbullying. Random Forest, a well-known machine-learning algorithm was used for cyberbullying classification (i.e., aggressor, spammer, bully, and normal), applied in conjunction with a baseline algorithm encompassing seven Twitter features.

Personality classification task fusion with a deception classifier and evaluating various ways to combine the two tasks, either as a single network with shared layers or by feeding personality labels into the deception classifier was done in [14]. They showed that including personality recognition improves the performance of deception detection. Examine Reddit users' posts to detect any factors that may reveal the depression attitudes of relevant online users was the key objective of [15]. For such purpose, the Natural Language Processing (NLP) techniques and machine learning approaches were employed to train the data and evaluate the efficiency of the proposed method. A novel detection system for identifying character assassination from social media platforms is proposed in [16], which first predicts the personality traits using users' textual data. Therefore, Linguistic Inquiry and Word Count (LIWC[1]), SlangNet, SentiWordNet, SentiStrength, Colloquial WordNet have been utilized as a psycholinguistic tool. LIWC-based feature engineering has been performed on the

[1] LIWC is a transparent text analysis program that counts words into the psychologically meaningful categories.

comments of the trolls as well as the victim user. SlangNet and Colloquial WordNet are used for detecting English slang words in the comments, as it is evident that slangs are the basic communicative way to defame someone.

Optimization techniques for automatic personality recognition (APR) based on Twitter in Bahasa Indonesia, are presented in [17], implementing hyper-parameter tuning, feature selection, and sampling to improve the machine learning algorithms. The proposed personality prediction system is built on Stochastic Gradient Descent (SGD), and two ensemble learning algorithms, Gradient Boosting (XGBoost), and stacking (super learner). Adaptive Network-Based Fuzzy Inference System (ANFIS) is also prevalent and is vastly used in different areas. For instance, in [18] an ANFIS model is applied to the personality traits of the Big Five Personality Model obtaining a Takagi-Sugeno-Kang (TSK) Fuzzy Inference System (FIS) type model with rules that are helping us identify Big Five Patterns for students that are studying Engineering Programs. A novel classification model is also proposed in [19], which chooses an optimal classifier from the pool of classifiers for predicting the overall performance (OP). Then, the chosen classifier is used to investigate the impact of trust and personality on OP.

Different combinations of data processing techniques were experimented upon to create personality models for each of the Big Five was done in [20], and it is depicted that Conscientiousness is consistently the easiest trait to model, followed by Extraversion. To predict the power of digital footprints on social media, a series of meta-analyses have been performed on [21], and the impact of different types of digital footprints on the accuracy of forecasting has been investigated. An advanced classifier such as XGBoost and Ensemble for personality prediction is proposed in [22], in which experimentation on the real-time Twitter dataset results in high accuracy. How a combination of the rich behavioral data obtained with smartphone sensing and the use of machine learning techniques is proposed in [24, 25], which help to advance the personality research and inform both the practitioners and researchers about the different behavioral patterns of personality. In general, most articles on personality recognition in social networks have worked on one of a variety of features: linguistic, structure of social networks or combining them with the user profiles.

Table 1. List of works on personality prediction in social networks based on the linguistic features.

Publications	Dataset	features used	Method used
Farnadi, G. *et al*. [2] (2013)	Facebook user status	Linguistic styles	SVM, KNN and Naive bayes
Alam *et al*. [4] (2013)	essays and personality datasets	bag-of-words approach, used tokens (unigrams) as features	SMO_2 with linear kernel, BLR and MNB sparse model
Majumder, N. *et al*. [7] (2017)	James Pennebaker and Laura King’s stream-of-consciousness essay dataset	Document-level stylistic features, per-word semantic features	CNN
Harrouk, A.I. *et al*. [9] (2018)	MBTI dataset from “Kaggle”	Lexical features	Deep neural networks on the (E-I) dichotomy, Linear regression models for the (T-F) dichotomy, SVM for the (J-P) dichotomy
An, G. *et al*. [14]- (2018)	Columbia X-Cultural and deception (CXD) corpus	Acoustic-prosodic low-level descriptor features (LLD), Word category features from LIWC, Word scores for pleasantness, activation, and imagery from the dictionary of effect in language (DAL) and GloVe vectors.	MLP, LSTM and a hybrid of the first two models
Al Marouf *et al*. [16] (2019)	Social media comments and crawling the HTML tags.	LIWC features Parts-of-speech tags, SlangNet percentage, Colloquial WordNet percentage, SentiWordNet percentage and SentiStrength features (positive value and negative value).	Multinomial Naïve Bayes (MNB), Decision tree (J48), sequential minimal optimization
Martínez, L. G *et al*. [18] (2012)	A sample of 100 students from different engineering programs	Options from multiple–choice, questionnaires	ANFIS
Tighe, E. *et al*. [20] (2018)	Twitter	Term frequency inverse Document, Frequency (TFIDF), term occurrence (TO)	Linear (LIN) regression, Ridge Regression, (linear SVM), and logistic regression (LOG)

[2] SMO is an optimization technique for solving the quadratic optimization problems that arise during training of SVM, and it has a better generalization capability.

