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Research Article

Novel Architecture For EEG Emotion Classification Using Neurofuzzy Spike Net

S. Krishnaveni*[1], R. Renuga Devi[2], Sureshraja Ramar[3], S.S.Rajasekar[4]

[1*]Assistant Professor, Department of Mathematics, Builders Engineering College, Kangeyam, Tirupur, Tamil Nadu, India-638108.
* **Corresponding Author Email:** krishnaveni.venus@gmail.com - **ORCID:** 0009-0002-1467-3153

[2]Associate Professor, Department of Computer Science and Applications, SRM Institute of Science and Technology, Ramapuram, Chennai, Tamilnadu, India-600089.
Email: drrrenugadevi86@gmail.com - **ORCID:** 0000-0002-6197-236X

[3]Lead Data Engineer, Optum, 9900 Bren Rd East, Minnetonka, MN,USA,
Email: sureshraja.rt@gmail.com - **ORCID:** 0009-0003-8353-0460

[4]Associate Professor, Department of Computer Science and Engineering,Bannari Amman Institute of Technology, Erode, Tamil Nadu, India. - 638401
Email: ssrajasekar80@gmail.com - **ORCID:** 0000-0001-9591-5833

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Temporal Pattern Detection,
Wearable Devices.

Abstract:

Emotion recognition from Electroencephalogram (EEG) signals is one of the fastest-growing and challenging fields, with a huge prospect for future application in mental health monitoring, human-computer interaction, and personalized learning environments. Conventional Neural Networks (CNN) and traditional signal processing techniques have usually been performed for EEG emotion classification, which face difficulty in capturing complicated temporal dynamics and inherent uncertainty in EEG signals. The proposed work overcomes challenges using a new architecture merging Spiking Neural Networks (SNN) with a Fuzzy Hierarchical Attention Membership (FHAM), the NeuroFuzzy SpikeNet (NFS-Net). NFS-Net takes advantage of SNNs' event-driven nature in the processing of EEG signals, which are treated independently as asynchronous, spike-based events like the biological neurons. It allows capturing temporal patterns in EEG data with high precision, which is rather important for correct emotion recognition. The local spiking feature of SNNs encourages sparse coding, making the whole system computational power and energy highly effective and it is very suitable for wearable devices in real-time applications.

1. Introduction

Emotion recognition from EEG signals is a fastest-growing area into the understanding and classification of human emotions by analyzing brainwave patterns. EEG measures electrical activity in the brain through electrodes on the scalp, giving information about the real-time neural processes. Emotions are complex and multifaceted, can affect the brainwave patterns and manifest as changes in frequency, amplitude, and other characteristics of the signal. This variation in signals is captured and interpreted, with the aim of developing systems that recognize emotional states automatically from such signals. The application areas are mental health monitoring, adaptive learning systems, and human-computer interaction. Emotion recognition in EEG signals involves non-stationary data of EEG in emotional cues, and variability of responses between subjects. Traditional approaches rely on feature extraction and classification methods fail to capture all the key aspects of temporal dynamics and complexities of emotional states. In contrast, recent works probe into deep learning, fuzzy logic, and even spike neural networks, which can model intricate relationships between patterns of EEG and their respective emotions with better strength [1]. Recent breakthroughs in fuzzy models of emotion recognition have tapped into the strengths from the standpoint of fuzzy logic to deal with the inherently uncertain and imprecise nature of emotional data. Fuzzy models make sense when capturing subtleties in human emotions that are often non-binary and spectrum in nature. Fuzzy C-Means (FCM) has been used to model the complex interdependencies among various physiological and psychological causes of emotional states. Fuzzy rules describe how EEG features and emotional states interact, allowing for a subtler interpretation of the data [2]. The embedding fuzzy logic into these models and manages those fuzzy boundaries and overlaps that are present in human emotional expressions, which enhances the robustness of emotion recognition systems. However, Fuzzy Logic based Neural Networks (FLNN) is now turning into one of the dynamically developing branches of an intelligent approach to emotion classification. The FLNNs embed fuzzy logic into neural network topography to improve the system capability of dealing with uncertainty and handling variations in different emotional contexts. The networks utilize fuzzy membership functions to weigh the importance of various features and dynamically adjust the decision boundaries. The FLNNs have lately been utilized with heightened success in emotion recognition. It present a more flexible and interpretable framework for EEG signal processing and classification. Thus the combination of fuzzy logic with progressive neural network techniques that permits the making of a strong tool in devising emotion recognition systems that are not only accurate but handle the complex nature of emotional data [3,4]. The most important challenge in the design of fuzzy-based emotion recognition systems is how to manage the variability and high noise present in the EEG data effectively. Biologically, the EEG signals are inherently noisy. It includes artifacts from different sources, such as muscle movements and electrical interference that can mask the refinement of emotional cues. Although the fuzzy models are adept at handling uncertainty in order to differentiate the meaningful emotional patterns from the unhelpful noise. In addition, such dynamic and complex nature of the emotions requires the fuzzy systems to be highly adaptive and able to perform real-time modifications on the rules and parameters by considering individual differences and variations in emotional states [5,6,7]. The major contributions of the proposed NeuroFuzzy SpikeNet toward addressing the challenges with emotion recognition from EEG signals are identified below.

- In the proposed work, SNNs for capturing the precise timing and dynamic nature of EEG signals.
- It realizes a hierarchical attention mechanism that dynamically focuses on the most relevant features at multiple levels of abstraction by utilizing fuzzy logic.
- Integrates fuzzy membership functions to define and manage the relationship between EEG features and emotional states.
- The system has a closed loop model constantly learns from new data and refines its understanding of the emotional states.
- A combination of spiking neural processing with fuzzy logic in order to filter out the irrelevant noise and artifacts from the EEG signals.

The remaining part of the proposed work is comprised as follows. Section II describes the related works. Section III explains the novel fuzzy method to overcome the challenges in related works. Section IV gives the results and discussion of the proposed method with others. Section V gives the conclusion of the proposed work.

