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Hybrid Classification Model for Emotion Prediction from EEG Signals: A Comparative Study

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Abstract: This paper introduces a novel hybrid algorithm for emotion classification based on electroencephalogram (EEG) signals. The proposed hybrid model consists of two layers: the first layer includes three parallel adaptive neuro-fuzzy inference systems (ANFIS), and the second layer called the adaptive network comprises various models such as radial basis function neural network (RBFNN), probabilistic neural network (PNN), and ANFIS. It is examined that the feature distribution graphs of the dataset, which includes three emotion classes: positive, negative, and neutral, and selected the most appropriate features for classification. The three parallel ANFIS structures were trained using the selected features as input vectors, and the outputs of these models were combined to obtain a new feature vector. This feature vector was then used as the input to the adaptive network, which produced the output of emotion prediction. In addition, it is evaluated the accuracy of the network trained using only the first features of the dataset. The hybrid structure was designed to enhance the system's performance, and the best accuracy result of 96.51% was achieved using the ANFIS-ANFIS model. Overall, this study provides a promising approach for emotion classification based on EEG signals.

Keywords: ANFIS, EEG, Emotion Classification, Hybrid Algorithm, Probabilistic Neural Network, Radial Basis Function Neural Network
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1 Introduction

The experience of emotion holds a pivotal position in people's daily lives, as it entails a transformation in an individual's emotional state that is contingent upon environmental factors [Song, 20]. There are two main approaches for evaluating a person's emotional reactions: non-physiological measures, which include facial expressions, vocal tones, and physical gestures, and physiological actions, such as electroencephalogram (EEG), electromyogram (EMG) and electrocardiogram (ECG).

While non-physiological measures may be subject to conscious control, thereby leading to potential inaccuracies in emotion recognition, EEG-based emotion recognition offers a more reliable alternative by capturing detailed emotional changes and recording the relationship between emotional states and brain activity that is beyond conscious control [Luo, 20], [Zhang, 20]. Recently, considerable attention has been given to studies involving emotion recognition from EEG signals. This method is highly reliable and can effectively capture even subtle emotional changes while also recording the relationship between emotional state and brain activity that is not subject to the individual's control [Yin, 21]. However, emotions are complex and can be highly sensitive to changes in circumstances, making them difficult to understand and categorize. In response, researchers have developed two approaches to describing emotions [Zhang, 20]. The first, known as discrete basic emotion identification, divide emotions into six categories: joy, sadness, surprise, fear, anger, and disgust. The second approach, known as dimensional emotion recognition, characterizes emotions based on two or three dimensions: valence, arousal, and dominance or valence and arousal. The valence dimension describes whether an emotion is positive or negative, while the arousal dimension describes how excited or calm an individual is feeling [Song, 20].

Emotion prediction is a critical aspect of human-machine interaction, enabling the machine to identify an individual's emotional fluctuations and offer appropriate responses. To achieve this goal, the utilization of different artificial neural networks (ANNs) or neuro-fuzzy inference systems has become vital, as numerous studies have emphasized the significance of emotion prediction [Zhang, 20], [Yin, 21].

ANNs are computer systems that draw inspiration from the human brain learning ability and are known for their universal approach. Neuro-fuzzy systems, on the other hand, combine the learning algorithm of ANN theory with fuzzy logic to process data. These systems transform input sets into output using IF-THEN fuzzy rules, where the fuzzy system component defines the membership functions (MF), and ANN extracts the fuzzy rules from numerical data and sets the MF parameters consistently with the learning process. As a result, neuro-fuzzy systems are known as universal estimators that can handle non-linear data well, deal with uncertainty, and resist noise [Gulbag, 06], [Güler, 05]. A special type of neuro-fuzzy system called the adaptive neuro-fuzzy inference system (ANFIS), first extracts the membership function parameters from a dataset that defines the system's behavior and then adjusts the system parameters according to the determined error criterion by learning the features in the dataset. ANFIS is particularly useful for modeling non-linear functions, leading to increased interest in fields such as decision-making, pattern recognition, information technology, and data analysis [Güler, 05].

The radial basis function neural network is a popular and widely used artificial neural network model that is particularly effective at classifying multi-class and high-dimensional data due to its greater potential for achieving a global minimum. Although it has a slower convergence rate compared to other ANN models, it offers significant benefits in terms of its ability to handle complex data. One important consideration when working with the RBFNN is that the number of nodes in the network's single hidden layer is typically equal to the number of training patterns. Therefore, increasing the size of the training set will also increase the size of the RBFNN. However, it is possible to reduce the size of the network through the use of statistical methods to decrease the training pattern size [Gulbag, 07], [Seyman, 13].

