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Original Article

EEG Signal in Emotion Detection Feature Extraction and Classification using Fuzzy Based Feature Search Algorithm and Deep Q Neural Network in Deep Learning Architectures

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Abstract *- EEG is a non-invasive method of recording evoked and induced electrical activity in the brain from the scalp. EEG data is increasingly used in artificial intelligence (A.I.) applications, including pattern recognition, group membership categorization, and brain-computer interface resolutions. This study presents unique EEG data approaches for emotion detection, feature extraction, and classification utilizing fuzzy-based deep learning techniques. This step has analyzed and separated The incoming EEG data as signal fragments. This signal has been pre-processed to remove and normalize noise for feature extraction. The processed signal was retrieved using a fuzzy neural network (FNN) for features. A deep Q neural network was used to classify these retrieved features. Four performance indicators, namely accuracy of 96%, Precision of 90%, Sensitivity of 92%, Specificity of 90% RMSE of 88% for 500 epochs, were used to assess the performance of four distinct classifiers. This investigation indicated that the proposed feature extraction method could accurately identify EEG data recorded during a demanding task. As a result, the suggested feature selection and optimization approach can potentially enhance classification accuracy.*

Keywords *- Electroencephalography, Emotion detection, Deep learning, Feature extraction, Classification, Neural networks.*

1. Introduction

The human brain is a complex system with 100 billion neurons and trillions of synaptic connections. The brain's electrical activity became a subject of study when Richard Caton captured rabbit brain impulses in the 19th century. Brain activity was also recorded by Hans Berger, the first to record EEG readings from a human scalp [1]. Since then, more EEG-based research has been conducted, and EEG is now the most widely used non-invasive technique for analyzing dynamic patterns in the human brain. EEG signals are primarily generated by dendritic inputs to massive pyramidal cells in the neuropil and reflect the instantaneous superposition of electric dipoles and voltage fluctuations at the scalp [2]. EEG readings can distinguish between three different types of brain activity: brain waves, event-related potentials, and steady-state visual evoked potentials. The most typical way that brain waves are used when performing different EEG signal analysis tasks. The five frequency bands that have been found in brain waves are theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-150 Hz). Previous publications [3] have more categories of brain signals. When properly evaluated and utilized, classification methods are not just for prediction but also for gaining neuroscientific knowledge. As a result, thorough pre-processing is frequently needed to remove artefacts, especially when EEG data are taken simultaneously and in an MRI scenario [4].

The goal of feature extraction is to minimize the amount of data by developing new features from the initially measured dataset that are non-redundant, contain meaningful data from the input data, and allow for better classification using the reduced representation created rather than the entire initial set of raw data. Feature extraction is required to reduce data dimensionality, i.e., convert a data set from a high-dimensional to a low-dimensional space. In this low-dimensional representation, the more significant characteristics of the original data are preserved [5].

Because raw data are frequently sparse, display redundant information, and use a significant amount of complex drive resources, operating in H.D. spaces is typically unfavourable. Machine learning algorithms may then be used to analyze the characteristics of the discovered simplified signal for categorization in the time or frequency domains. With machine learning techniques, algorithms may be built to learn from the past and grow better over time. You can do this knowing or not knowing the outcome. In order to make predictions or choices, such as to diagnose mental disorders or impairments, it is possible to build a classification system to compare particular feature signal qualities [6].

The contribution of this paper is as follows:

1. To propose a novel technique in EEG signal for emotion detection feature extraction and classification using fuzzy-based deep learning techniques
2. To process EEG signal for noise removal and normalization for feature extraction
3. To extract features using a Fuzzy neural network (FNN) and classify the features using a deep Q neural network which results in the detection of emotion based on classification results.

2. Related Works

Currently, subject-specific emotion recognition tasks are the main focus of studies on EEG emotion recognition. It is obviously impossible to gather the EEG signals of many subjects in advance for engineering applications to create a universal emotion recognition model that can recognize the emotions of every person. Determining how to realize the subject-dependent pattern classification is, therefore, one of the challenging problems in the practical application of emotion recognition. Due to variations in stimulus paradigm, subjects, and EEG acquisition technology, traditional emotion recognition models are frequently unable to perform well under new tasks because they are typically built for a specific task on a small dataset.

