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

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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.*

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 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

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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 [3-5]. 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 [6]. 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.

accelerates training by copying model parameters from apreviously trained task to a new domain task [7-8].

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 setto 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-domainproperties [10-11].

The Stockwell transform and wavelet-based feature extraction are used in time-frequency analysis [12]. 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 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 classifiedcognitive activities with an 85.4-97.5 per cent accuracy using a weighted SVM with an immune feature. Discovered a categorization accuracy of 72.4-76.4 per cent. Using the EEG power feature and an SVM classifier with anRBF kernel, the author classified three cognitive tasks with 70% accuracy.

The study used the wavelet packet transform for featureextraction using an RBF classifier, and the accuracy was 85.3 per cent. In one study, wavelet pack entropy features and an SVM classifier were used to distinguishbetween a baseline task and a cognitive activity with an 87.5-

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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. Researchers employed an SVM for multiple kernel learning.

Author also employed an SVM but turned it into an adaptive multi-class SVM. A study used Fisher linear discriminate analysis to classify EEG signals. The author supplied a Feature vector to a multilayer perceptron (MLP) N.N. classifier. 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 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).

to classify these extracted features. Figure 1 displays theoverall 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.

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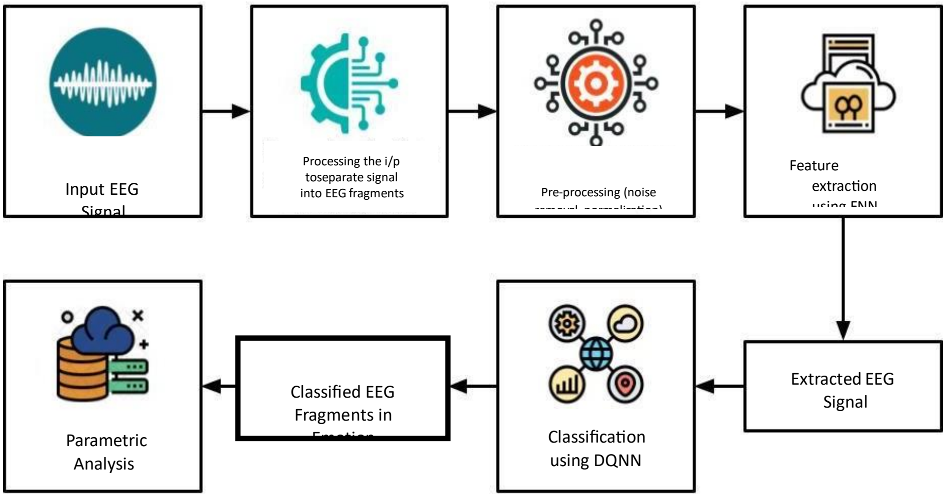