The widely used probabilistic neural network (PNN) is capable of classification, prediction, and recognition applications, which are derived from the probability density function. The PNN model utilizes competitive learning based on winner-take-all logic to provide a general solution for pattern classification problems with the Bayesian classifier approach. Additionally, PNN employs Parzen Estimators to generate the probability density functions required in Bayesian theory. With its four-layer structure, consisting of the input layer, pattern layer, summation layer, and output layer, PNN is frequently chosen for its fast-training features and efficient layer structure [Gulbag, 08]-[Zhang, 17].

The use of EEG signals for recognizing human emotions has become an active research area in recent years. This field of research has been used commonly, particularly in the application of fuzzy logic and artificial neural network (ANN) methodologies. Several studies have been conducted to investigate the potential of EEG signals for identifying different emotional states, which can have various applications in fields such as psychology, neurology, and human-computer interaction. [Krisnandhika, 17] proposed a method for extracting features from EEG signals using relative wavelet energy features, which were used as inputs to a modified RBFNN for emotion classification. The system achieved an average accuracy of 86.6% in recognizing four basic emotions and an overall accuracy of 70.4% in recognizing six emotions. [Zhang, 20] presented a method for emotion recognition using EEG signals and an improved RBFNN. The system achieved high accuracy in recognizing emotions, with an average accuracy of 90.83%. The proposed method outperformed other existing methods in terms of accuracy and computational efficiency. In another study, [Bird, 18] conducted a study on using EEG-based brain-machine interfaces (BMIs) for mental state classification. EEG signals were recorded using a 14-channel system, and machine learning algorithms were used to classify the different mental states. The EEG-based BMI was able to classify different mental states with an average accuracy of 87.16%. On the other hand, [Liu, 20] used a deep neural network (DNN) with a sparse autoencoder as a feature extractor to classify four different emotional states. The extracted features were then used as input to a support vector machine (SVM) classifier, which achieved an overall accuracy of 83.16% for the emotion classification task. The other study [Rozgić, 13] proposed a method for classifying emotions based on EEG signals using a segment-level decision fusion technique. The authors propose a segment-level decision fusion approach that combines the outputs of multiple classifiers to improve the accuracy and robustness of the emotion classification system. The overall accuracy of the proposed method was reported to be 84.9%. [Zhang, 16] proposed a novel approach to EEG-based emotion recognition using a probabilistic neural network (PNN). They used the DEAP dataset to evaluate the proposed method, achieving an accuracy of 66.5% in classifying four emotional states (valence and arousal) using a leave-one-subject-out cross-validation method. The authors compared their method with several other state-of-the-art methods and showed that their method outperformed the others in terms of accuracy. Similarly, [Li, 18] proposed a method for recognizing emotions from multichannel EEG signals using K-nearest neighbor (KNN) classification. The method was effective in recognizing emotions from EEG signals, with an average classification accuracy of 70.5%. [Nakisa, 18] focused on the use of evolutionary computation algorithms for feature selection in EEG-based emotion recognition using mobile sensors. They proposed using evolutionary computation algorithms to search for the optimal subset of features that can improve the accuracy of emotion recognition. The authors evaluated their approach using a dataset of EEG signals collected from mobile sensors and compared the performance of their approach with other feature selection methods. They reported an accuracy of 89.3% for emotion recognition using the proposed approach. Finally, [Moreira, 21] discussed the importance of understanding the emotional content of music and introduced ANFIS. The authors tested the ANFIS system for emotion recognition in music and achieved an overall accuracy of 83.4%. The system performed best in recognizing happy and sad emotions, while the lowest accuracy was achieved in recognizing scary emotions. However, more research is needed to improve the accuracy of the system, particularly in recognizing more complex emotions.

The main motivations of our paper are as follows:

1. The existing literature suggests that ANN and ANFIS models are commonly utilized for emotion prediction, yet they do not consistently exhibit high-performance rates. To address this issue, this study proposes a hybrid approach that combines different adaptive networks with ANFIS, using EEG signals to enhance the accuracy of emotion prediction.
2. The dataset for emotion prediction is divided into classes, and each class is trained separately using the first three and five features of the EEG signals in parallel ANFIS models. Subsequently, the prediction results from this stage are utilized as input to an adaptive network structure for further emotion prediction.
3. The high accuracy achieved in emotion prediction with the selected first features and the proposed hybrid model is supported by performance results, thus validating the effectiveness of this approach over training the network with all the features of the dataset.

The structure of the paper is as follows: Chapter 2 provides a detailed explanation of the dataset used, the training algorithms employed, and the proposed network structure. Chapter 3 focuses on the obtained results and accompanying comments. Finally, Chapter 4 presents the consequences of the study.