The learning process of deep neural networks is crucial. It frequently requires a significant amount of labelled data, although acquiring EEG signals is more challenging than acquiring image, speech, and text signals. How to train a highly effective classifier with a constrained number of labelled samples is thus another issue to take into account. This paper uses transfer learning to address the problems mentioned above.

One of several transfer learning techniques is to use the pre-trained model from the source domain in the target domain, and it depends on how similar the data, tasks, and models are in the two domains [7]. Transfer learning accelerates training by copying model parameters from a previously trained task to a new domain task [8].

For the categorization of EEG signals, time domain, frequency domain, and wavelet-based feature extraction techniques have been presented in the literature [9]. These approaches incorporate time and frequency domain features into the classification procedure to obtain the best feature set to combine with classifiers for the best classification results. Sample entropy, approximation entropy, permutation entropy, fractal dimension, Hjorth requirements, Hurst component, and Lyapunov exponent are all time-domain properties [10-11].

The Stockwell transform and wavelet-based feature extraction are used in time-frequency analysis [12]. In [13], the Stockwell transform was used for feature extraction, and SVM was used for categorizing EEG signals from various cognitive tasks. Authors claim that their categorization accuracy ranges from 84.72 to 98.95 per cent. Authors [14] employed empirical mode decomposition for cognitive task classification, including temporal and frequency domain characteristics.

The authors used linear classifiers and achieved 97.78 per cent classification accuracy. Work [15] classified cognitive activities with an 85.4-97.5 per cent accuracy using a weighted SVM with an immune feature. [16] Discovered a categorization accuracy of 72.4-76.4 per cent. Using the EEG power feature and an SVM classifier with an RBF kernel, the author [17] classified three cognitive tasks with 70% accuracy.

The study used the wavelet packet transform for feature extraction using an RBF classifier [18], and the accuracy was 85.3 per cent. In one study [19], wavelet pack entropy features and an SVM classifier were used to distinguish between a baseline task and a cognitive activity with an 87.5-93% accuracy.

After feature extraction, the selected features should be categorized to distinguish various EEG signals. For EEG classification, various classifiers are grouped into five categories: linear classifiers, N.N.s, nonlinear Bayesian classifiers, closest neighbour classifiers, and classifier combinations [20]. Researchers employed an SVM for multiple kernel learning [21].

Author [22] also employed an SVM but turned it into an adaptive multi-class SVM. A study used Fisher linear discriminate analysis to classify EEG signals [23]. The author supplied a Feature vector to a multilayer perceptron (MLP) N.N. classifier [24, 25]. Because a single classification technique's capability is limited, many researchers attempt to increase classification accuracy by combining two or more approaches.

3. Materials and Methods

3.1. The System Model

The extraction and categorization of unique EEG signal features using fuzzy-based deep learning approaches are covered in this section. Here, the raw EEG signal has undergone processing and signal fragmentation. This signal has first undergone pre-processing for feature search, including noise reduction and normalization. The collected signal is then used to extract features using a fuzzy neural network (FNN). Finally, a deep Q neural network was used to classify these extracted features. Figure 1 displays the overall suggested architecture.

3.2. Subjects and Data Recording

Three boys and two girls with epilepsy and no other health issues, aged 28.87G15.27 (mean GSD; range 6-43), participated in the study. The bipolar EEG channels F7-C3, F8-C4, T5-O1, and T6-O2 were chosen for use. Individuals were methodically chosen from a database of patients with clinical and neurophysiological data stored for analysis. Following the 10-20 worldwide electrode placement procedure, Ag/AgCl disc electrodes were installed. Video and EEG synchronization was captured and preserved to allow for offline examination of clinical onsets. In our study, EEG data from epileptic patients as well as healthy individuals were used. Seizures separated by at least 2 hours from the end of the onset of another episode were classified as lead seizures. If data epochs were separated by at least 2 hours from the start or end of an electrographic seizure, they have been deemed 'baselines'. They also went over each tape again, looking for epileptic seizures that had gone unnoticed during the first pass as well as marking them as definite or possible. The Sensitivity and Specificity of computer scorings were estimated using this validated set as a reference.