The social network used, features, and machine learning methods in each of the articles varied. The works on personality prediction in social networks are categorized, and those based on the linguistic features are listed in Table 1; both the linguistic and social network features listed in Table 2, and the linguistic, social networks, and user profile features are listed in Table 3.

Table 2. List of works on personality prediction in social networks based on the linguistic and social network features.

Publications	Dataset	Features used	Method used
Tandera, T. *et al*. [1] (2017)	Facebook	LIWC, SPLICE, SNA features	MLP, LSTM, GRU, CNN 1D
Ong, V. *et al*. [7] (2017)	Twitter	Number of: Tweets, followers, following, favorites, retweets, hashtags, URLs, Average time difference between each tweet	SVM, XGBoost
Tadesse, M.M. *et al*. [8] (2018)	Facebook personality	Linguistic features, Social network features, Social interaction, behavior analysis	XGBoost, support vector machine (SVM), logistic regression, and gradient boosting
Balakrishnan, V. *et al*. [13] (2019)	Twitter communities	Number of: Mentions, followers and following, popularity, favorite, status, hash tags	Random Forest
Adi, G.Y.N *et al*. [17] (2018)	Twitter in Bahasa Indonesia	Tweets, Retweets, Replies, HIGH Followers, Hashtags, Low following, Quotes, URL, Favorites, Mentions and Tweet content	Stochastic gradient descent (SGD), Gradient boosting (XGBoost) and Stacking (super learner)

Table 3. List of works on personality prediction in social networks based on the linguistic, social networks, and user profile features

Publications	Dataset	Features used	Method used
Schwartz *et al*. [3] (2013)	Facebook	Words, Phrases, Topic, Gender and Age	Differential language analysis (DLA)
Krishankumar, R. *et al*. [19] (2018)	Several CFT (cross-functional teams)	Factors that correspond to trust and personality and E-Questionnaire system (EQs)	ANFIS method

3. Proposed Hybrid Framework

In this section, a hybrid framework based on the concept of the classifier combination for personality prediction is proposed. To this aim, three Fuzzy Neural Networks (FNN) classifiers along with a Deep Neural Networks (DNN) classifier are used, each of which will be trained by a different subset of features obtained from a Feature Extractor (FE) module. Two types of features are designed to be extracted by the FE module, structural features of Social Networks Analysis (SNA), and Linguistic Analysis (LA) feature of status description. The three FNN classifiers are designed to be trained with the SNA features, and the DNN classifier is designed to be trained with the LA feature. In the proposed framework, in order to combine the classifier results, a two-stage decision fusion scheme is developed. At first, the results of the FNN classifiers are combined through a majority-based fusion algorithm. Then the result obtained from the previous decision fusion is combined with the result of the DNN classifier through the awaited decision fusion algorithm. The proposed framework aims to make an extended perspective, and increase the accuracy of the personality prediction system by the classifiers combination. In contrast, each classifier, based on the different features that are used, looks at the data from a different viewpoint. The reason for choosing FNN is the uncertainty in personality traits, and the reason for choosing DNN is the complexity of the

LA features. The proposed framework is illustrated in Fig. 1. As shown in Fig. 1, the proposed framework is composed of several main modules, which in the following of this section are described in more detail.

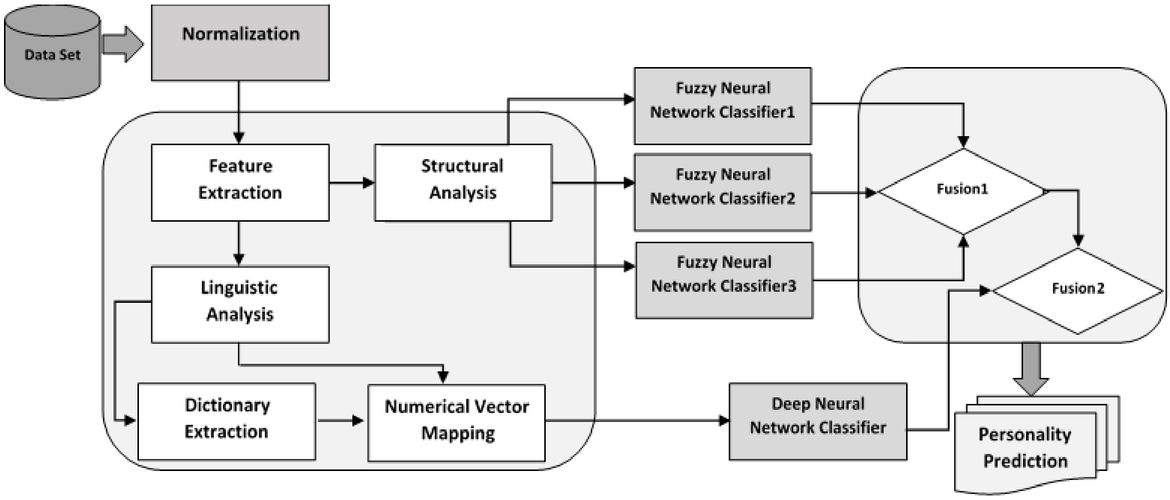

Figure 1. Proposed hybrid framework for personality prediction.