2 Material and Methods

The study proposes a hybrid structure for emotion prediction using EEG signals constructed by combining ANFIS and PNN, RBFNN, and ANFIS models. The dataset utilized in the study comprises EEG signals collected from TP9, AF7, AF8, and TP10 electrodes of two individuals, one male, and one female, as reported by [Bird, 18], [Bird, 19]. The dataset consists of 2132 samples and 2548 features and involves the use of six movie clips as stimuli to elicit positive and negative emotions, without any neutral stimulus. The duration of the EEG signal collection is 36 minutes, while Table 1 shows the movie clips used in the study.

Stimulus	**Class**
Marley and me	Negative
My girl	Negative
Up	Negative
La La Land	Positive

Slow Life	Positive
Funny Dogs	Positive

Table 1: Emotional classes and movie clips

In this study, classification is achieved using three separate ANFIS structures due to its output structure. The primary objective of classification is to assign input values to specific classes, represented by outputs in the range of 0 to 1, indicating the probability of class membership. The research focuses on three types of feelings: negative emotions (class 1), happy emotions (class 2), and neutral emotions (class 3). ANFIS 1 classifies negative emotions, while ANFIS 2 and ANFIS 3 are responsible for classifying positive and neutral emotions, respectively.

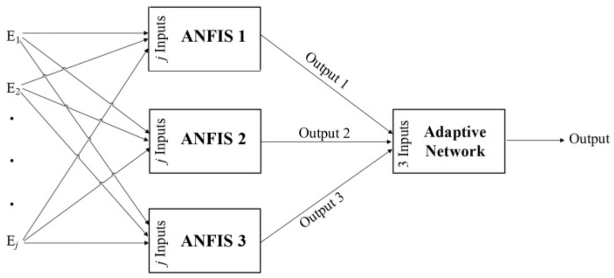


Figure 1: Proposed model for emotion classification from EEG signals

Figure 1 illustrates the system model of the proposed hybrid structure. E_j is input to predict emotions from EEG signals, j=1, 2, …,5 for this study. In the first step of the model, the feature vector that best describes the dataset is trained by giving input to each ANFIS structure. Eventually, the outputs that range from 0 to 1 are obtained from parallel ANFIS structures. Moreover, a feature vector is generated from the outputs and then given to the adaptive network as an input vector in the second phase. On the other hand, the ANFIS classifiers are trained using a combination of the back-propagation gradient descent method and the least-squares technique. Consequently, the output of the trained system provides information about which emotion class the inputs fall into. In this system, the models used as adaptive networks are ANFIS, PNN, and RBFNN, respectively.

2.1 Adaptive Neuro-Fuzzy Interference System (ANFIS)

ANFIS is a system that combines the benefits of ANN's learning ability and fuzzy logic system mapping techniques. The ANFIS model is formed by incorporating fuzzy control into the ANN model, allowing it to accurately represent non-linear relationships between system inputs and outputs [Saucedo, 19]. n practical applications such as pattern matching, classification, and estimation, ANFIS is widely used due to its ability to generate a set of fuzzy rules that describe the system's behavior [Seyman, 08], [Seyman, 12]. These rules are typically expressed in a general form, as shown in Eq. (1) and Eq. (2) [Seyman, 08]:

Rule 1: If E_1 is A_1 and … and E_j is F_1 then,

$$k_1 = p_1 E_1 + \ldots + q_1 E_j + r_1 \tag{1}$$

Rule 1: If E_1 is A_2 and … and E_j is F_2 then,

$$k_j = p_j E_1 + \ldots + q_j E_j + r_j \tag{2}$$

where E_j is the input, A_i and F_i are the fuzzy membership function, and p_j, q_j, r_j are the training parameters.

Fuzzy inference methods are typically classified into two distinct structures, with the Mamdani fuzzy inference method being the first approach to employ fuzzy set theory in control systems. The Sugeno fuzzy inference method is the second approach, and it shares many similarities with the Mamdani method. In both methods, the initial two steps of the fuzzy inference process, which involve blurring the inputs and applying the fuzzy operator, are identical. The primary distinction between Mamdani and Sugeno is that the output membership functions of Sugeno's type FIS are either linear or constant, whereas Mamdani's output membership functions are non-linear. Moreover, the Sugeno type FIS's membership function parameters are identified by ANFIS using a hybrid learning algorithm that combines least-squares and back-propagation (BP) algorithms [Gulbag, 06]. Consequently, the ANFIS model presents an effortless approach to determining membership function parameters and fuzzy rules for more intricate problems with the Sugeno fuzzy inference method [Seyman, 08], [Seyman, 12].

In ANFIS, where inputs and outputs are shown with membership functions, the type and number of membership functions, the number of inputs, outputs, and rules determine the number of parameters to be updated to the most appropriate value through a learning process. Furthermore, the number of rules to be created in ANFIS is determined by the number of membership functions set to cluster the input space for each input, and fuzzy rules are generated as a result of this clustering process. The purpose of clustering is to divide the K dataset into b clusters. The techniques used for clustering are unsupervised methods used to divide the data into clusters according to the similarities between the datasets and the Euclidean distance. Thereby, the smaller the Euclidean distance between two points, the higher the degree of membership of that point in the cluster [Kasule, 18]. However, the ANFIS structure generally allows for inputs of up to five. When more input data is given, the ANFIS structure enters an infinite loop due to the increase in processing load and complexity, and therefore, the system cannot be expected to be efficient and the results reliable [Başçıl, 15].

