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Deep Learning Approach EEG Signal Classification

Kai Liang Lew [a], Kok Swee Sim [a,*], Zehong Ting [a]

[a] *Faculty of Engineering and Technology, Multimedia University, Malacca, Malaysia*

*Corresponding author: *kssim@mmu.edu.my*

***Abstract*—The introduction of deep learning technology has greatly benefited the neuroscience field by improving the electroencephalogram (EEG) signal analysis. These technologies have greatly improved the understanding of complex brain activity by interpreting the signal as normal or abnormal. The EEG signal requires expertise to interpret the pattern, and only then can the EEG signal be differentiated as normal or abnormal. However, some variations always complicate the analysis of the EEG signal by creating noise in the signal. This paper introduces a deep learning model, NeuroNetFlex (NFF), to classify the EEG signal as normal or abnormal. The NNF is designed to classify the EEG signal by using multiple combinations of modules such as one-dimension convolutional neural networks (1D-CNN), Squeeze-and-Excitation (SE) blocks, and the parallel processing fusion of recurrent neural networks (RNN), Long Short Term Memory (LSTM), and Gated Recurrent Unit (GRU) layers are used to analyze the temporal features of the EEG data and learn the signal pattern. The performance of the NNF was evaluated using evaluation metrics such as accuracy, precision, recall, and f1 score. The model achieved an accuracy of 75.33%, a precision of 76.39%, a recall of 75.33%, and an F1 score of 75.08% with a training time of 16.88 minutes, outperforming the existing models. These results demonstrate the promising potential of the NNF to significantly improve the analysis of brain activities.**

***Keywords*— EEG signal classification; temporal feature extraction; deep learning; electroencephalogram; parallel processing.**

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I. INTRODUCTION

The electroencephalography (EEG) tool is used to analyze brain activity. This is to identify the conditions such as stroke, sleep disorders, encephalopathies, etc [1]–[3]. By identifying the pattern of the EEG signal, the patient can receive effective treatment. Due to its low-cost and non-invasive nature, the EEG device has become a standard tool in clinical diagnostic [4]. Studying the EEG analysis can provide valuable insight into brain function and mechanisms of neurological disease, which can benefit both healthcare and research. However, interpreting the EEG signal can be time-consuming because the neurologists must inspect the signal manually [5]. In addition, manual interpretation of EEG signals can result in low inter-observer agreement (IOA), potentially leading to the misdiagnosis of brain disorders [6].

There have been many methods of EEG signal classification developed to analyze the EEG signals, which have significant improvements in the field of signal classification and analysis [7]. However, these methods require expertise to manually interpret the EEG signal based on visual examination and fit the data into early automated techniques, which can affect the efficiency of the method [8]. This process can lead to different diagnostic outcomes based on different observers. Interpretation poses a significant challenge in achieving a consistent and reliable diagnosis, showing essential areas for improvement in neurological assessment. Moreover, the traditional methods are time-consuming, requiring limited diagnostic evaluations within a given timeframe. These early automated techniques can reduce the manual interpretation process but require expertise analysis to verify the generated result. Although there are some gaps in these approaches, they have provided insights into brain function and development through advanced analytical techniques. Brain signals can be used to develop more applications [9], [10].

Before deep learning was introduced, traditional machine learning techniques, such as Support Vector Machines (SVMs), decision trees (DT), and random forests (RF), were commonly used to analyze EEG signals [11]. These methods extract the features from EEG signals automatically and can perform classification. However, expert knowledge is required for these methods because the features must be pre-processed manually before fitting into the methods [12]. This is due to the complexity of the EEG signals. Although traditional machine learning can automatically extract the features, it heavily depends on hand-picked features [13] because the classifiers cannot identify the complexity pattern of the EEG signal. This has shown a limitation where a more advanced method is needed to learn from data in a more dynamic style.

Deep learning, a subset of machine learning, represents a paradigm shift in EEG analysis. There are many applications used for deep learning [14]–[27]. The recent advancements in deep learning have highlighted new opportunities for artificial intelligence in analyzing EEG signals and have the potential to overcome the challenges by providing consistent, reliable, and efficient diagnostic evaluation. Researchers have developed deep learning models that use Recurrent Neural Network (RNN) [28] or Long Short Term Memory (LSTM) [29] network to analyze the time-series EEG data for feature extraction due to their ability to process data sequentially and mimic the temporal dynamics of brain activity. The models were trained on large datasets of EEG signals, which have multiple channels so the model can recognize the EEG signal pattern to identify the normal or abnormal signal. The time taken to analyze the signal can be reduced as the deep learning approaches can self-learn based on the data input, and this can remove the need for manual interpretation of the EEG signal as the deep learning model mitigates the IOA. The combination of EEG analysis and deep learning techniques can make a considerable improvement in the field of neurological assessment by providing both accurate and efficient diagnostic processes.