Fig. 1 Overall proposed architecture

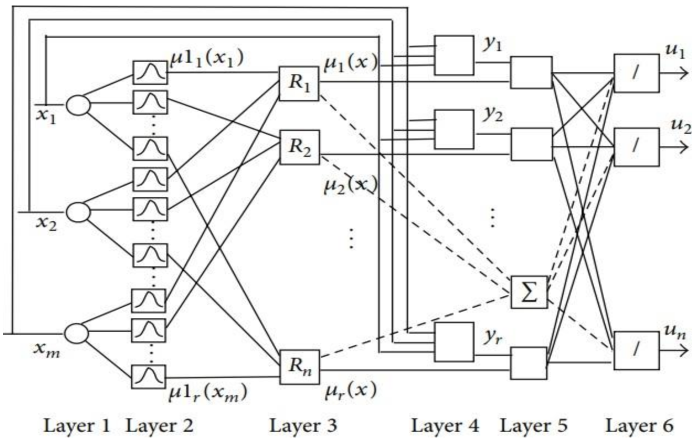

Fig. 2 The FNN architecture

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

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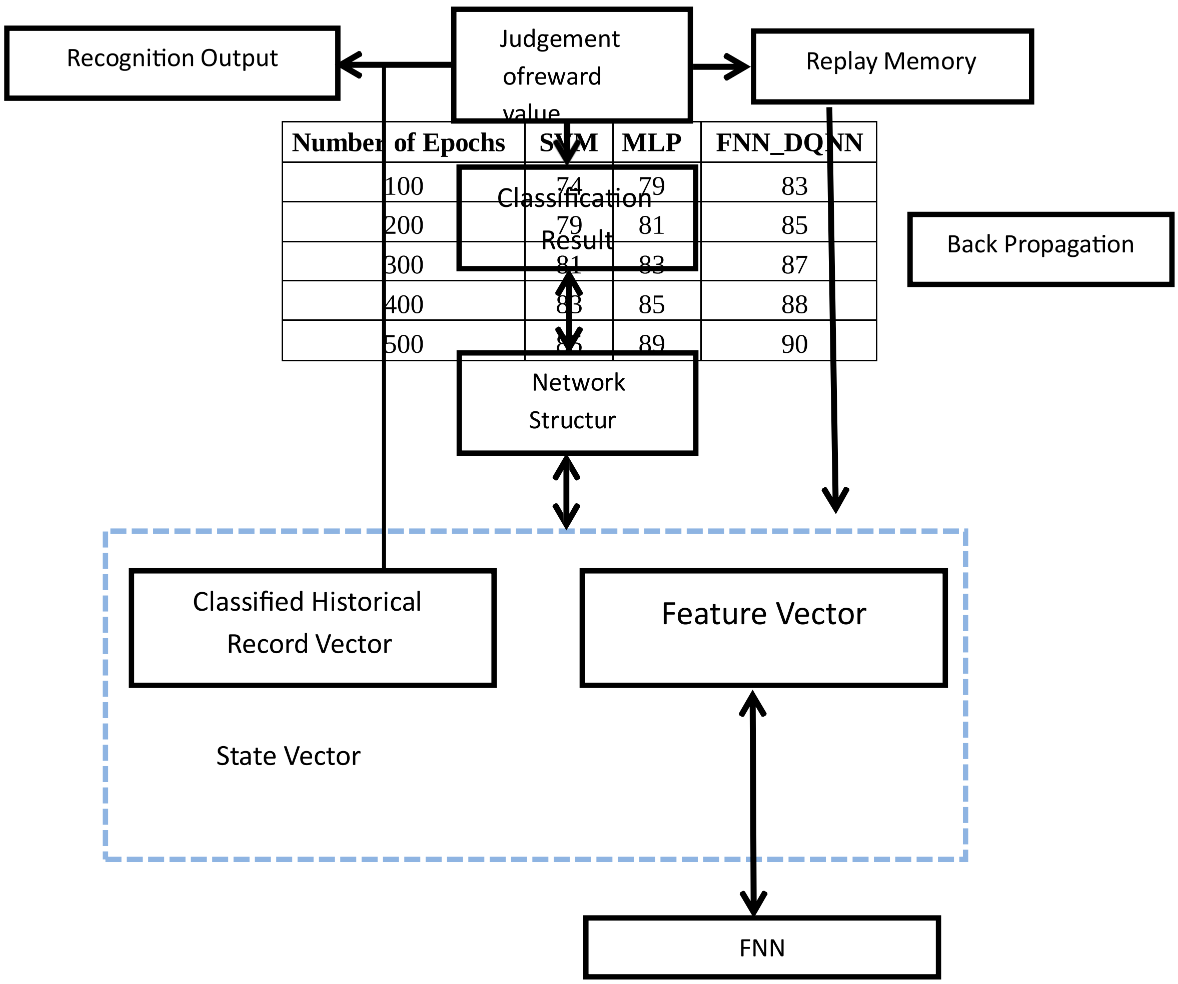
400	88	90	95
500	91	92	96



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

Fig. 3 Training and recognition procedure of DQN Table 3. Comparative analysis of precision

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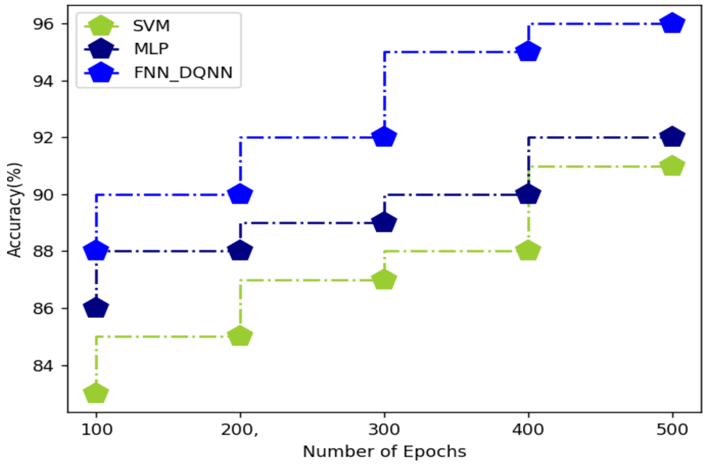