3.1. Normalization

A pre-processing phase is generally used in order to prepare the data to fit the models. In the proposed framework, the normalization module is responsible for refining the values existing in the dataset. For this purpose, the numeric values are mapped in the range between 0 and 1 using Eq. 1, and the text values are processed using the text processing algorithms in order to remove the unnecessary special characters and stop words.

$$V = (V - min\,(V)) / (max\,(V) - min\,(V)) \tag{1}$$

where, V is a numerical vector in the dataset, min (V) is the minimum value, and max (V) is the maximum value that exists in vector V.

3.2. Feature Extraction

There are two feature extraction schema in the proposed framework: one for extracting the structural features of social network analysis (SNA) and the other for extracting linguistic analysis (LA) feature of status description. The SNA features are network size, betweenness, density, brokerage, and transitivity; while the status description is mapped to a numerical vector using a dictionary extracting method, as shown in Eq. 2.

$$Dictionary = \left\{ (i, W_i) \left| \begin{array}{c} (\forall i \Rightarrow \exists j : W_i \in D_j) \wedge \\ (\forall i \rightarrow \neg \exists (i' \neq i) : W_i = W_{i'}) \wedge \\ (\forall i, i' : i < i' \rightarrow W_i < W_{i'}) \wedge \\ (i = 1, 2, 3, \ldots, K) \end{array} \right. \right\} \tag{2}$$

where, W is a word in linguistic description D and k is the size of the dictionary. Also Eq. 3 demonstrates the mapping from words to a numerical vector.

$$\begin{array}{ll} R_1 : D^K \rightarrow Dic^K, & R_2 : Dic^K \rightarrow Z^K, \\ \quad R_1(D^K) = (i, W)^K & \quad R_2((i, W)^K) = i^K \end{array}$$

$$\begin{array}{l} R = R_2 O R_1 = R_2(R_1(D^K)) \\ R : D^K \rightarrow Z^K \\ \quad R(D^K) = i^K \\ \qquad i \in Z \end{array} \tag{3}$$

where R1 maps the linguistic description to the dictionary, R2 maps the dictionary to the numerical positive values, and R is a direct mapping. Note that here, the zero values are used to generate the fixed-length vectors for all the linguistic descriptions, and are equal to the longest description.

3.3. Fuzzy Neural Network (FNN) Classifiers

Due to the uncertainty in the personality traits, a fuzzy-based approach is also considered in the proposed framework [18]. A simple five-layer FNN classifier is shown in Fig. 2, which has two input and one output. As depicted in this figure, first, the input is presented to layer 1, and then the fuzzy values are represented using the membership functions in layer 2. In layer 3, the fuzzy rules are fired, and in layer 4, the output of the rules is normalized. Finally, in layer 5, after aggregation, the output value, according to the classes of data, is obtained.

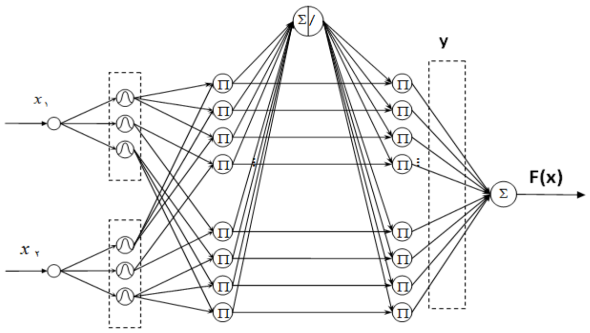

Figure 2. A simple FNN classifier [27].

In the proposed framework, three FNN classifiers are used, each of which is trained using a different subset of SNA features. In this way, each classifier decides the personality label of people from a different perspective in feature space. Then, the decisions of classifiers will be combined, using a 2-stage decision fusion algorithm. To select the best features to be used in the FNN classifiers, it is essential to make a series of experiments based on training data. At each stage, a different combination of features must be selected. Then, using the validation data, the accuracy of each classifier must be determined. Eventually, three of the best classifiers must be chosen to use in the proposed framework.

3.4. Deep Neural Network (DNN) classifier

We proposed to use a DNN classifier to decide the personality of people based on the linguistic description, which is mapped to the numerical feature vector. Since this feature is more complicated than others, then a deep neural network seems better to fit to classifying the personality.