This paper introduces a novel deep learning architecture, NeuroNetFlex (NNF) networks, specifically designed to analyze the EEG signal. NNF uses the one-dimension Convolutional Neural Network (1D-CNN) [30] enhanced by squeeze-and-excitation (SE) [31] blocks to extract the temporal feature. The architecture uses parallel processing fusion on LSTM, RNN, and Gated Recurrent Unit (GRU) [32] layers, each combined with multi-head attention [33]. The hybrid model can capture the complex temporal of EEG data with improved precision to classify whether the EEG signal is normal or abnormal. The main objectives of the paper are summarized as follows:

- To propose a deep learning approach for performing EEG signal classification.
- To compare the performance of proposed methods with other state-of-the-art models by evaluating them on two comprehensive datasets.

The paper is organized as follows: Section 2 reviews related work based on EEG classification. Section 3 explains the proposed methodology for EEG signal classification using the proposed architecture. This section provides a detailed explanation of the architecture and training procedures used to develop the classification model. Section 4 shows the results of the assessment and experiments, highlighting key findings and areas of strength and weakness in the model, discusses the implications of these results, and compares them with deep learning models. Lastly, Section 5 concludes the effectiveness of the work and suggests recommendations for further work.

This work contributes to the ongoing exploration of neural network designs to implement signal classification for normal or abnormal EEG signals. It provides insight into the performance of different deep-learning classification models. The findings highlight the potential for modular approaches to achieve targeted improvements for EEG classification and emphasize the need for further research to refine signal analysis methods.

II. Materials and Method

A. Materials

Before deep learning was widely adopted, machine learning techniques were at the leading edge of computational efforts to improve EEG signal analysis. The author of this study [34] used resting state EEG data and machine learning techniques, including k-nearest Neighbor (KNN), Linear regression (LR), DT, RF, and SVM, to diagnose schizophrenia. Linear and non-linear measures were computed and selected to distinguish patients from healthy controls effectively. Kumar et al. [35] presented a method for automated detection of schizophrenia (SZ) using EEG signals. The method introduces a novel feature representation through a local descriptor, histogram of local variance (HLV), and symmetrically weighted-local binary patterns (SLBP). After feature extraction, a correlation-based feature selection algorithm is applied to optimize the feature vector. Alshebeili et al. [36] proposed a novel method to predict epilepsy seizures effectively by using EEG signals and combining statistical analysis, digital band-limiting filters, and artificial intelligence techniques. K-means clustering is used for a two-phase prediction process (training and testing) along with Multi-Layer Perceptron (MLP) networks. The results show high accuracy, efficient prediction time, and minimal false alarms. Savadkoohi et al. [37] presented a novel methodology to predict epilepsy seizures by differentiating brain electrical activity across various recording regions and physiological states. Feature engineering was performed by extracting time, frequency, and time-frequency domains using Butterworth, Fourier, and Wavelet Transforms. Feature selection was conducted using a T-test and Sequential Forward Floating Selection (SFFS). The study employed SVM and KNN algorithms for signal classification and compared their performance in terms of Accuracy, Sensitivity, and Specificity. SVM demonstrated slightly superior results. Richhariya et al. [38] presented a machine learning approach that used the Universum Support Vector Machine (USVM) and Universum Twin Support Vector Machine (UTSVM) to classify EEG signals to diagnose neurological disorders like epilepsy and sleep disorders. UTSVM outperformed traditional SVM and other baseline methods. Warsito et al. [39] evaluated the performance of the EEG head caps with a flexible force sensor. Lim et al. [15] used EEG signals with the combination of augmented reality to assess the student's memorizing capability. Gupta et al. [40] presents a novel method for automatically detecting seizures in EEG signals. The EEG signal is classified using a discrete cosine transform-based multi-rate filter bank, statistical modeling through fractional Brownian motion and fractional Gaussian noise, and a binary SVM classifier.