Related works

Asif, M. et al. (2024) present a deep fuzzy framework with emotion recognition from EEG signals, using Type-2 Fuzzy Logic in order to extend the capabilities of dealing with uncertainty in EEG data[8]. Type-2 fuzzy sets are combined with deep learning models in order to classify emotions for improving accuracy via the management of imprecision in the emotional representation. It handles uncertainty, but it is generally at a bigger computational cost and calls for extensive tuning [8]. Dhara, T. et al. (2024) proposes a fuzzy ensemble-based model which fuses a number of deep learning methods with fuzzy logic for EEG-based emotion recognition [9]. While the ensemble approach improves feature extraction and classification, the use of fuzzy logic maintains uncertainty. Therefore, the model gains both improved accuracy and robustness but also suffer from issues related to higher computation cost and training time [9]. Sudha and Bharathi (2024) propose a neuro-fuzzy AI model of classification of the cognitive state based on analysis results from the EEG [10]. The approach has combined neuro-fuzzy systems with AI techniques to analyze and classify cognitive states. It gives flexibility and interpretability to the model. In adding the integration of the systems, increased complexities and computational demands drop the efficiency and result in a decrease in model performance [10]. Kaya, Ü. et al. (2024) discuss EEG-based emotion recognition with respect to neuro marketing using fuzzy linguistic summarization for the representations of emotional responses [11]. It leads to a simplification of the emotions and struggle with high variability and noise in the EEG signal [11]. Versaci and La Foresta (2024) present a method contributing to an improvement in the diagnosis of Alzheimer's disease by the precise removal of artifacts in EEG data, applying fuzzy and intuitionistic fuzzy logic techniques [12]. This approach can improve diagnostic accuracy since it controls uncertainty and noise. It is quite complicated to implement, and success rates could vary based on the quality of the EEG data [12]. Khalaf et al. (2024) propose a conceptual system that integrates neuro-fuzzy emotion recognition and adaptive content generation in Virtual Reality (VR) experiences[13]. This allows the VR content to adapt because of real-time emotional feedback, greatly improving user experience. However, it increases the cost of such improvement based on computational resources [13]. Singh et al. (2024) propose a hybrid method that combines similarity-based feature selection with deep maxout fuzzy network approaches to detect ASD from EEG signals [14]. The proposed approach demonstrated improvement in feature selection and classification accuracy. However, the complexity and high computational demands lead to low efficiency and longer training times in the model [14]. Palanisamy et al. (2024) propose a technique to recognize the anxiety-based epileptic seizures using EEG signals with the integration of fuzzy features and Parrot Optimization-Tuned Long Short-Term Memory (LSTM) [15]. The model improves seizure detection performance by applying fuzzy logic for capturing complex patterns in the signal and optimization of LSTM parameters, though a loss in the intricacy of model tuning and increased computational complexity [15]. Al-asadi et al.(2024) have proposed a robust semi-supervised deep learning approach in emotion recognition from EEG signals [16]. The model leverages semi-supervised learning to handle the small amount of labeled data effectively and improves recognition performance in handling data scarcity but detailed tuning of balancing labeled and unlabeled data is required [16]. Upadhyay, P. K. & Nagpal, C. (2021) use time-frequency analysis and a fuzzy-based method for the detection of heat-stressed sleep EEG spectra [17]. The proposed technique gives a keen analysis of EEG signals under heat stress while applying fuzzy logic in order to enhance accuracy in identification, although it has some challenges relating to variability in sleep patterns [17]. Xing, M. et al. (2022) propose the use of a spatial-frequency-temporal convolutional recurrent network to enhance EEG-based emotion recognition with olfactory stimuli [18]. It utilizes the model by integrating the spatial, frequency, and temporal features in order to enhance the accuracy of emotion detection, which include complex network architecture and heavy computational resources [18].

Chen et al. (2021) propose a two-stage fuzzy fusion-based convolutional neural network for dynamic emotion recognition [19]. It incorporates fuzzy fusion into CNNs to handle dynamic variations of the emotional state, enhancing the recognition accuracy but it has high cost of due to model complexity and time consumption in training [19]. Lin et al. (2023) develop an automatic sleep stage classification by using the Taguchi-based multiscale convolutional compensatory fuzzy neural network [20]. The proposed approach has improved accuracy in classification by optimizing the structure in the network through methods using Taguchi. It requires heavy parameter tuning and computational resources [20]. Davoodi and Moradi (2023) propose a new nonlinear deep fuzzy rule-based model that should be suitable for biomedical analysis applications [21]. This model incorporates the deep learning concept with a fuzzy rule-based system to tackle the nonlinear relationship in biomedical data, achieving better interpretability while improving accuracy but it increases the model complexity and training burdens [21]. Zhang et al. (2024) proposed a temporal adaptive fuzzy neural network for fatigue assessment based on facial features [22]. It adapts to the temporal variation of facial expressions to perform effective fatigue evaluations but involve complex neural network configurations and high-quality data of facial features [22].

Research gap analysis:

Despite the improved approaches to emotion recognition based on EEG signals and fuzzy models, it has some challenges. The most of the existing models, proposed by Asif et al. (2024) and Dhara et al. (2024) work well in terms of improving accuracy while handling uncertainty but mostly result in a number of computational demands and complexities which limit the scope of practical applications [8,9]. Other techniques use virtual reality, promising personalized experiences but at the cost of heavy computational resources [13]. Further, the methods proposed by Palanisamy & Rengaraj (2024) [15], which go one step further in seizure detection accuracy, involve complex model tuning that could limit scalability. There still remains a need for more solid, scalable, and computationally efficient models, especially regarding models that could integrate real-time data smoothly and operate under various conditions with limited complexity.

2. Material and Methods

2.1 Proposed work

NFS-Net represents a new architecture for emotion recognition from EEG signals, which is aimed at the exploitation of the strengths of SNNs and FHAM. Being one of the potentially effective methods, it would address challenges regarding the extraction of rich temporal dynamics and inherent uncertainty of EEG signals for robust real-time emotion

Table 1. *Summary of Recent Approaches for Emotion Recognition Using EEG Signals and Fuzzy Models*