A simple DNN classifier with three hidden layers is shown in Fig3. Increasing total neurons and hidden layers leads to an increase in model parameters, including weight and bias, and hence, the model could learn more complex spaces in features and relations.

The feed-forward networks are among the simplest deep learning models for text representation. They have achieved a high accuracy on many text classification benchmarks. These models view the text as a bag of words. For each word, they learn a vector representation using an embedding model such as Glove, take the vector sum or average of the embedding's as the representation of the text, pass it through one or more feed-forward layers known as Multi-Layer Perceptrons (MLPs), and then perform classification on the final layer's representation using a classifier [23].

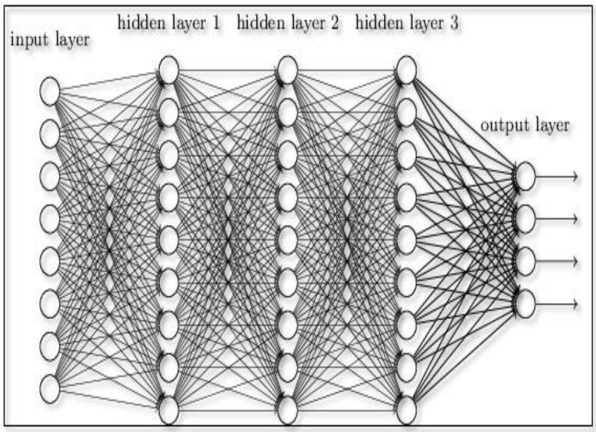

Figure 3. A simple DNN classifier with 3 hidden layers [28].

Convolutional neural network (CNN) and Recurrent Neural Network (RNN) are the deep learning methods that have been extensively applied for text analysis [29]. They also adopt different ways of understanding linguistic description but have advantages and disadvantages in text modeling. Although CNN exploits different convolution filters to extract the higher-level features, they do not preserve the historical and context information in long text. RNN, a biased model, has a memory that captures long-term sequential correlation, in which computation takes into account historical information and allows the previous outputs to be used as inputs while having the hidden states. RNN might decrease efficiency due to learning the context information of the whole document. Therefore, the long short-term memory (LSTM) model uses to solve the crisis of the RNN [1, 9, 23].

In order to improve the representation of the linguistic features, a large variety of the modified architectures was presented by combinations of DNN including feed-forward, CNN, and LSTM, applying to the proposed framework. In order to make it easier to use the names of the DNN algorithms used in the proposed framework, we assigned an abbreviated name to each of these algorithms, which is shown in Table 4.

Table 4. Abbreviations for the deep neural network algorithms used in the proposed framework.

Abbreviation	Method description
M1	Proposed method using MLP in the framework
M2	Proposed method using CNN in the framework
M3	Proposed method using LSTM in the framework
M4	Proposed method using CNN and LSTM in the framework

In order to select the best structure for the DNN classifier, it is also essential to do a series of experiments based on the training data, and the parameters of the DNN classifier must be tuned using the validation data. The most important parameters of the DNN classifier are the number of hidden layers, number of neurons in each layer, and transfer function of each neuron. After determining these parameters, the DNN classifier must be trained using the whole train and validation data. The accuracy of the proposed framework is next measured using the test data.

3.5. Decision Fusion

In addition to the innovations in the design of the proposed framework including the three Fuzzy Neural Networks (FNN) classifiers along with a Deep Neural Networks (DNN) classifier, each of which trained by a different subset of features, the article has another innovation that includes using a 2-stage decision fusion algorithm in deciding the final personality based on the decision of each classifier. In the first stage, a majority function is proposed to be used due to a different perspective of the FNN classifiers, and then, in the second stage, the first fused decision is proposed to be fused with the DNN classifier decision throughout a weighted decision fusion approach. An iterative entropy-based tuning method is also proposed to tune these weights. The proposed majority function for the first decision fusion algorithm that fuses the decisions of FNN classifiers is depicted in Eq. 4.

$$D_1 = \left\lfloor \frac{1}{2} + \frac{\sum_{i=1}^{3} D(FNN_i) - \frac{1}{2}}{3} \right\rfloor \tag{4}$$

where, $D(FNN_i)$ denotes the decision of the ith FNN classifier. The second decision fusion algorithm that fuses the first decision D1 with the decision of the DNN classifier is depicted in Eq. 5.

$$D_2 = \frac{(\alpha \times D_1 + \beta \times DNN)}{2 \times \alpha \times \beta} \tag{5}$$

Where α and β are the weights that must be tuned using the whole train and validation data. For this aim, an entropy-based tuning algorithm is used in the proposed framework.