The analysis of EEG signals has significantly improved with deep learning techniques, which will enhance the accuracy and efficiency in diagnosing neurological disorders.

Xiao et al. [41] developed a novel four-dimensional attention-based neural network (4D-aNN) to recognize EEG emotion. The model transforms the spatial, spectral, and temporal domains of EEG signals into 4D representations and uses spectral and spatial attention mechanisms. The model was tested on the DEAP, SEED, and SEED-IV datasets and demonstrated superior performance. Wang et al. [42] presented a novel method based on an optimized random forest (IRF) classifier to classify five levels of attention. It has three modes: targeting sustained mode, selective mode, and focused attention mode. The experiments were conducted on the Personal EEG Concentration Tasks dataset, and attention training performance was significantly improved. The study's author [43] developed a method that used EEG signal data to detect seizures. This method filters the raw EEG data, generates spectrogram feature matrices, and fits the feature into 1D-CNN. The proposed method outperforms the existing method by achieving high performance based on evaluation metrics such as sensitivity, specificity, and accuracy. Lew et al. [44] developed a novel deep-learning approach to classify the EEG, EMG, and ECG signals by assessing the condition of the post-stroke patients who participated in virtual reality-based upper limb rehabilitation. These signals were converted into images and fit into the CNN and LSTM networks. The results showed that it can accurately classify the condition of the patients. Fawaz et al. [45] demonstrated a novel method to detect stroke and monitor patient recovery using a deep learning model. The EEG signal was fitted into a deep learning model, and the signals were classified into stroke or non-stroke categories.

B. Methods

This paper proposes a deep learning approach to classify the EEG signal by using a neural network architecture that combines 1D-CNN, SE blocks [31] and recurrent neural layers with attention mechanisms. The NNF processes the EEG data with 21 channels and 15,000 time steps to classify the EEG signal as normal or abnormal. The combination of 1D-CNN and SE blocks can extract the features more efficiently. The parallel fusion technique is used where the 1D-CNN features are simultaneously passed to GRU, LSTM, and RNN layers. Each layer is enhanced with attention mechanisms and fuses the features together. This method can represent a significant advancement in the analysis of EEG signals. Fig. 1 shows the flowchart of the proposed EEG signal classification method.

The Abnormal EEG Corpus [46] from the Temple University Hospital (TUH) was used in this study. The channels with zero variance in the EEG signal files were excluded, and the channels present in the dataset were selected. This is to ensure that only active channels and non-zero channels are considered. The EEG signals were extracted for 1 minute (15,000-time steps). The dataset is split into three sets, namely, a training set, a validation set, and a test set. The NNF architecture used the training and validation sets to perform training and validation of the model. The test set was used to evaluate the performance of the NNF, and the confusion matrix was used to show the insight of the performance of the NNF based on the test set.