3.3. Fuzzy Neural Network (FNN)

Classification and control action are determined using features retrieved from EEG signals. This study offers a unique scheme for the categorization of brain signals that are based on FNN[26]. The FNN-based classifier uses retrieved features as input signals. The classifier divides signals into six categories based on the retrieved features: move ahead, backward, turn left, turn right and turn on and off. Constructing fuzzy rules with an IF-THEN form is part of the FNN design. This is accomplished through the training of fuzzy N.N.s and optimal definition of premise as well as subsequent sections of fuzzy IF-THEN rules for classification method. As shown in eq, TSK-type fuzzy methods approximate nonlinear with the linear method and take form. (1):

$$\text{Then } y_j \text{ is } \sum_{i=1}^{m} a_{ij} x_i + b_j \tag{1}$$

The fuzzy input sets are aij, and the coefficients are bj and aij. Figure 2 shows the topology of fuzzy NNsutilized for EEG signal classification based on TSK-type fuzzy rules. Membership functions (M.F.) are included in the second layer. Each node in this diagram represents a single linguistic phrase. The membership degree where an input value belongs to a fuzzy set is evaluated for every input signal entering method. Gaussian M.F. is utilized to describe linguistic words in eq. (2).

$$1_j(x_i) = e^{-(x_i - c_{ij})^2/\sigma_{ij}^2}, i = 1, \dots, m, j = 1, \dots, r \tag{2}$$

Where cij and σij are the Gaussian membership functions' centre and width, for the jth term, $\mu 1(xi)$ is M.F. of the ith input variable. m is the number of input signals, whereas r denotes the number of fuzzy rules. The rule layer is the third layer. Rules are represented by R1, R2,...,r. This layer's output signals are evaluated using the t-norm min (AND) process as shown in eq. (3):

$$\mu_j(x) = \prod_i \quad \mu 1_j(x_i), i = 1, \dots, m, j = 1, \dots, r \tag{3}$$

When $\prod$ minimum operation. These (x) signals are the fifth layer's input signals. A subsequent layer is the fourth layer. It consists of n linear methods. Values of the rules output are defined as eq. (4):

$$y_j = \sum_{i=1}^{m} x_i w_{ij} + b_j$$

$$y1_j = \mu_j(x) \cdot y_j \tag{4}$$

Output signals of FNN are defined in the sixth layer as shown in eq. (5)

$$u_k = \frac{\sum_{j=1}^{r} w_{jk} y1}{\sum_{j=1}^{r} \mu_j(x)} \tag{5}$$

Output signals of FNN (k = 1,..., n) are represented by uk. The training of the network starts after the output signal has been evaluated. The training of FNN parameters is provided in the following section. Initial values of subsequent portions parameters are generated at random. Parameters were trained using mistakes calculated from the network's output. We have included the learning approach for all FNN parameters for generality: a gradient descent algorithm with an adaptive learning rate. The adaptive learning rate ensures convergence while also accelerating the learning method. Furthermore, momentum is utilized to accelerate the learning process. Inaccuracy in the network's output is evaluated as eq. (6)

$$E = \frac{1}{2} \sum_{k=1}^{n} \quad \left(u_k^d - u_k\right)^2 \tag{6}$$

Overall network's output is a linearly weighted sum of unit outputs. Unit inputs are multiplied by the bias term bi. Ith feuron's dynamic constant is Ti, while the term's bias (or polarization) is bi. Centres c, spreading s and output centres are parameters of the fuzzy activation function. Therefore, it is necessary to specify initial conditions for state variables xi(0).

3.4. Deep Q Neural Network-Based Classification

In this study, FNNs built in the earlier stage are trained using reinforcement learning to improve the classification network's accuracy. The output value of deep network models is severely constrained by the one-hot code used in traditional supervised learning training labels. This work presents a reinforcement learning-based training method. Reinforcement learning agents can discover the best tactic by interacting with the environment and continuously learning from mistakes [24].

After watching the environment, acting there, and receiving feedback from the environment (rt), the agent moves on to stage st+1 and repeats the process until the interaction is complete. This section uses the deep Q-learning method to train the agent to become DQN, a multilabel classification agent. Figure 7 shows the DQN's training and recognition process. The state vector of the DQN serves as the input vector for the RNN in the previous section. The state vector before the current step changes depending on the categorization outcome of the network output.