S.No	Author(s) & Year	Dataset	Methodology	Advantages	Disadvantages
1	Asif, M. et al. (2024) [8]	EEG signals	Deep fuzzy framework with Type-2 fuzzy VAD space	Enhanced uncertainty handling in emotion representation	Increased computational complexity
2	Dhara, T. et al. (2024) [9]	EEG signals	Fuzzy ensemble-based deep learning model	Improved accuracy and robustness with ensemble learning	Higher computational cost and training time
3	Sudha, T. & Bharathi, V. (2024) [10]	EEG signals	Neuro-fuzzy AI modeling for cognitive state classification	Flexible and interpretable model for cognitive states	Increased model complexity and computational demands
4	Kaya, Ü. et al. (2024) [11]	EEG signals	Fuzzy linguistic summarization for emotion recognition	Intuitive representation of emotional responses	Potential oversimplification of emotions
5	Versaci, M. & La Foresta, F. (2024) [12]	EEG signals	Fuzzy and intuitionistic fuzzy logic for Alzheimer’s diagnosis	Enhanced diagnostic accuracy through uncertainty management	Complex implementation and variable effectiveness
6	Khalaf, O. I. et al. (2024) [13]	Virtual reality data	Neuro-fuzzy emotion recognition integrated with content generation	Personalized VR content based on real-time emotional feedback	High computational resource requirements
7	Singh, J. K. & Kakkar, D. (2024) [14]	EEG signals	Hybrid similarity-based feature selection with deep maxout fuzzy network	Improved feature selection and classification accuracy	Increased model complexity and training time
8	Palanisamy, K. K. & Rengaraj, A. (2024) [15]	EEG signals	Fuzzy features and Parrot Optimization-Tuned LSTM for anxiety-based seizures	Enhanced seizure detection accuracy	Intricate model tuning and computational complexity
9	Al-Asadi, A. W. et al. (2024)[16]	EEG signals	Semi-supervised deep learning approach	Effective handling of limited labeled data	Balancing labeled and unlabeled data can be challenging
10	Upadhyay, P. K. & Nagpal, C. (2021) [17]	Sleep EEG spectra	Time-frequency analysis and fuzzy-based detection	Detailed analysis of sleep EEG under heat stress	Variability in sleep patterns and heat-induced changes
11	Xing, M. et al. (2022) [18]	EEG signals with olfactory stimuli	Spatial-frequency-temporal convolutional recurrent network	Improved emotion detection with olfactory enhancement	Complex network architecture and high computational needs
12	Chen, L. et al. (2021) [19]	Dynamic emotion data	Two-stage fuzzy fusion-based CNN	Handles varying emotional states dynamically	Increased model complexity and training time
13	Lin, C. J. et al. (2023) [20]	EEG signals	Taguchi-based multiscale convolutional compensatory fuzzy neural network	Enhanced classification accuracy with optimized network structure	Requires extensive parameter tuning and computational resources
14	Davoodi, R. & Moradi, M. H. (2023) [21]	Biomedical data	Non-linear deep fuzzy rule-based model	Improved interpretability and accuracy in biomedical analyses	Model complexity and training requirements
15	Zhang, Z. et al. (2024) [22]	Facial feature data	Temporal adaptive fuzzy neural network for fatigue assessment	Accurate fatigue assessment based on facial features	High-quality facial feature data needed and complex neural network configurations

classification. The main idea is to combine the event-driven processing capabilities of SNNs with flexibility and interpretability inspired by Fuzzy Logic, enabling the system therefore to function at an optimal level in regard to accuracy and efficiency.

A) Spiking Neural Networks (SNN)

SNNs bring a revolution in the analysis of Electroencephalogram signals by representing the event-driven processing of biological neurons. SNNs opens the possibility of capturing the EEG signals, complex temporal patterns that traditional neural networks, based on continuous information. Event-driven mechanisms allow SNNs to achieve sparse coding with only a few neurons firing at any instant, which is highly optimized in computational efficiency and energy consumption. Besides, SNNs are good at handling temporal dynamics and long-term dependencies in sequential data [8].

2.2 Event-Driven Processing

SNNs differ significantly from conventional neural networks because of the use of discrete spikes or events, not continuous signals in the main processing units. Actually, this type of event-driven processing is similar to biological neurons because it is tend to communicate in bursts of electrical activity. It has a great advantage when it comes to the analysis of EEG signals. These are streams of raw information that traditional neural networks have a hard time handling for temporal complexity because it processes the information in a continuous stream, losing crucial timing information. An SNN captures each spike as a discrete event and the temporal dynamics of an EEG signal. It is more accurately reflects the time and sequence of neural activity-essential in emotional states. The SNN give much more detail about, and a precise analysis of, EEG signals by improving the accuracy of emotion recognition.

2.3 Sparse Coding

One of the key properties of SNNs is sparse coding, which means that at any given time, only a small number of neurons fire. Hence, it results in very efficient information representation regarding computational resources and energy consumption. Traditional neural networks usually maintain more neurons firing continuously, which might result in higher computational demands and increased energy consumption. SNNs fire only a small portion of neurons depending on the occurrence of salient spikes, thereby saving overall computational resources. Such sparsity not only optimizes performance but also makes SNNs suitable for real-time applications ranging from wearable EEG monitoring devices. SNNs are an attractive choice in several applications where the analyses of EEG are to be provided in a continuous and responsive manner without compromising on performance [9].

2.4 Temporal Dynamics

The SNNs are explicitly best suited for dealing with temporal dynamics. The EEG signals are displaying complex temporal patterns and long-term dependencies. Traditional neural networks does not capture the dynamics to processing data in a continuous stream that fails to explain detailed timing and sequencing of neural activity. SNNs, being intrinsically tied up with the temporal nature of spikes, hence should respond better while modeling long-term dependencies and variations in EEG data. In emotional contexts, specific emotional states might relate to certain temporal patterns of activity in the brain. By accurately capturing the temporal aspects and analyzing them, SNNs can provide deeper insight into the emotional content contained in EEG signals. The improved temporal sensitivity allows for finer levels of emotion recognition, enhancing overall effectiveness in EEG-based monitoring systems.

$$S(t) = \sum_i \delta(\mathrm{t} - t_i) \quad (1)$$

Equation (1) represents a spike train where (t-t_i) is a dirac delta function that indicates the spike at time t by capturing the discrete nature of spiking events.

$$T_m \frac{\mathrm{dV(t)}}{dt} = -\mathrm{V(t)} + \mathrm{R(t)I(t)} \quad (2)$$

Equation (2) models the membrane potential v(t) of a neuron where T_m is the membrane time constant. Equation (3) models the spike response of a neuron where wi is the weight of the ith spike and T_s is the time constant for the spike response.

$$R(t) = \sum_i \frac{\mathrm{wi}}{T_s}\left(\exp\left(\frac{\mathrm{t} - t_i}{T_s}\right)\right) \quad (3)$$

B) Fuzzy Hierarchical Attention Membership Component

The FHAM module improves the outputs of SNN by using fuzzy logic to map continuous spike-based data onto fuzzy sets representative of different emotional states, which in turn solves the inherent uncertainty and imprecision in EEG data. Then, FHAM selects the more informative features and fuzzy sets at each relevant level and underlines for the system the most important information useful for the task of emotion classification. The temporal patterns from the SNN are integrated with the nuanced fuzzy membership from FHAM [10].

2.2 Fuzzy Processing

FHAM module makes sense of the output from SNNs through fuzzy principles. Continuous spike-based data in the module are mapped into fuzzy sets that are indicative of different emotional categories through membership functions. Any feature obtained by the extraction with SNNs is assigned a degree of membership to given categories concerning how strongly the feature represents every possible emotional state. With this step of fuzzy processing, the uncertainty and imprecision inherent in any given input are accentuated for EEG data, hence providing a more sophisticated representation of emotional states beyond the crisp categorization approach.