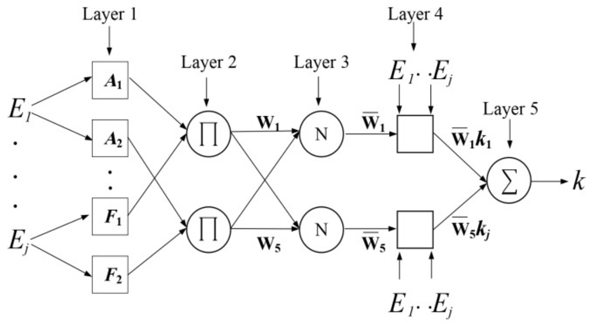


Figure 2: Equivalent ANFIS structure to the Sugeno fuzzy model

As a result of the non-linearity, instability, and low signal-to-noise ratio of EEG signals, predicting emotion from those signals can be considered a difficult problem as it requires hundreds of fuzzy rules and membership function parameters. Therefore, in the first part of the study, the ANFIS structure trained using the Sugeno-type fuzzy inference method for emotion classification is used, as shown in Figure 2.

2.2 Radial Basis Function Neural Network

Radial basis function neural networks using a supervised learning algorithm have a parallel structure consisting of an input layer, hidden layer, and output layer. RBFNN differs from other feed-forward networks in that it has only one hidden layer. Therefore, it is also considered a good candidate for prediction problems, with the ability to learn faster compared to other feed-forward networks [Aslan, 08]. In basic RBFNN, the activation function and target function of the network is determined using the Gaussian Function and the least-squares (LS) approach, respectively. However, to minimize the error between the target and the actual output, the weight parameters, node centers, and span widths of each node are updated using the gradient descent method. These updates continue until the specified stopping criteria are fulfilled. More detailed information can be found in [Seyman, 13].

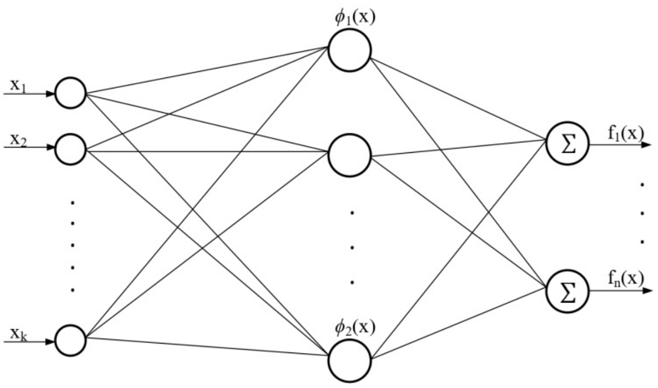


Figure 3: The architectural structure RBFNN

The RBFNN structure shown in Figure 3 is used as the adaptive network in the proposed hybrid model. The input vector of this system is the result values produced by each parallel ANFIS, in the range of 0–1, as well as the output, which is the emotion class index.

2.3 Probabilistic Neural Network

The PNN is another adaptive network structure employed in this study to classify the outputs generated by the parallel ANFIS model. The PNN has a multilayer structure created by connecting the radial basis layer, which has a single hidden layer, to the output layer (competitive layer), as seen in Figure 4. However, the PNN system's inputs are the ANFIS's output results connected in parallel, and the system's outputs are the emotion class indexes. While no computation is done in the input layer of the PNN, only the input vector, $E = [E_1, E_2, \dots, E_i]$, is transferred to the network. Therefore, the number of neurons in this layer is equal to the size of the feature vector, E. In the sampling layer where the radial basis weight functions are located, the distance between each sample with the simultaneously given input vector is calculated, and a vector is then created that shows how close the input vector is to the samples. The summation layer accumulates the probability of being a participant in a certain class. Eventually, the output layer compares the competitive attitude to the probability density of the outputs and returns the outputs with the highest probability. PNN networks, on the other hand, are similar to RBFNN except for the output layers. The PNN model, which utilizes Gaussian or a different kernel function in the sampling layer, generates classification decisions via binary neurons at its output nodes, whereas the RBFNN model has linear output nodes [Zhang, 17], [Bardak, 22]. More detailed information can be found in [Gulbag, 08].