DQN then gives the classification in light of the current situation. In a recurrent step, DQN selects a signal modulation type before acting. To obtain results for recognition, DQN employs two classification techniques. The environment feedback is obtained by comparing recognition results with signal labels. The output quality of the network is reflected in the environment feedback space R, which has two values of 1 and -1. If the recognition result is within that set, the identified label is removed from the set of labels for the current radar signal; otherwise, the network receives a negative value from the environment feedback.

During the training phase, network parameters are acquired. The feature vector of TFI that FNN obtained is used to estimate the forward-looking Q value of each action. The cycle then restarts after changing the status vector. In order to further improve the efficacy of the recognition method, we also modify the DQN's recognition outcomes in the following section using a sub-network.

Algorithm 1: The training procedure by Deep Q-Learning Network

Require: f

$$\theta=(\theta_1,\theta_2,\theta_o)=\big((W_1,b_1),(W_2,b_2),(W_o,b_o)\big)$$

1: Startθ, D;

2: for every TFI, do

3: Startch

4: for every step $= 1{:}\,2$, do

5: $o \leftarrow Q_\theta(s_{\text{step}}) \leftarrow Q_\theta((f, ch))$

6: Choose an action a_{step} based on o and ε-greedy policy;

7: Evaluate action a_{step} And observe reward r_{step}

ts step;

10: for every step $= 1{:}\,2$, do

11: Store $(s_{step}, a_{step}, r_{step}, s_{step}+1, a_{step}+1, ts_{step})$ in D

$Q_{\text{target;}}$;

Samples:

12: $(s_j, a_j, r_j, s_{j+1}, a_{j+1}, ts_j), j \in \{1,2,\cdots,m\}$;

13: $Q_{\text{target}}^{(j)} \leftarrow \begin{cases} r_j & ts_j \text{ is true} \\ r_j+\gamma\max\big(Q_\theta(s_{j+1},a_{j+1})\big) & ts_j \text{ is false}\end{cases}$;

14: $L \leftarrow \frac{1}{2m}\sum_{j=1}^{m}\Big(Q_{\text{target}}^{(j)} - Q_\theta(s_j,a_j)\Big)^2$;

15: $\frac{\partial L}{\partial \theta} \leftarrow$ Backpropagation;

16: $\theta \leftarrow \theta - \alpha\frac{\partial L}{\partial \theta}$;