2.3 Attention Mechanism

The hierarchical attention mechanism works at different levels, each level focusing on different aspects or granularity of EEG data. The attention mechanism decides the relative importance of different features and fuzzy sets, dynamically shifting the focus toward the most relevant information for the classification task. This attention acts like emphasizing the important features to allow the system to capture complex emotional cues from the EEG signals correctly for better classification.

2.4 Fusion Layer

The fusion layer plays the key role in the combination of outputs from SNN and FHAM components. The spike-based temporal information processed by the SNN is combined with the fuzzy membership assessments developed by FHAM through a process of aggregation. The temporal patterns captured by the SNN are united with the fuzzy degrees of membership in order to form a unified and comprehensive representation of emotional state. It leverages the fusion layer for both precise temporal dynamics in SNNs, uncertainty-handling capabilities of fuzzy logic toward delivering an accurate and robust emotion classification. This is a holistic approach where the final output reflects a well-rounded understanding of the emotional context derived from both spatiotemporal features of EEG data and fuzzy interpretations.

Equation (4) defines a sigmoid shaped fuzzy membership function where x in a feature set. The parameters k and x0 control the steepness and center of the membership function, respectively.

$$\mu_A(x) = \frac{1}{1+\exp(-k(x-x0))} \quad (4)$$

Equation (5) represents the output y of a fuzzy inference system where α_i are the weights associated with different fuzzy rules and $\mu_i(x)$ are the degree of membership for feature x.

$$y = \sum \alpha_i . \mu_i(x) \quad (5)$$

Equation (6) calculates the attention weight for a feature x based on its score relative to a query. It normalizes the scores and determines the relative importance of each feature in the context of the query.

$$\alpha_i = \frac{\exp(\text{score}(\text{x}_i,\text{query}))}{\sum \exp\left(\text{score}(\text{x}_j,\text{query})\right)} \quad (6)$$

Equation (7) combines the outputs from the SNN and FHAM components. The fusion weight β controls the contribution of each output to the final combined output.

$$O_{fusion} = \beta \cdot \text{OSNN} + (1-\beta) \cdot O_{fuzzy} \quad (7)$$

Equation (8) models the temporal dynamics of the convolving the spike $\text{S}(\tau)$ train with a kernel function$\text{K}(\text{t}-\tau)$. The integral accumulates the effects of spike over time by capturing past spikes influence the current state.

$$T(t) = \int_0^t \text{S}(\tau) \cdot \text{K}(\text{t}-\tau)\text{d}\tau \quad (8)$$

Equation (9) represents the output R of a fuzzy rule based system, where w_i are the weights of the fuzzy rules and $\mu_i(x)$ are the degree of membership for input feature x.

$$R = \sum_i w_i \, \mu_i(x) \quad (9)$$

Equation (10) calculates the firing rate of a spiking neuron where T is the observation periods. The firing rate is determined by the average number of spikes per unit time represented by the Dirac delta functions $(t - ti)$.

$$r(t) = \frac{1}{T}\sum_{i} \delta(\mathrm{t} - \mathrm{t}_i) \quad (10)$$

Equation (11) represents the temporal convolution where the spike train $\mathrm{S}(\mathrm{t}_i)$ in convolved with kernel $(\mathrm{t} - \mathrm{t}_i)$. It captures the temporal relationships.

$$C(t) = \sum_{i} kernel\big((\mathrm{t} - \mathrm{t}_i) \cdot \mathrm{S}(\mathrm{t}_i)\big) \quad (11)$$

Equation (12) defines an adaptive fuzzy membership function where θ is a dynamic parameter that adjusts the center of the membership function.

$$\mu_A(x,\theta) = \frac{1}{1+\exp\left(-k(x-\theta)\right)} \quad (12)$$

Figure 1 illustrates the overall steps of the work involved in the proposed NeuroFuzzy SpikeNet architecture-integrating Spiking Neural Networks and Fuzzy Hierarchical Attention Membership. The process chain begins with raw EEG signals, translates them to spike trains by SNN, encoding discontinuous events and temporal patterns in those spike trains. The SNNs will provide the spike-based temporal data to the processing via the Fuzzy Hierarchical Attention Membership component. The spike data is mapped into fuzzy sets through fuzzy logic, while the relative importance of various features is assessed by a hierarchical attention mechanism. The outputs obtained from both SNN and FHAM are then combined in the fusion layer to comprehensively represent the emotional state, considering temporal dynamics and fuzzy interpretation to classify emotions accurately [13].

Figure 2 illustrates the NeuroFuzzy SpikeNet architecture, which integrates both SNNs and FHAM modules for the boosting of emotion recognition. The architecture starts with the SNN part dealing with EEG signals by processing discrete spikes, efficiently capturing the complex temporal patterns with sparsecoding.

Output from SNN feeds the module FHAM, which interprets the spike data using fuzzy logic principles, thereby quantifying the degree of membership to several different emotional categories. The hierarchical attention mechanism of FHAM is dynamically highlighting the most relevant features forclassification. Finally, the output from both SNN and FHAM is combined in the fusion layer to develop the temporal dynamics with fuzzy membership assessments for a complete and robust representation of the emotional states. Therefore, the proposed approach that combines the strength of SNNs and fuzzy logic is guarantee higher accuracy and robustness for EEG signal-based emotion classification.

3. Results and Discussions

The SEED-IV is a sub-dataset of SEED, focusing on the approach of the emotion recognition by EEG recording. It was provided by Shanghai Jiao Tong University, and contains the EEG recordings of three different sessions for each participant, with corresponding labels of the induced emotions, which includes neutral-0, sad-1, fear-2, and happy-3.

Each session has sequence labels, which present the emotional state during the recording. For feature extraction, a 4-second sliding time window is used to obtain the temporal pattern in an EEG signal [7].

The SEED-IV dataset was used for emotion classification, where the EEG data was collected for 15 subjects in 3 sessions, each session containing 24 trials. There were 1080 trials in the dataset.

The four categories it classified were Neutral, Sad, Fear, and Happy emotions. It was a collection of EEG signals using 62 channels, at a sampling rate of 1000 Hz, for each trial lasting 4 minutes.

In total, the whole dataset is of size around 50 GB for the analysis of emotional responses based on brainwave patterns. Table 2 is dataset summary and table 3 provides information used for the preprocessing of raw EEG data are identified.