-Entropy-based tuning algorithm steps:

1. Change one of the weights (α, β) randomly by $\pm\lambda$.
2. Compute $D_2(k)$ for each data k.
3. Normalize $D_2(k)$ such that $\sum_k D_2(k) = 1$
4. Compute the Shannon entropy $H = -\sum_k D_2(k) \times \ln D_2(k)$

where λ is a growing coefficient and is a minimal value according to the weights.

4. Evaluation

In this section, the dataset used and the experimental results are described. The dataset and its specifications are introduced in detail in the first sub-section. In the second sub-section, a series of experiments are performed to evaluate the proposed framework, and the same conditions of the experiments are stated. The proposed framework is simulated using MATLAB 2018b. We trained our data with 10-fold cross-validation with 10 iterations. Each time, a single fold was used for testing, and the other 9 folds were used for training.

4.1. Evaluation measures

Considering the user's required information, there were relevant and non-relevant items. The relevant items were those that met the needs, and vice versa. Practically, there are four possible combinations of the actual labels and system assigned labels (observations), as shown in Table 5: true positive or TP (number of the retrieved items that are relevant), false positive or FP (number of the retrieved items that are non-relevant), false negative or FN (number of not retrieved).

4.2. Dataset

In order to evaluate the accuracy of the proposed method, the personality dataset was used to compare the results of the implementation with the Anchor article [1]. The personality dataset used in our work was a sample of personality scores on the Facebook profile data. The data was collected by Schwartz *et al*. [26] using a Facebook application that implemented the Big 5 personality traits' test among the other psychological tests. The application includes obtaining the consent from the users to record their data and use it for various research purposes. The dataset consists of 250 data of the Facebook users with approximately 10,000 status with a given personality label based on the Big Five personality traits model. The distribution of the dataset based on the personality type is presented in Table 5.

Table 5. Distribution of the personality dataset.

Value	OPN	CON	EXT	AGR	NEU
Yes	176	130	96	134	99
No	74	120	154	116	151

4.3. Experimental Results

In this section, a series of experiments are performed. In the first experiment, in order to develop the FNN classifiers, a feature analysis was done, and the distribution of the SNA features was explored. Fig. 4 depicts the distribution of the SNA features one by one. Each point in this figure represents one of the SNA feature values of a person. Besides, the x-axis shows one feature and the y-axis shows the other feature. It also represents a combination of two of the seven features, namely the distribution of 21 binary sets of the features. It could be derived that those features are the best that have more discrimination space and less correlation.

Generally, there are two main reasons why feature analysis was done for the FNN classifiers in the proposed framework. First, it reduces the high dimensionality of the dataset by removing the features not essential for training, improving the generalization of the models, and reducing the training time. Secondly, the framework gains a better understanding of the features and their relationships to the response features. Additionally, it improves the accuracy of the learning algorithms, and reduces the processing requirements.