17: end for

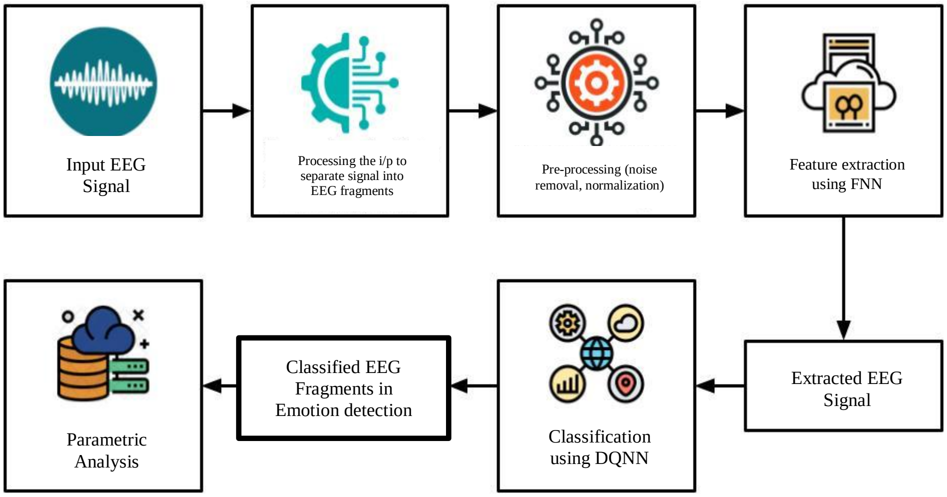

Fig. 1 Overall proposed architecture

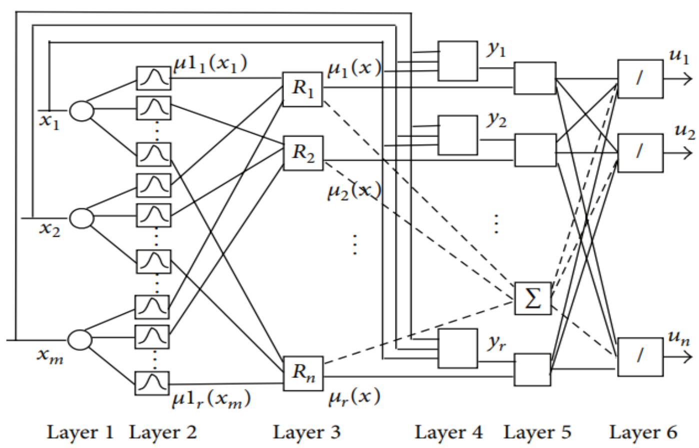

Fig. 2 The FNN architecture

Table 1. Specifications of training and test sets

Class	Training Set	Test Set	Total Set
Normal	500	300	800
Epileptic	500	300	800
Total	1000	600	1600

Table 2. Comparative analysis of accuracy

Number of Epochs	SVM	MLP	FNN_DQNN
100	83	86	88
200	85	88	90
300	87	89	92
400	88	90	95
500	91	92	96