The noise filtering is carried out using a 0.5–45 Hz bandpass filter, which removes the unwanted frequencies and enhances the clarity of the signals. Normalization involved min-max scaling to

Table 2. *Dataset Summary*

Parameter	Description
Dataset Name	SEED-IV
Number of Subjects	15
Sessions per Subject	3
Total Trials	1080 (15 subjects × 3 sessions × 24 trials)
Emotions Classified	4 (Neutral, Sad, Fear, Happy)
EEG Channels	62
Sampling Rate	1000 Hz
Duration per Trial	4 minutes
Total Data Size	~50 GB

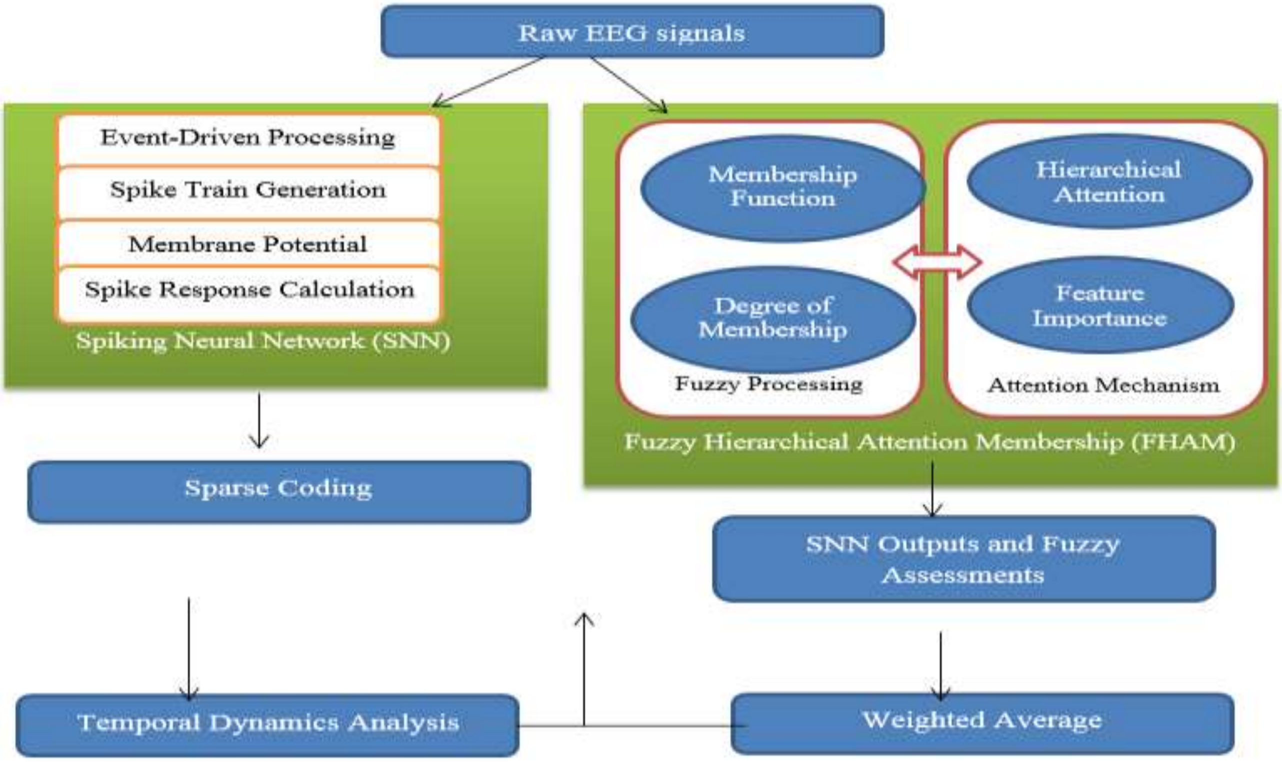

Figure1. *Working flow of the proposed NeuroFuzzy SpikeNet (NFS-Net) architecture*

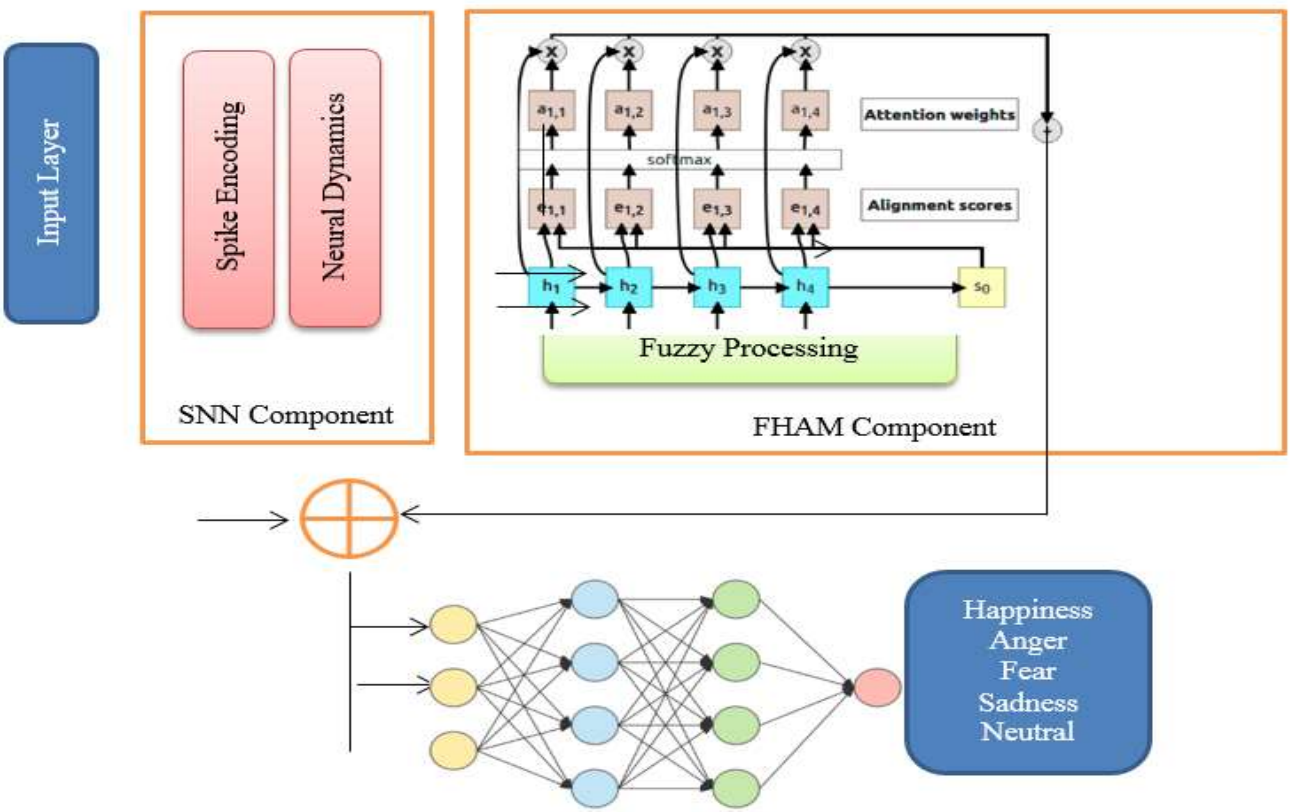

Figure 2*. An architecture of the NeuroFuzzy SpikeNet*

regularize the scale of data. Feature extraction calculates features including Power Spectral Density, mean, and variance for useful information capture from the EEG signals. Data is segmented in 4-second windows in order to manage the temporal resolution and avoid breaking the continuity of the signal through time. Table 4 shows the feature extraction methods lists the features extracted from the EEG data. The time-domain features outlined by means, variance, and skewness describe the distribution and dispersion of a signal in the time domain. Frequency-domain features are mainly represented by PSD, which characterizes the power in a signal is distributed along frequencies.