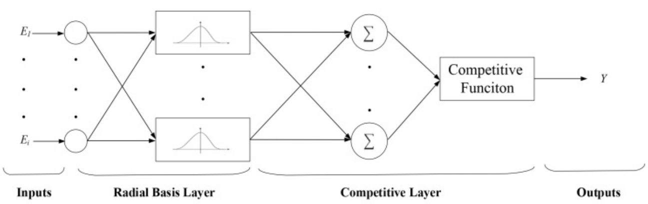


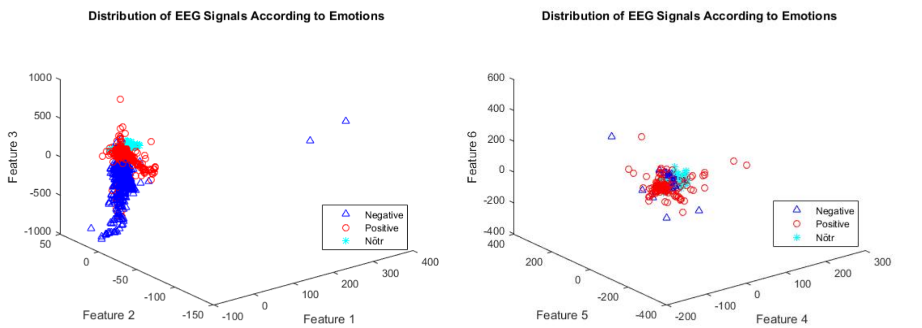
Figure 4: PNN network architecture

3 Results and Discussion

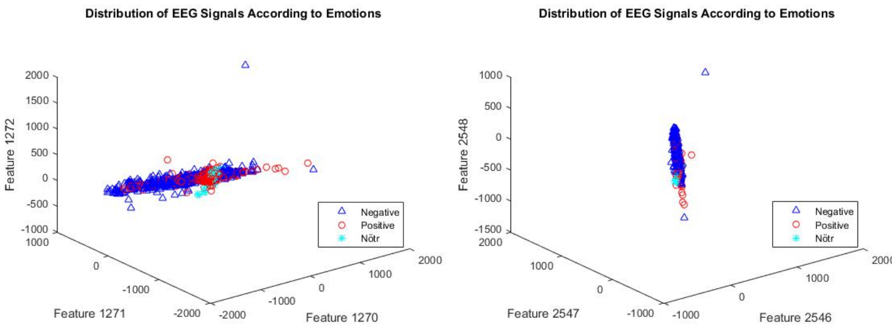
The success of a neural network classifier relies heavily on the distribution and distinguishability of the chosen inputs. Therefore, input selection plays a crucial role in the design of a neural network. The ability to identify the features of an input vector that best represents a given sample directly impacts the performance of the classifier. In this study, the feature distribution graph in Figure 5 indicates that the first features of the input vector are the most accurate descriptors of the EEG-based emotion prediction dataset. However, a closer examination of the feature distributions reveals that the most effective features for classification are those that can be readily distinguished from the other features. Therefore, the proposed system model was trained to evaluate the impact of feature size on classifier performance by employing the top five features, which correspond to the maximum number of inputs in ANFIS. As a result, the first three features of the dataset were selected as the input vector for the proposed hybrid model.

The ANFIS classifiers utilized in this study are trained using a combination of the back-propagation gradient descent method and the least-squares technique, while the ANFIS fuzzy rule structure is designed with the generalized bell-shaped membership function. For target output sets Output 1, Output 2, and Output 3, samples are given binary target values of (1, 0, 0), (0, 1, 0), and (0, 0, 1), respectively. To improve the classifier accuracy of the study, the ANFIS, PNN, and RBFNN classifiers are trained using an input vector that incorporates the outputs of the three ANFIS classifiers. The dataset is divided into a training dataset consisting of 1706 samples and a test dataset consisting of 426 samples using the 3-fold method. The k-fold cross-validation technic was employed to avoid data leakage and to provide reliable outcomes in this dataset. The parallel ANFIS classifiers are trained using the training set, while the accuracy of the trained network for emotion prediction from EEG signals is tested using the test set.

Evaluating the test performance of classifiers typically involves calculating the classification accuracy, sensitivity, and specificity parameters. Accuracy is determined by the ratio of correct decisions to the total number of cases, while sensitivity and specificity are calculated by the ratio of true positive decisions to actually positive cases and true negative decisions to negative cases, respectively. On the other hand, the F1 score is a commonly used metric in classification tasks that measures the balance between precision and recall. It provides a more comprehensive measure of a classifier's performance in classification tasks, especially when there is an imbalance in the class distribution. Therefore, in the present study, the performance of the structures used was assessed using accuracy, specificity, sensitivity, F1 score, and mean square error (MSE) rate.