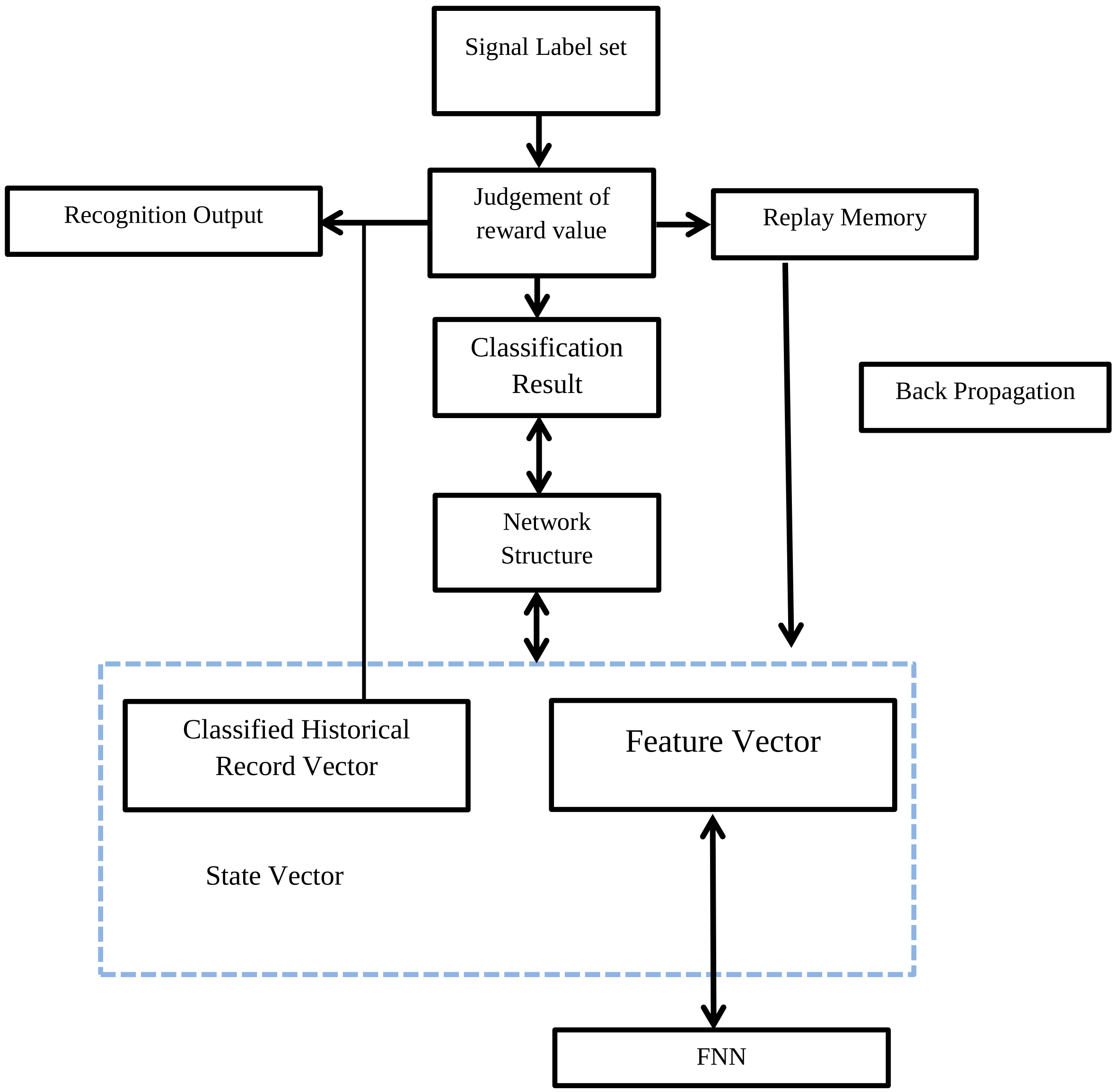

Fig. 3 Training and recognition procedure of DQN

Table 3. Comparative analysis of precision

Number of Epochs	SVM	MLP	FNN_DQNN
100	74	79	83
200	79	81	85
300	81	83	87
400	83	85	88
500	85	89	90

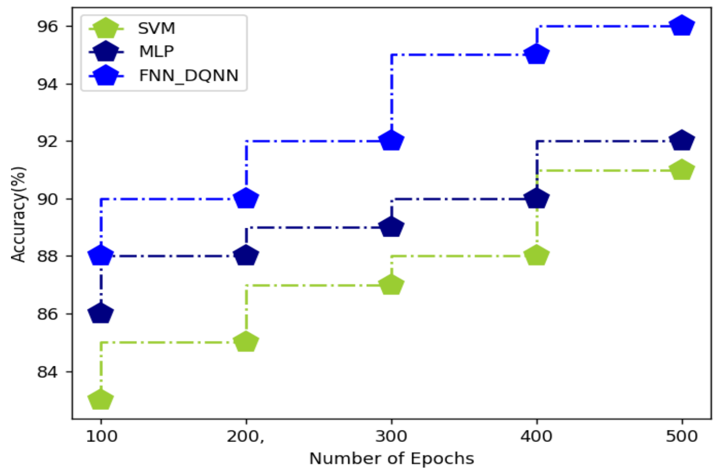

Fig. 4 Comparative analysis of accuracy

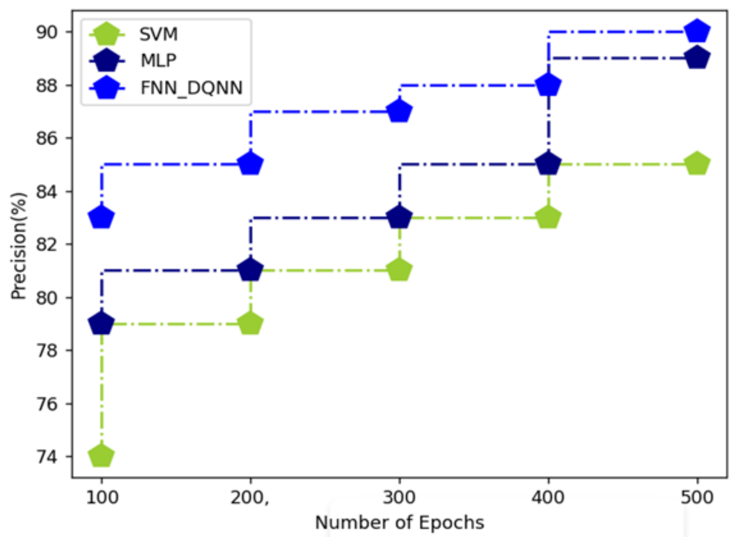

Fig. 5 Comparative analysis of precision

Table 4. Comparative analysis of sensitivity

Number of Epochs	SVM	MLP	FNN_DQNN
100	70	75	77
200	75	81	83
300	78	85	88
400	82	89	90
500	85	88	92