Table 3. *Preprocessing Techniques*

Step	Description
Noise Filtering	0.5–45 Hz Bandpass Filter
Normalization	Min-Max Scaling
Feature Extraction	Power Spectral Density (PSD), Mean, Variance, etc.
Window Size	4 Seconds

Table 5 represents the architecture of the proposed model for the classification of EEG emotions. The Input Layer takes EEG data preprocessed as channel-wise spikes, hence preserving temporal dynamics of the signal. The Spike Layer is comprised of 128 neurons to model the temporal dynamics of the EEG spikes concerning the sequence and timing of neural activities. Now, the Fuzzy Layer applies fuzzy sets and membership functions to process uncertainty and, therefore, to classify emotional states subtlety. The Attention Mechanism leverages a hierarchical multi-level approach for dynamic focusing of attention on the most relevant features, which seriously enhances the

Table 4. *Feature Extraction Methods*

Feature Type	Extracted Features
Time-Domain Features	Mean, Variance, Skewness
Frequency-Domain Features	Power Spectral Density (PSD)
Statistical Features	Kurtosis, Entropy, Energy

Table 5. *NeuroFuzzy SpikeNet (NFS-Net) Architecture*

Layer Type	Details
Input Layer	EEG Data (Channel-wise spikes)
Spike Layer (SNN)	128 Neurons, Temporal Dynamics
Fuzzy Layer	Fuzzy Sets, Membership Functions
Attention Mechanism	Hierarchical, Multi-Level Focus
Output Layer	4 Classes (Neutral, Sad, Fear, Happy)

Table 6. *Hyper parameters for Training*

Hyper parameter	Value
Learning Rate	0.001
Batch Size	32
Epochs	100
Optimizer	Adam
Regularization	Dropout (0.2)

capability of distinguishing subtle emotional cues in this model. Finally, data in the Output Layer is classified into one of four emotional states: Neutral, Sad, Fear, or Happy, providing the final emotion classification.The hyperparameters used to train the NeuroFuzzy SpikeNet are listed in Table 6. The model was trained with a Learning Rate of 0.001, a Batch Size of 32, and running for 100 Epochs. The weights were adjusted using the Adam Optimizer, while the Dropout Regularization was set to 0.2 to avoid overfitting of the model. Table 7 shows the performance of the model achieved an accuracy of 95.5% with the number of correct classifications. Precision was 95.2%, showing the ratio of true positive predictions against all positive predictions. Recall of 95.7% reflected the model skill in finding all relevant instances. The F1 score is a balance between precision and recall and accounted for 95.4%. The model has a loss of 0.18, representing the difference in error between predicted values and true values during training. Table 8 shows the accuracy results for various configuration setups in NeuroFuzzy SpikeNet to measure the contribution of each component individually. First, it is observed that the SNN only configuration has reached an accuracy of 90.2%, exhibiting the power in spike-based neural processing. On the other hand, Fuzzy Layer Only can provide an accuracy of 88.5%, depicting thereby the intrinsic contribution of fuzzy logic in uncertainty handling. It point out that attention-only setup has an accuracy of 92.1%, underlining the dynamic focusing on relevant features. The Full

Table 7. *Performance Metrics*

Metric	Value
Accuracy	95.5%
Precision	95.2%
Recall	95.7%
F1 Score	95.4%
Loss	0.18

Table 8. *Ablation Study Results*

Model Component	Accuracy (%)
SNN Only	90.2%
Fuzzy Layer Only	88.5%
Attention Only	92.1%
Full NFS-Net	**95.5%**

NFS-Net integrated all components and had the highest accuracy with 95.5%. It clearly underlines that the SNN, fuzzy logic, and attention mechanisms are combined for most robust performance in emotion classification in EEG data. Figure 3 visualizes these results and underlines the increment brought in by each component of the model toward the final accuracy.