(a) (b)



(c) (d)

Figure 5: The division by features,(a) 1-3 features, (b) 4-6 features, (c) 1270-1272 features, (d) 2546-2548 features

The initial phase of learning for the parallel ANFIS structure involves training the first five features of the dataset. The number of membership functions used in the first ANFIS model determines the number of fuzzy rules and influences the network's learning speed. To this end, a membership function value of (3 3 3 3 3) for the five inputs is chosen to cluster the input space. However, in the second phase of the system, an ANFIS-ANFIS model with three inputs is employed, and separate membership function values of (3 3 3) and (5 5 5) are chosen to examine the effect on the system's accuracy.

The spread factor plays a critical role in the performance of the PNN classifier, and its optimal value may vary depending on the characteristics of the data being used [Gorur, 18]. In this study, it is conducted a search for the optimal spread factor by exploring a range of values from 0.1 to 1, in increments of 0.01. This was done to ensure that the PNN achieved the best possible performance and to identify the most appropriate value for the spread of activation functions. After conducting the spread factor search, it is found that the optimal value for achieving the highest PNN accuracy in this study was 0.072.

On the other hand, the MSE factor serves as a performance criterion for the RBFNN, enabling it to minimize the difference between its output and the target output. In this study, the training goal was set to an MSE factor of 0.02, while the other parameters were not explicitly set, which means that the function used default values for them. The model trained for a total of 110 epochs, indicating that the network required a sufficient number of iterations to achieve the specified training goal. Table 2 shows the parameters of the PNN and RBFNN used in this study.

Parameters	**PNN**	**RBFNN**
Activation Function	Radial Basis Function	Gaussian
Neurons	5	20
Layers	2	2
Spread Factor	0.072	1

Table 2: Parameters of PNN and RBFNN

Table 3 presents the accuracy, sensitivity, specificity, F1 score, and MSE parameters for the first five features of the proposed system model. By using the outputs of the parallel ANFIS networks as the input vector to the adaptive network's RBFNN, PNN, and ANFIS structures, the highest accuracy of 96.51% is achieved with a membership function of (3 3 3) for the three-input ANFIS-ANFIS classifier. When compared to other networks, the ANFIS-RBFNN model exhibits the lowest accuracy at 91.22%, while the ANFIS-PNN model has the second-highest accuracy at 95.53%. The reason for this the ANFIS-PNN model uses the training set in only one training step and selects the class at the output layer of the network by choosing the highest probability from the total output values.

ANFIS + Adaptive Network	Accuracy (%)	Sensitivity (%)	Specificity (%)	MSE	F1 Score (%)
ANFIS + RBFNN	91.22	88.05	86.67	0.0139	83.98
ANFIS + ANFIS (Number of MFs: 5 5 5)	94.04	100.00	92.85	0.0595	93.62
ANFIS + PNN	95.53	95.78	97.52	0.0280	94.66
ANFIS + ANFIS (Number of MFs: 3 3 3)	96.51	96.42	96.55	0.0349	95.73

Table 3: Accuracy, sensitivity, specificity and MSE rates for the first five features

The study conducted experiments using different membership function numbers to train the network, which received training outputs from the parallel ANFIS model in the first phase, to obtain accuracy, specificity, sensitivity, and MSE values. Table 4 shows the system performance values when the number of inputs is reduced to three and the membership function number is selected as (5 5 5). The findings show that the system performance improves when the number of membership functions is increased while the input vector is decreased for ANFIS-RBFNN and ANFIS-PNN networks, as demonstrated in Tables 3 and 4. This is because all the features describing the samples have different levels of distribution, and therefore, these feature distributions are more highly classifiable in the first three features of the examined dataset. Additionally, ANFIS-ANFIS performance outputs maintain a similar rate of accuracy with the increase of membership functions even when the number of inputs is reduced to three. This is because ANFIS expresses the input and output values with the membership function. Tables 4 and 5 reveal that the accuracy of a low-input ANFIS system is directly affected by the variability of membership functions.

ANFIS + Adaptive Network	Accuracy (%)	Sensitivity (%)	Specificity (%)	MSE	F1 Score (%)
ANFIS + RBFNN	92.97	87.29	89.41	0.8023	84.25
ANFIS + ANFIS (Number of MFs: 5 5 5)	94.04	92.85	92.98	0.0706	93.62

ANFIS + PNN	96.24	99.29	95.07	0.0280	94.07
ANFIS + ANFIS (Number of MFs: 3 3 3)	96.47	100.00	94.64	0.0353	93.38

Table 4: Accuracy, sensitivity, specificity and MSE rates for the first three features (ANFIS membership function number (5 5 5))

Table 5 shows the accuracy, sensitivity, specificity, and mean square error values obtained by training the first three features with a membership function of (3 3 3) in the parallel ANFIS-ANFIS classifier. Upon examining Tables 5 and 3, it was discovered that reducing the number of inputs leads to a decrease in accuracy performance for ANFIS-RBFNN and ANFIS-ANFIS structures when the same membership function number is selected. However, the ANFIS-PNN network achieves a system accuracy of 95%. As a result of the ANFIS-ANFIS training, the F1 score value was obtained as 0.95. A better F1 scoring performance has been achieved than other models.