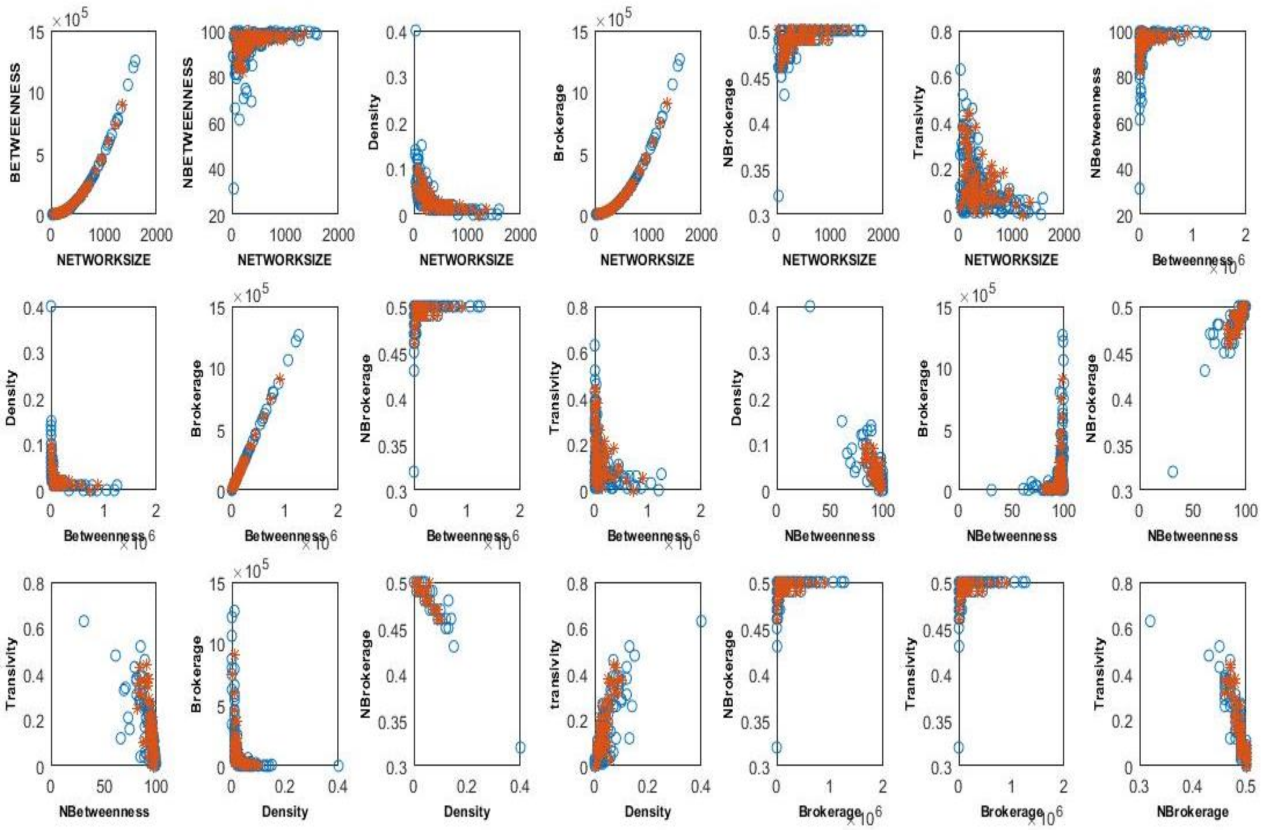

Figure. 4. An analysis of the distribution of the SNA features.

After the SNA feature analyzing, three different subsets of features were selected, and respectively, three different FNN classifiers were trained using the training data.

In parallel, in the second experiment, the DNN classifier was constructed and trained based on the LA feature, which was a numerical vector of the linguistic status description. Figure 5 depicts the DNN structure.

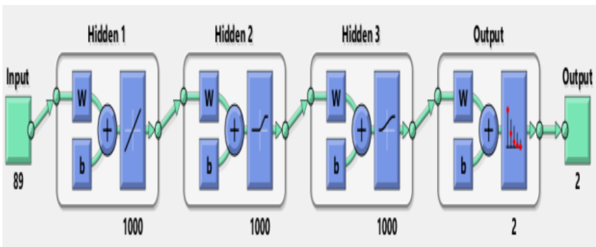

Figure 5. Structure of DNN classifier.

According to Fig. 5, the final structure of the DNN classifier, which is used in the proposed framework, has three hidden layers with 1000 neurons in each layer, and the transfer function of neurons is, respectively, Purelin, Poslin, and Logsig. In another experiment, the performance of the DNN classifier was assessed by the cross-entropy criteria. It increases as the predicted probability diverges from the actual label. Fig. 6 depicts the training state of the DNN classifier.

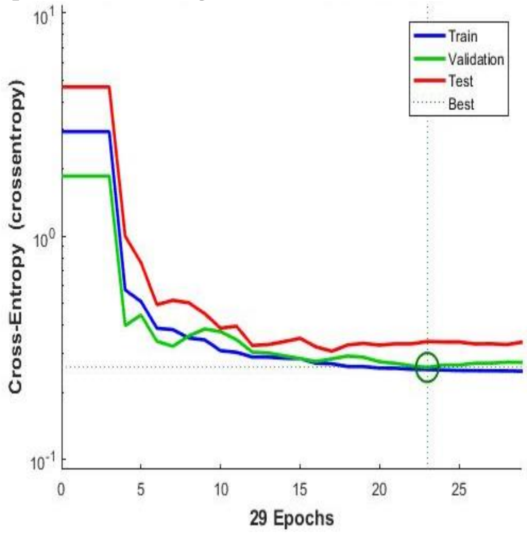

Figure 6. Training state of the DNN classifier.

5. Discussion

Concerning the facts, it must be admitted that the task of predicting personality is very complex for both the humans and machines. Regarding the personality prediction systems' functionality and also to compare the outputs obtained from the proposed framework with the outputs of referenced articles, an accuracy measure is preferable to precision and recall. Despite the fact, both the accuracy and f-measure were used for evaluation. Of course, precision and recall also have meaningful interpretations. According to the results presented in Table 6, among the four proposed methods, the term M1 method unexpectedly obtained the best results for accuracy measure in all of the five personality traits and exceeded the accuracy of the personality prediction from the previous methods up to 82.3%. Nevertheless, as it could be seen in Table 7, among the suggested methods, the M1 method achieved the highest precisions for the two personality traits, and the remaining highest three precisions were achieved by the term MLP and CNN1 method. As shown in Table 8, the M1 method also has the highest recalls for two personality traits, and the remaining highest three recalls were for the M4, MLP, and CNN1+LSTM methods when they were used independently.