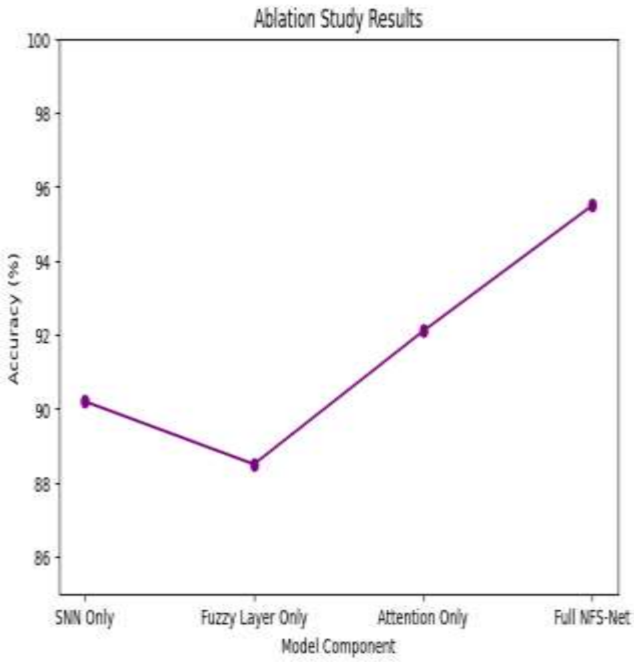

Figure 3. *Results of ablation study*

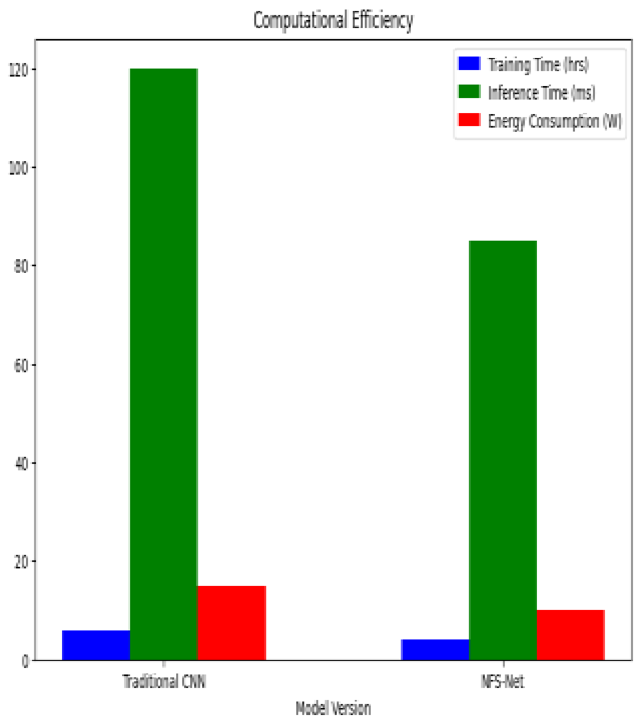

Figure 4. *The computational efficiency of proposed work with traditional CNN*

Table 9 gives the performance comparison between NeuroFuzzy SpikeNet and classic CNN regarding training time, inference time, and energy consumption. The NFS-Net depicts better efficiency and took 4 hours for training instead of 6 hours taken by a classic CNN, and it lowers the inference time to 85 ms against 120 ms of a classic CNN. Energy consumption by NFS-Net is 10 W compared to 15 W by a classic CNN. Figure 4 pictorially presents the efficiencies mentioned above and reflects that NFS-Net has faster processing at low energy consumption compared to a traditional CNN. Table 10 presents the p-values of a statistical significance test comparing performances of NeuroFuzzy SpikeNet (NFS-Net) against CNN and LSTM models. The two values (0.003 and 0.002) represent that differences in performance by NFS-Net from those models are statistically significant, which signifies that NFS-Net outperforms both the CNN and LSTM models. Figure 5 visualize the statistical comparisons and highlight the significant performance gains of NFS-Net compared to CNN and LSTM models.

Table 9. *Computational Efficiency*

Comparison	p-value
CNN vs NFS-Net	0.003
LSTM vs NFS-Net	0.002

Table 10. *Statistical Significance Testing*

Model Version	Training Time (hrs)	Inference Time (ms)	Energy Consumption (W)
Traditional CNN	6	120	15
NFS-Net	4	85	10

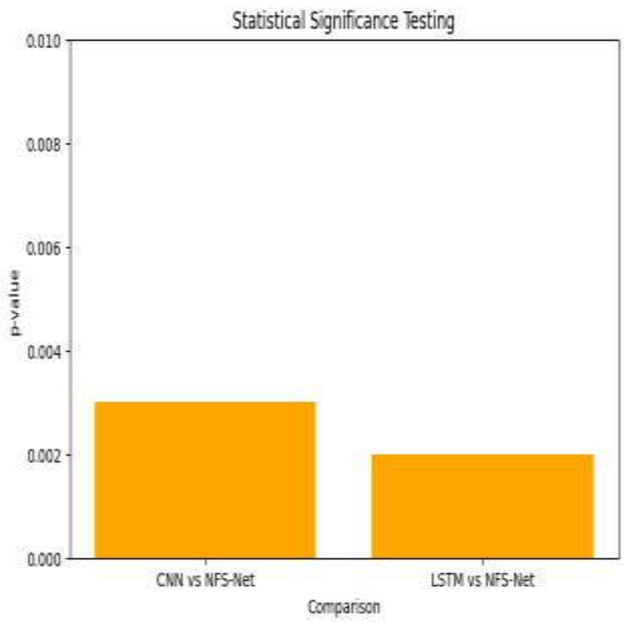

Figure 5. *Statistical Significance Testing*

Table 11. *Hyper parameter Tuning Results*

Hyperparameter	Tested Values	Best Value
Learning Rate	0.0001, 0.001, 0.01	0.001
Batch Size	16, 32, 64	32
Dropout Rate	0.1, 0.2, 0.3	0.2

Table 12. *Feature Importance Ranking*

Feature	Importance Score
PSD (Alpha Band)	0.85
Mean (Time-Domain)	0.78
Variance (Frequency-Domain)	0.72

Table 11 summarizes the best values found for some important hyper parameters in the model. The best learning rate is 0.001. The optimum batch size is 32 and the optimum dropout rate is 0.2 based on the performance metrics during tuning. Table 12 lists the importance scores that are associated with the usage of various features within the model. It is observed that, out of all the generated features, the PSD in the Alpha band has the highest importance score of 0.85, seconded by the Mean in the Time-Domain with an importance score of 0.78 and followed by the Frequency-Domain variance with an importance score of 0.72. Figure 6 represents the importance scores and PSD features to the performance of model in comparison with time-domain and frequency-domain features.

The accuracy, precision, recall and f1 score of performance metrics are calculated using the equations (13) to (16) [12].

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \quad (13)$$

$$Precision = \frac{TP}{TP + FP} \quad (14$$

$$Recall = \frac{TP}{TP + FN} \quad (15)$$

$$F1\,Score = 2 * \frac{precision * recall}{precision + recall} \quad (16)$$

Figure 7 reveals the performance of an emotion classification model on how well it can distinguish between one emotional state and the rest. The matrix shows how many instances have been correctly and incorrectly classified in each kind of emotion category. Figure 8 represents the performance of a model during training. Accuracy Curve shows the improvement of the model with the classification of emotions correctly as it progresses over an epoch. Loss Curve is used to show the decrease in classification error, hence the learning progress and convergence of the model. Table 13 and figure 9 show the performances of various models concerning the tasks of emotion classification in terms of accuracy, precision, recall, and F1 score. The proposed model, NFS-Net, outperforms all other models by showing 95.5% accuracy, 95.2% precision, 95.7% recall, and 95.4% F1 score. The Attention-Based LSTM reaches an accuracy of 94.9% and obtains an F1 score of 94.9%. While TCN