ANFIS + Adaptive Network	Accuracy (%)	Sensitivity (%)	Specificity (%)	MSE	F1 Score (%)
ANFIS + RBFNN	92.36	86.62	89.79	0.2674	84.12
ANFIS + ANFIS (Number of MFs: 3 3 3)	92.94	89.28	94.73	0.0706	93.22
ANFIS + PNN	95.30	97.19	94.71	0.0496	92.45

Table 5: Accuracy, sensitivity, specificity and MSE rates for the first three features (ANFIS membership function number (3 3 3))

Furthermore, the proposed method's experimental findings are contrasted with several previous comparison techniques for predicting emotions. Table 6 presents a comparison of the outcomes obtained from the proposed methodology against those of previous benchmarking studies, and it reveals that the proposed approach surpasses the previous methodologies in terms of performance. This result not only validates the effectiveness of the proposed approach but also highlights its ability to be replicated and repeated consistently.

Paper	Model	Feature	Accuracy (%)
[Zhang, 16]	PNN	-	66.5%
[Li, 18]	KNN	-	70.5%
[Liu, 20]	SVM	DNN	83.16%
[Moreira, 21]	ANFIS	-	83.4%
[Rozgić, 13]	RBF-SVM	Segment-Level	84.9%
[Krisnandhika, 17]	RBFNN	Wavelet Energy Features	86.6%
[Bird, 18]	Random Forest	OneR	87.16%

[Nakisa, 18]	Evolutionary Computation Algorithms	-	89.3%
[Zhang, 20]	RBFNN	-	90.83%
Proposed Hybrid Method	**ANFIS-ANFIS**	-	**96.51%**

Table 6: Comparison of existing methods of assessment for emotion detection based on EEG

4 Conclusions

This article presents a hybrid system model designed for predicting emotions using EEG signals. The proposed model utilizes parallel ANFIS models to classify three emotional states based on input EEG signals. To evaluate the performance of the system, an adaptive network has been employed to combine the prediction results of the three ANFIS classifiers.

ANFIS-ANFIS structures have been shown to produce superior classification results for emotion classification when compared to ANFIS-RBFNN and ANFIS-PNN algorithms. This is primarily attributed to the fact that the ANFIS model uses a hybrid learning algorithm that combines the strengths of both the least-squares and back-propagation methods. As a result, ANFIS is able to learn about the features present in the dataset. In addition, compared to the previous studies surveyed in this article, the proposed system achieved the highest accuracy of 96.51% for recognizing three basic emotions (positive, negative, neutral) using EEG signals. Unlike the other studies that used all available features for classification, the proposed system utilized only five and three selected features to train the classification model, which could potentially improve the system's computational efficiency and reduce overfitting. While the previous studies have made significant contributions to emotion recognition using EEG signals, the proposed system's high accuracy and feature selection strategy demonstrate its potential for real-world applications.

References

[Aslan, 08] Aslan, K., Bozdemir, H., Şahin, C. et al.: A radial basis function neural network model for classification of epilepsy using EEG signals. Journal of Medical Systems, 2008, 32(5), 403-408.

[Bardak, 22] Bardak, F. K., Seyman, M. N., Temurtas, F.: EEG Based Emotion Prediction with Neural Network Models. Tehnički Glasnik Technical Journal, 2022, 16(4), 497-502.

[Başçıl, 12] Başçıl, M. S., Çetin, O., Er, O. et al.: A study on Parkinson's Disease Diagnosis Using Probabilistic Neural Network. Electronic Letters on Science & Engineering, 2012, 8(1), 1-10.

[Başçıl, 15] Başçıl, M. S.: Classification of EEG Signals Occured in the Brain Under the Imagination of the Directions with the Help of Feature Extraction. PhD Thesis. Sakarya Universtiy, Institute of Natural Sciences, 2015, 159p, Sakarya, Turkey.

[Bird, 18] Bird, J. J., Manso, L. J., Ribiero, E. P., Ekart, A., and Faria, D. R.: A study on mental state classification using EEG-based brain-machine interface. 9th International Conference on Intelligent Systems, IEEE, 2018, 1541-1672.

[Bird, 19] Bird, J. J., Ekart, A., and Faria, D. R.: Mental Emotional Sentiment Classification with an EEG-based Brain-machine Interface. The International Conference on Digital Image and Signal Processing (DISP'19), 2019.

[Gorur, 18] Gorur, K., Bozkurt, M. R., Bascil, M. S., Temurtas, F.: Glossokinetic potential based tongue–machine interface for 1-D extraction using neural networks. Biocybernetics and Biomedical Engineering, 2018, 38(3), 745-759.