Notably, the M1 method achieves the highest accuracy in all the personality traits. It means that the deep learning-based method for linguistic features in the proposed framework causes the most accurate predictions. The classifier's combination based on the different features used made an extended perspective and increased the accuracy of the personality prediction system. For this purpose, the fuzzy classifiers were used due to uncertainty in personality traits and DNN due to the complexity of the linguistic features. Of course, we believe that considering the task's complexity, enriching the dataset will cause to improve the precision of the proposed methods. Generally, the results obtained approve that among the suggested methods, the term M1 method is so competent to predict personality in all the five personality traits in the Big Five model.

From the results obtained from the experimental results, the following points can be made:

Among the four proposed methods, the term M1 method was the first one that unexpectedly obtained the best results for the accuracy measure in all of the five traits (as can be seen from Table 6). This method also achieved the highest average for the used measure values in five traits.

1) From the seven features of SNA in Fig. 4, the three subsets of features betweenness, brokerage, and density are less correlated, and have a more discrimination space. Thus these three subsets are used in the FNN 3 steps.
2) Using CNN or LSTM only cannot achieve the desired outcomes; this is because CNN fails to capture the long-term sequential information, while LSTM is unable to learn the high-level features. Although the model based on CNN and LSTM cannot attain the hopeful result, since CNN directly feed the original input sequence into LSTM. This means that one layer of LSTM is unable to extract the long-term dependencies.
3) CNN's work well where detecting the local and position-invariant patterns are important. The patterns could be the key phrases that express a particular sentiment like "I like" or a specific topic [23], and hence, this may be the reason why MLP performs better than CNN in the dataset used.
4) As the results of the experiment in Fig. 6 show, 23 is where the training and testing status is at its optimum.

Table 6. Accuracy comparison of the proposed method.

Measure	Method	OPN	CON	EXT	AGR	NEU	Avg
Accuracy	**M1**	**80.20%***	**72.40%***	**82.30%***	**81.70%***	**76.50%***	**78.62**
	M2	79.2 %	58%	61.30%	68.38%	63.45%	66.06
	M3	71.23%	58.65%	58.30%	58%	61.34%	61.50
	M4	76.8%	59.68%	73.45%	59%	60.97%	65.98
	Naive Bayes	70.00%	59.20%	68.80%	56.40%	54.40%	61.76
	SVM	70.40%	56.00%	61.60%	56.80%	60.40%	61.44
	Logistic regression	70.40%	54.40%	68.40%	53.60%	60.40%	61.44
	Gradient boosting	63.20%	56.40%	68.00%	63.20%	59.20%	63.8
	LDA	70.00%	58.40%	68.00%	58.00%	60.80%	63.04
	MLP	79.31%	59.62%	78.95%	56.52%	79.49%	70.77
	LSTM	68.00%	52.00%	58.00%	56.52%	58.62%	58.62
	GRU	68.00%	62.00%	58.00%	65.22%	64.00%	63.44
	CNN 1D	79.31%	50.00%	60.94%	67.39%	61.54%	63.83
	LSTM+CNN	75.86%	57.69%	71.05%	50.00%	58.97%	62.71
	Naive Bayes	49.70%	57.50%	62.9%	55.94%	56.40%	56.48
	SVM	62.80%	52.30%	54.25%	61.20%	57.40%	57.59
	Logistic regression	63.21%	52.20%	62.70%	51.90%	63.40%	58.68
	Gradient boosting	59.80%	54.9%	69.90%	64.30%	53.78%	60.53
	LDA	61.58%	52.34%	65.90%	55.46%	59.90%	59.03
	MLP	71.96%	49.62%	68.50%	57.18%	**69.90%***	63.43
	LSTM	65.12%	51.58%	59.20%	51.97%	49.82%	55.53
	GRU	65.19%	56.90%	63.30%	63.12%	59.70%	61.64
	CNN 1D	70.03%	57.9%	63.94%	65.19%	62.88%	63.98
	LSTM+CNN	**73. 4%***	58.58%	61.9%	59.50%	61. 7%	63.01

*Best result

Table 7. Precision comparison of the proposed method.

Measure	Method	OPN	CON	EXT	AGR	NEU	Avg
Precision	**M1**	**71.30%**	68.30%*	**69.70%**	72.10%*	**66.30%**	69.54
	M2	63.8 %	54.2%	52.30%	61.35%	57.54%	57.83
	M3	65.2%	53.5%	55.1%	57.4%	59.34%	58.10
	M4	71.9%	62.3%	72%	55.7%	57.7%	63.92
	Naive bayes	56.70%	58.20%	63.8%	57.54%	61.40%	59.52
	SVM	65.50%	58.40%	63.80%	58.90%	59.40%	61.20
	Logistic regression	69.90%	49.90%	65.70%	53.60%	60.40%	59.90
	Gradient boosting	65.80%	54.75%	71.40%	65.20%	58.20%	63.07
	LDA	60.90%	59.34%	65.70%	59.50%	54.90%	60.06
	MLP	74.15%	55.92%	**76.50%***	52.78%	**71.90%***	66.25
	LSTM	69.10%	53.20%	58.20%	55.92%	56.62%	58.60
	GRU	61.89%	64.00%	67.00%	59.62%	61.70%	62.84
	CNN 1D	**78.13%***	52.57%	58.94%	68.10%	60.38%	63.62
	LSTM+CNN	75.14%	58.5%	66.35%	53.20%	57.47%	62.13

*Best result

Table 8. Recall comparison of the proposed method.