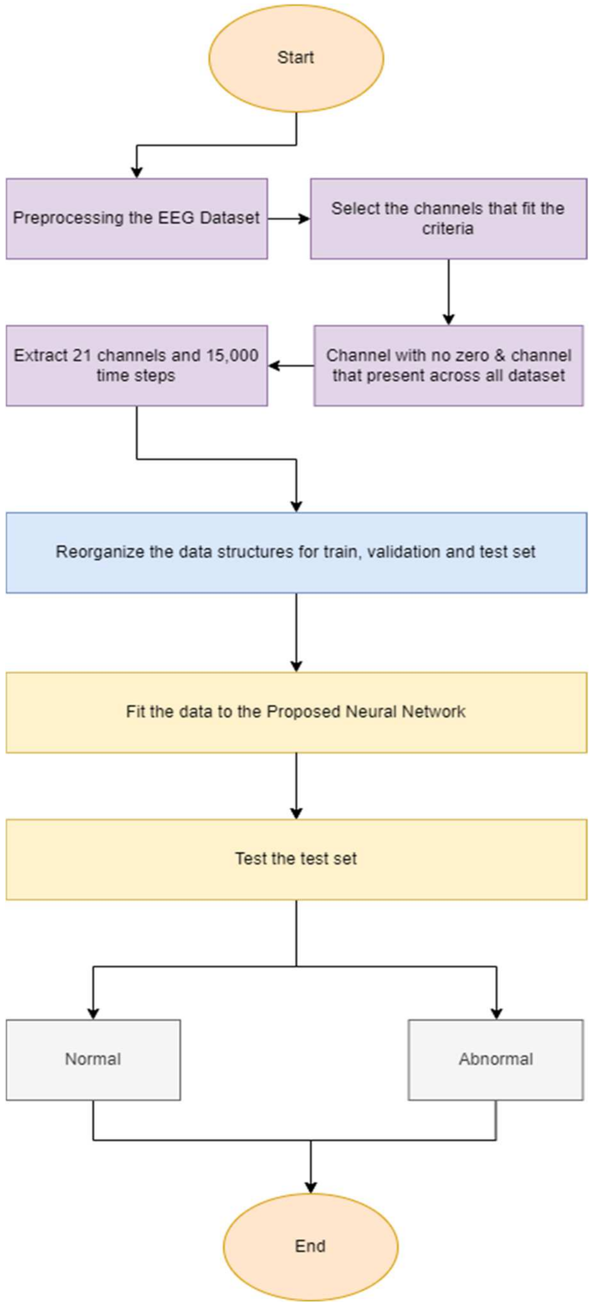

Fig. 1 Process Flowchart for EEG Signal Classification

The network is designed to classify the EEG signals, as either normal or abnormal. Fig. 2 shows the architecture of the proposed method. NNF starts 1D-CNN layers with Batch Normalization (BN), Rectified Linear Unit (ReLU) activation function with SE block. Then, it moves through the parallel fusion of LSTM, GRU, and RNN layers with multi-head attention. Finally, the features are passed to the classification output layer to classify whether the EEG signal is normal or abnormal. The network begins with an input layer designed to fit the EEG data with 21 channels. Unlike two-dimensional convolutional layers (2D-CNN), which are used for image processing, 1D-CNN is used to capture sequential patterns in time-series data. The EEG signals then pass through four 1D-CNN to extract temporal features. The architecture processes the EEG signals by reshaping the input to fit the model's requirements. The input shape is [batch size, sequence length, EEG channels)] as shown by

[32, 15000, 21)]. This structure ensures that the network can handle the data efficiently while maintaining the integrity of the temporal sequences and channel information. The first 1D-CNN uses 42 filters with a kernel size 5, increasing to 336 by the fourth 1D-CNN. The increase in the number of filters doubles with each layer to improve the network's ability to detect finer details as the depth increases.