[Gulbag, 06] Gulbag, A., Temurtas, F.: A study on quantitative classification of binary gas mixture using neural networks and adaptive neuro-fuzzy inference systems. Sensors and Actuators, B: Chemical, 2006, 115(1), 252-262.

[Gulbag, 07] Gulbag, A., Temurtas, F., Tasaltin, C. et al.: A study on radial basis function neural network size reduction for quantitative identification of individual gas concentrations in their gas mixtures. Sensors and Actuators, B: Chemical, 2007, 124(2), 383-392.

[Gulbag, 08] Gulbag, A., Temurtas, F., Yusubov, I.: Quantitative discrimination of the binary gas mixtures using a combinational structure of the probabilistic and multilayer neural networks. Sensors and Actuators, B: Chemical, 2008, 131(1), 196-204.

[Güler, 05] Güler, I., Übeyli, E.: Adaptive neuro-fuzzy inference system for classification of EEG signals using wavelet coefficients. Journal of Neuroscience Methods, 2005, 148(2), 113-121.

[Kasule, 18] Kasule, A.: Using Hybrid Algorithm to Model and Forecast Electricity Consumption: A Case Study of Uganda. PhD Thesis. Sakarya Universtiy, Institute of Natural Sciences, 2018, 117p, Sakarya, Turkey.

[Krisnandhika, 17] Krisnandhika, B., Faqih, A., Purnamasari, P. D., Kusumoputro, B.: Emotion Recognition System Based on EEG Signals Using Relative Wavelet Energy Features and a Modified Radial Basis Function Neural Networks. 2017 International Conference on Consumer Electronics and Devices, 2017.

[Li, 18] Li, M., Xu, H. P., Liu, X. W., et al.: Emotion recognition from multichannel EEG signals using K-nearest neighbor classification. Technol Heal Care. 2018, 26, 509–519.

[Liu, 20] Liu, J., Wu, G., Luo, Y., Qiu, S., Yang, S., Li, W., and Bi, Y.: EEG-Based Emotion Classification Using a Deep Neural Network and Sparse Autoencoder. Frontiers in Systems Neuroscience, 2020, 14 (43).

[Luo, 20] Luo, Y., Fu, Q., Xie, J. et al.: EEG-Based Emotion Classification Using Spiking Neural Networks. IEEE Access, 2020, 8, 46007-46016.

[Moreira, 21] Moreira, P., Tsunoda, D.: Recognition of emotions in music through the Adaptive-Network-Based Fuzzy (ANFIS). Journal of New Music Research, 2021, 50(4), 342-354.

[Nakisa, 18] Nakisa, B., Rastgoo M. N., Tjondronegoro D, et al.: Evolutionary computation algorithms for feature selection of EEG-based emotion recognition using mobile sensors. Expert Syst Appl. 2018, 93, 143–155.

[Rozgić, 13] Rozgić, V., Vitaladevuni, S. N. and Prasad, R.: Robust EEG emotion classification using segment level decision fusion. 2013 IEEE International Conference on Acoustics, Speech and Signal Processing, 2013, 1286-1290.

[Saucedo, 19] Saucedo, J., Hemanthi J., Kose, U.: Prediction of Electroencephalogram Time Series with Electro-Search Optimization Algorithm Trained Adaptive Neuro-Fuzzy Inference System. IEEE Access, 2019, 7, 15832-15844.

[Seyman, 08] Seyman, M., Taspinar, N.: Channel estimation based on adaptive neuro-fuzzy inference system in OFDM. IEICE Transactions on Communications, 2008, 2426-2430.

[Seyman, 12] Seyman, M., Taspinar, N.: MIMO-OFDM channel estimation using ANFIS. Elektronika ir Elektrotechnika, 2012, 4, 75-78.

[Seyman, 13] Seyman, M., Taspinar, N.: Radial Basis Function Neural Networks for Channel Estimation in MIMO-OFDM Systems. Arabian Journal for Science and Engineering, 2013, 38(8), 2173-2178.

[Song, 20] Song, T., Zheng, W., Song, P. et al.: EEG Emotion Recognition Using Dynamical Graph Convolutional Neural Networks. IEEE Transactions on Affective Computing, 2020 11(3), 532-541.

[Yin, 21] Yin, Y., Zheng, X., Hu, B. et al.: EEG emotion recognition using fusion model of graph convolutional neural networks and LSTM. Applied Soft Computing, 2021, 100.

[Zhang, 16] Zhang, J., Chen, M., Hu, S. et al.: PNN for EEG-based emotion recognition. 2016 IEEE International Conference on Systems, Man, and Cybernetics, SMC, 2016, 2319-2323.

[Zhang, 20] Zhang, J., Zhou, Y., Liu, Y.: EEG-based emotion recognition using an improved radial basis function neural network. Journal of Ambient Intelligence and Humanized Computing, 2020.