Table 5. Comparative analysis of specificity

Number of Epochs	SVM	MLP	FNN_DQNN
100	80	75	80
200	82	81	82
300	84	85	86
400	85	89	88
500	87	88	90

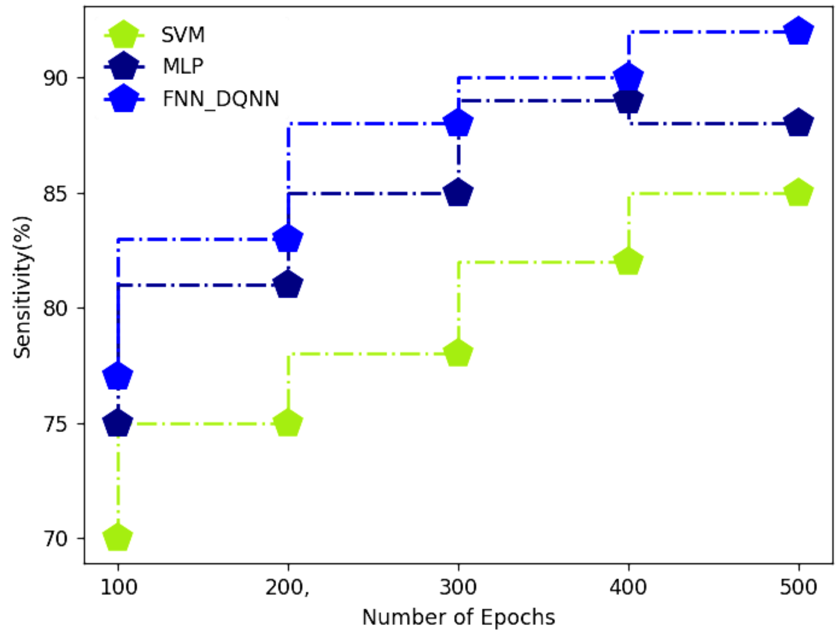

Fig. 6 Comparative analysis of sensitivity

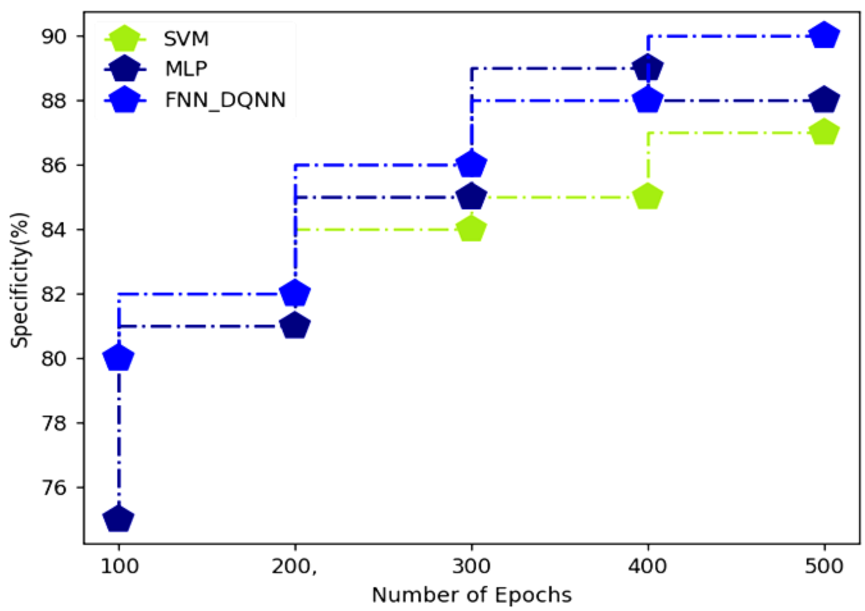

Fig. 7 Comparative analysis of specificity

Table 6. Comparative analysis of RMSE

Number of Epochs	SVM	MLP	FNN_DQNN
100	69	74	76
200	71	76	79
300	73	79	82
400	75	80	85
500	78	82	88