Measure	Method	OPN	CON	EXT	AGR	NEU	Avg
Recall	M1	**73.14%**	68.25%*	**61.90%**	68.50%*	**61.23%**	66.60
	M2	58.7 %	57.5%	49.30%	64.53%	59.1%	57.82
	M3	63.3%	57.1%	57.54%	55.9%	58.74%	58.51
	M4	67.9%	63.3%	**65.93%***	56.7%	51.8%	61.12
	Naive Bayes	49.70%	57.50%	62.9%	55.94%	56.40%	56.48
	SVM	62.80%	52.30%	54.25%	61.20%	57.40%	57.59
	Logistic regression	63.21%	52.20%	62.70%	51.90%	63.40%	58.68
	Gradient boosting	59.80%	54.9%	69.90%	64.30%	53.78%	60.53
	LDA	61.58%	52.34%	65.90%	55.46%	59.90%	59.03
	MLP	71.96%	49.62%	68.50%	57.18%	**69.90%***	63.43
	LSTM	65.12%	51.58%	59.20%	51.97%	49.82%	55.53
	GRU	65.19%	56.90%	63.30%	63.12%	59.70%	61.64
	CNN 1D	70.03%	57.9%	63.94%	65.19%	62.88%	63.98
	LSTM+CNN	**73. 4%***	58.58%	61.9%	59.50%	61. 7%	63.01

*Best result

6. Conclusions

The experimental results show that the proposed hybrid framework for predicting the personality of the social network users based on the Big Five model improves the accuracy better than all the other related methods studied in this scope. Utilizing the efficiency of the fuzzy neural networks and the deep neural networks from a different feature perspective and the decision fusion method used in this research work are vital concepts that cause the overall accuracy improvement concerning the other methods. However, several subjects must be regarded in the future research works. The dataset is essential, and more cases must be studied to validate the existing methods. Tuning the parameters of the proposed framework in more feature analysis also may lead to better results. Thus we suggest extending the feature space with novel feature extraction models such as deep feature extraction in order to continue this research work. Examining more classifier combinations and an enhanced method using ensemble modeling is the other suggestion that we confirm to be done in the future.

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یک چارچوب ترکیبی برای پیش‌بینی شخصیت افراد مبتنی بر شبکه‌های عصبی فازی و شبکه‌های عصبی عمیق

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چکیده:

به‌طورکلی، انسان موجودی بسیار پیچیده است؛ به همین علت، در سال‌های اخیر، پژوهش در مورد ابعاد و جنبه‌های مختلف سلامت روان افراد، به‌ویژه تحلیل شخصیت، به موضوعی جذاب در کارهای تحقیقاتی تبدیل شده است. با ظهور فناوری‌های نوین، فضای ارتباطاتی جدیدی در بستر شبکه‌های اجتماعی پدید آمده که شکل نوینی از ارتباطات اجتماعی را برای افراد به همراه داشته است. شناخت و طبقه‌بندی افراد در این فضا، به یکی از چالش-های جدید تحقیقاتی تبدیل شده است. در این مقاله، ابتدا با توجه به مدل پنج عاملی شخصیت، یک دسته‌بندی از کارهای مرتبط، پیشنهاد شده است؛ در ادامه یک چارچوب ترکیبی بر اساس شبکه‌های عصبی فازی (FNN) و شبکه‌های عصبی عمیق (DNN) ارائه و شبیه‌سازی شده که با پیشنهاد به‌کارگیری روش دومرحله‌ای در ترکیب تصمیمات، دقت تشخیص شخصیت را بهبود می‌بخشد. روش پیشنهادی نهایی از تلفیق ویژگی‌های ساختاری تحلیل شبکه‌های اجتماعی (SNA) و ویژگی‌های تحلیل زبانی (LA)، استخراج شده که از شرح فعالیت‌های افراد در شبکه اجتماعی فیس‌بوک استفاده می‌کند. نتایج به‌دست‌آمده نشان می‌دهد که عملکرد چارچوب پیشنهادی تا ۸۳,۲٪ نسبت به میانگین دقت در کارهای تحقیقاتی مشابه، بر روی مجموعه داده‌های شخصیتی یکسان، بهبودیافته است.

کلمات کلیدی: پیش‌بینی شخصیت، مدل پنج بزرگ، شبکه‌های عصبی فازی، شبکه‌های عصبی عمیق، تحلیل شبکه‌های اجتماعی.