Fig. 4 Comparative analysis of accuracy

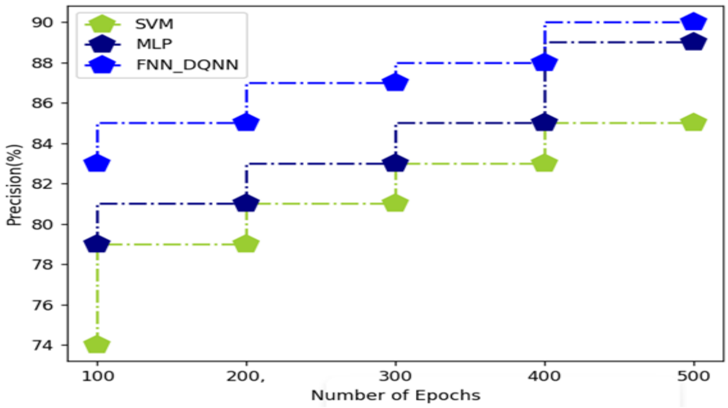

Fig. 5 Comparative analysis of precision **Table 4. Comparative analysis of sensitivity**

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

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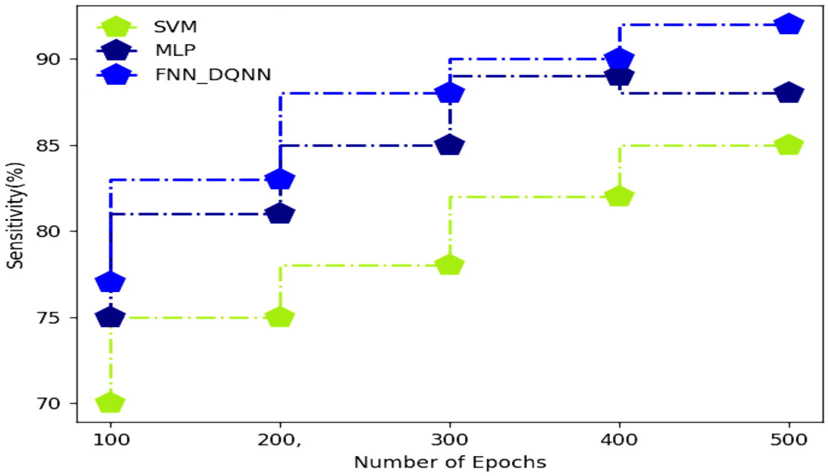

Fig. 6 Comparative analysis of sensitivity

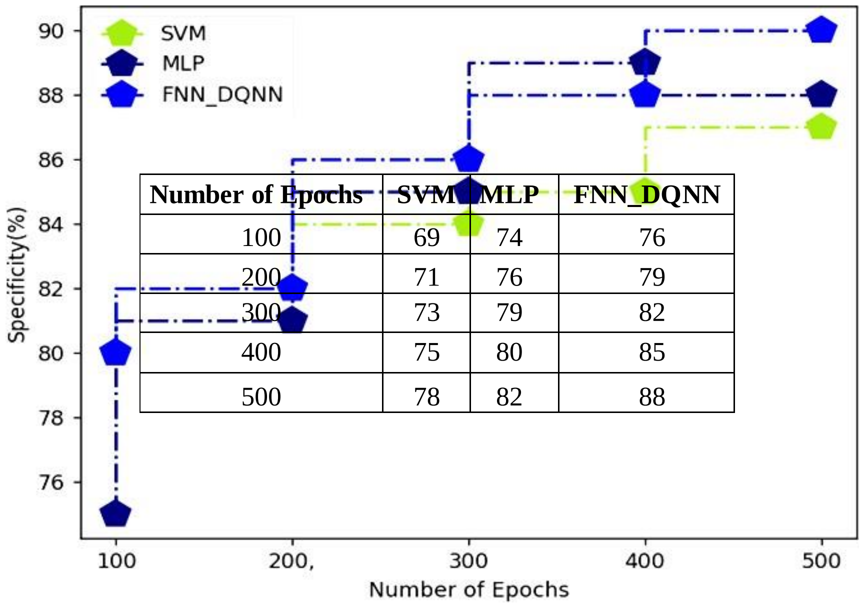

Fig. 7 Comparative analysis of specificity

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

4. Results and Discussion

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4.1. Performance Analysis

Tables 2-5 and 4-7 compare suggested and current 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% ofthe 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 fromcalm to agitated, and valence, which ranges from pleasant tounpleasant. 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 SEEDdataset, we re-sampled the EEG signals to 128 Hz.

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 usinga 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

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suggested feature selection and optimization approach can potentially boost classification accuracy.

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