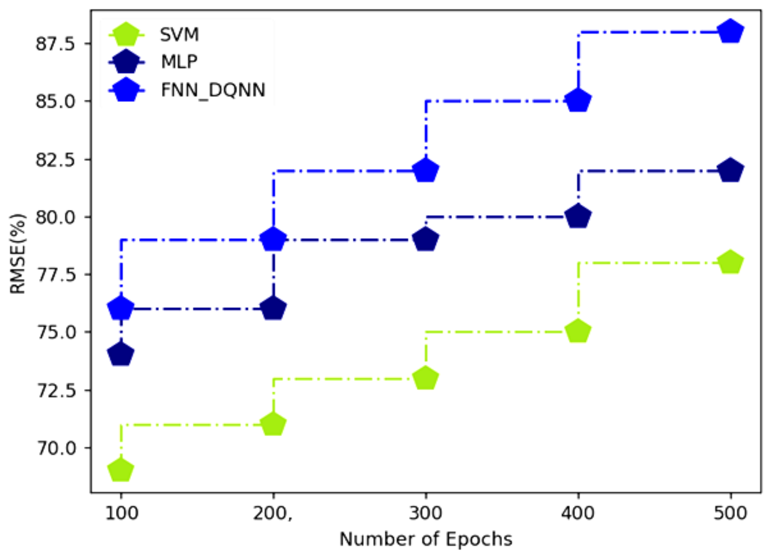

Fig. 8 Comparative analysis of RMSE

4. Results and Discussion

4.1. Performance Analysis

Several tests are provided to assess how well the suggested model performs. A machine that complied with the following specifications was used to test the suggested hybrid model: Intel(R) Core(T.M.) i5-7500 CPU, 32-bit O.S., 4 GB RAM, Windows 7, SciPy, NumPy, Pandas, Keras, and Matplotlib frameworks, as well as Python 2.7[27].

4.2. Dataset Description

Using emotion EEG signals from four freely accessible datasets, this study assesses the effectiveness of our method for emotion detection[28]. Here, we compare the DEAP and SEED datasets in Table 1 and give an overview of each. According to the measurement device, either 14, 32, or 62 electrodes were used to collect the raw EEG data from all brain regions for each dataset.

The EEG electrodes are positioned on the scalp using the 10-20 international system, which shows the relationship between the electrode position and the area of the cerebral cortex beneath it. According to the system, 10% and 20% of the total space should be between the head's front and back or left and right electrodes. EEG signals only use two emotional space dimensions.

The two dimensions are arousal, which ranges from calm to agitated, and valence, which ranges from pleasant to unpleasant. Rating scales for the DEAP, AMIGOS, and DREAMER datasets were 1 to 9 and 1 to 5, respectively. Using the 4.5 and 2.5 criteria, we divided the trials into two groups. To compare the datasets, we combined pre-processed data from the DEAP dataset, which has a sampling rate of 128 Hz, with raw signals from DREAMER and AMIGOS. After retrieving the data from the SEED dataset, we re-sampled the EEG signals to 128 Hz.

Tables 2-5 and 4-7 compare suggested and current methodologies regarding the accuracy, Precision, sensitivity, Specificity, and RMSE. In this case, the number of epochs was compared between the suggested and current methodologies. For 500 epochs, the proposed technique achieved 96% accuracy, 90% precision, 92% sensitivity, 90% specificity, and an 88% RMSE. Existing techniques SVM obtained an accuracy of 91%, Precision of 85%, Sensitivity of 85%, and RMSE of 78%; MLP obtained an accuracy of 92%, Precision of 89%, Sensitivity of 88%, RMSE of 82% for 500 epochs.

5. Conclusion

This study provides unique strategies for emotion detection feature extraction and classification in EEG signals utilizing fuzzy-based deep learning algorithms. This step has analyzed and separated The incoming EEG data into signal fragments. This signal has been pre-processed to remove noise and normalize it in preparation for feature extraction.

The processed signal is then extracted for features using a fuzzy neural network (FNN). Finally, these retrieved characteristics were categorized with the help of a deep Q neural network. Four performance indicators, namely accuracy of 96%, Precision of 90%, Sensitivity of 92%, Specificity of 90% RMSE of 88% for 500 epochs, were used to assess the performance of four distinct classifiers. This investigation indicated that the proposed feature extraction method could accurately identify EEG data recorded during a demanding task. As a result, the suggested feature selection and optimization approach can potentially boost classification accuracy.

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