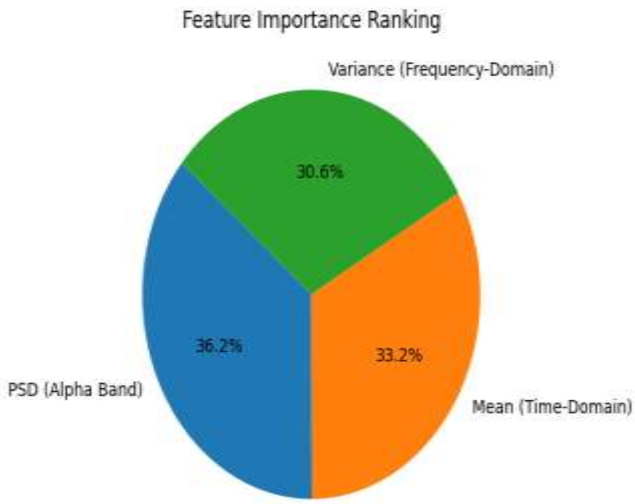

Figure 6. *Ranking of feature importance*

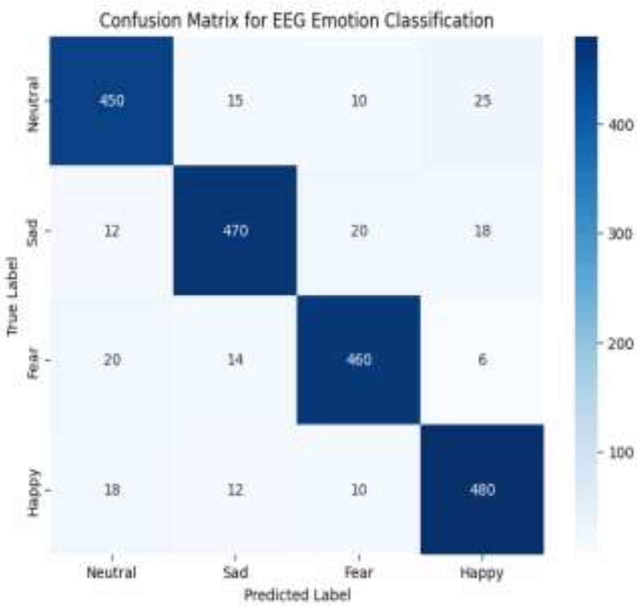

Figure 7. *Confusion matrix for EEG emotion classification*

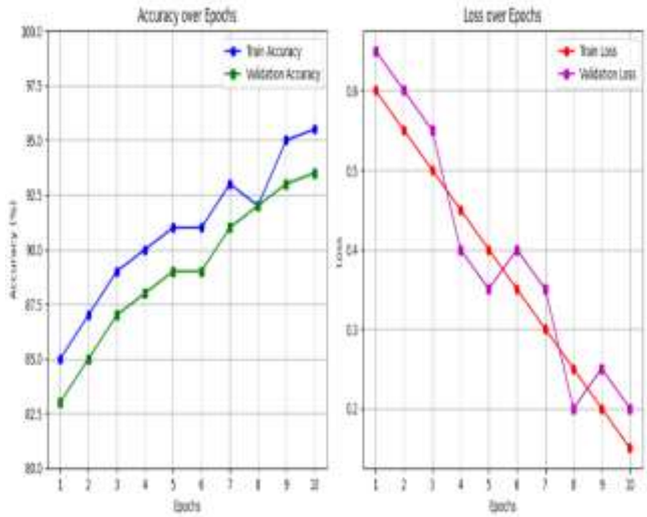

Figure 8. *Accuracy and loss visualization over epochs (NFS-Net)*

Table 13. *Comparison with State-of-the-Art Methods*

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
CNN	92.0%	91.8%	92.2%	92.0%
LSTM	93.1%	93.0%	93.5%	93.2%
BiLSTM	93.8%	93.5%	94.0%	93.7%
GRU	92.5%	92.3%	92.8%	92.6%
Deep Belief Network	91.7%	91.5%	92.0%	91.7%
Temporal Convolutional Network (TCN)	94.3%	94.0%	94.6%	94.3%
RNN-Transformer	94.8%	94.5%	95.0%	94.7%
Attention-Based LSTM	94.9%	94.6%	95.2%	94.9%
NFS-Net (Proposed)	**95.5%**	**95.2%**	**95.7%**	**95.4 %**

and the RNN-Transformer show good performances with 94.3% and 94.8% accuracies, respectively, NFS-Net outperforms than all for EEG emotion classification.

4. Conclusions

Emotion identification through neural signals is a challenging task in EEG-based emotion classification. The various fuzzy-based systems are effective in handling the uncertainty by the low adaptability to dynamic temporal patterns, and high-dimensional processing inefficiency. Most approaches either have trouble effectively combining the temporal and spatial features. The traditional fuzzy methods are event-driven nature of EEG signals. These are important in distinguishing

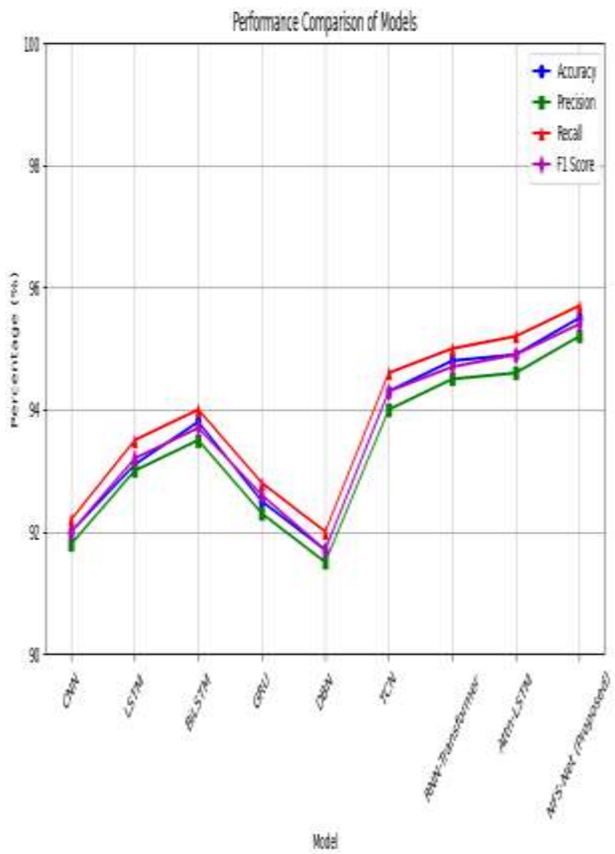

Figure 9. *Comparison with state of art models*

nuanced emotional states. The proposed NeuroFuzzy SpikeNet is focused on addressing major challenges, such as dealing with high variability in the data, recognizing complex relationships in the information and handling noises when using EEG records. The NeuroFuzzy SpikeNet integrates SNNs, fuzzy logic, and attention mechanisms to leverage temporal dynamics and the spiking nature of EEG signals effectively. A spike-based input layer for NFS-Net architecture is combined together with a fuzzy membership layer that handles uncertainty. It is combined with an attention mechanism to pay attention to the relevant features. The result shows accuracy 95.5% in comparison with other methods. These results confirm that the proposed model outperforms than other models in emotion recognition from EEG data. Future works focused on deeper, more powerful deep learning methods coupled with real-time processing for better performance of fine-tuned emotion classification. Neural network is interesting approach and it has been widely studied for different application [23-39].

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.

- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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