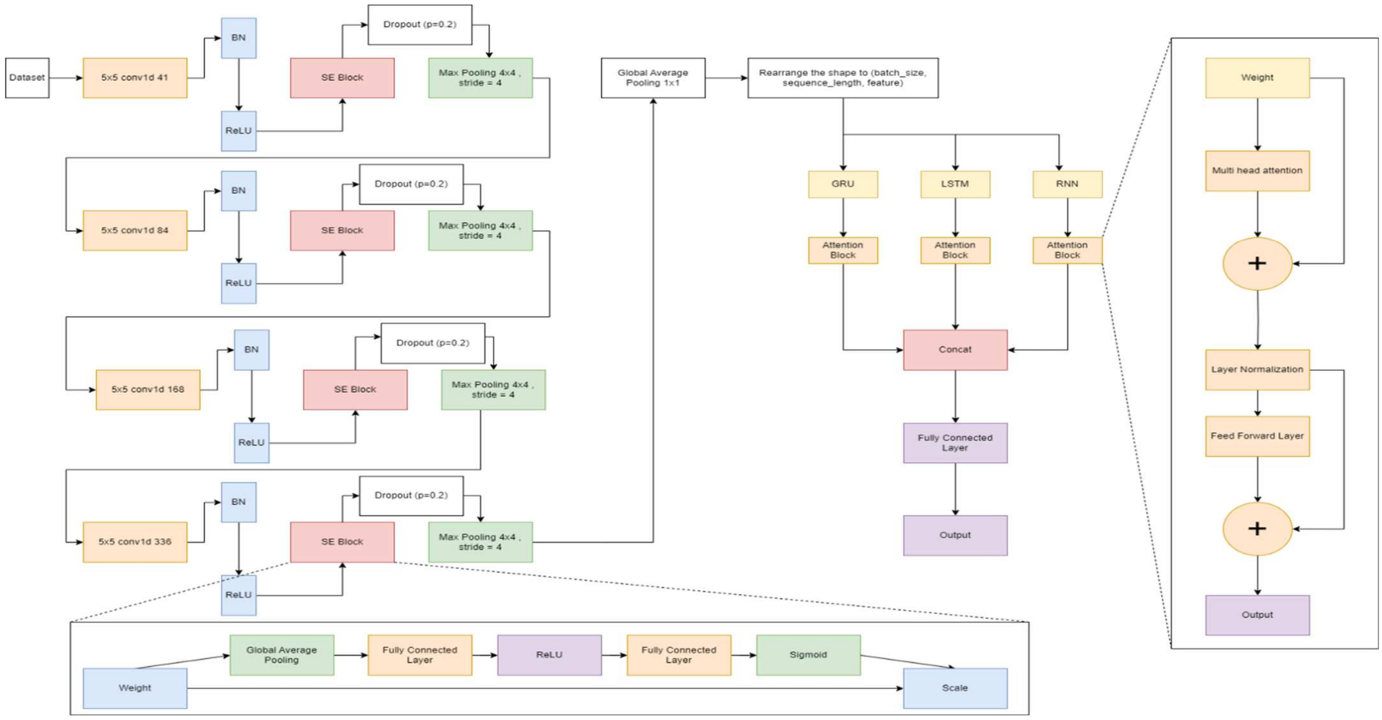

Fig. 2 The architecture of the proposed network

The SE blocks are used after each ReLU activation is used to recalibrate the channel-wise feature responses. The process consists of two phases, 'squeeze' phase and 'excitation' phase. The 'squeeze' phase compressed each channel feature map into a single numerical number using global average pooling to capture global information. The 'excitation' phase uses two fully connected layers and a sigmoid activation function to learn each channel's scaling factors.

The LSTM, RNN, and GRU are used in architecture for post-feature extraction. Each recurrent layer is enhanced by a multi-head attention module, which helps to identify short-term and long-term dependencies within the EEG signal. The parallel processing fusion of LSTM, RNN, and GRU layers allows each layer to focus on temporal data. The LSTM layer is good at capturing long-term time series data due to its memory cell and gate mechanisms. The GRU layer has a more straightforward gating structure to process information efficiently. The RNN layer provides a direct approach to modeling short-term time series data. The multi-head attention modules are used in parallel processing fusion to allow the network to focus on the important temporal features. The parallel processing fusion used is a novel approach to analyzing EEG signals. The 1D-CNN and the parallel processing fusion used on the recurrent layers allow the neural network to process the temporal data efficiently and focus on the essential temporal data. This work shows the good potential for deep learning architectures to improve EEG signal analysis. Table 1 shows the proposed algorithm.

TABLE I
THE ALGORITHM OF THE PROPOSED METHOD

Algorithm 1 Proposed Method

Input: x - Input tensor of shape (batch_size, time_steps, num_features)
Output: Classification results of shape (batch_size, num_classes)

1: **Permute x to have the shape (batch_size, num_features, time_steps)**
2: Pass x through Convolutional Block 1:
3: Apply Conv1D with 42 filters.
4: Apply Batch Normalization.
5: Apply ReLU activation function.
6: Apply SEBlock.
7: Apply Dropout with a probability of 0.2.
8: Apply Max Pooling.
9: Repeat Step 2 for Convolutional Blocks 2, 3, and 4 with respective configurations.
10: Apply Adaptive Average Pooling to the output of the last convolutional block
11: **Permute the result to have the shape (batch_size, seq_len, num_features)**
12: Set `skip` as the current state of the tensor for later use.
13: Pass the result through GRU Layer with attention mechanism:
14: Apply GRU.
15: Apply Multihead Attention with 8 heads.
16: Add `skip` to the output of Multihead Attention.
17: Apply Layer Normalization.
18: Apply Feed-Forward Neural Network.
19: Repeat Step 13 for LSTM and RNN branches.
20: Concatenate the outputs from GRU, LSTM, and RNN

Algorithm 1 Proposed Method

```
        branches along the feature dimension.
        Select the last time step's features from the
        concatenated tensor.
        Pass the selected features through the Fully Connected
        Layer to get the classification output
    Return the classification output.
    Training phase:
        for each epoch i=1 to E do
            Shuffle the patches to ensure variability in
            training data for each epoch.
            Perform training and validation phases
            Set the model to training or validation
            mode accordingly.
                Iterate over batches of data
                from train_loader or
                valid_loader
                For each batch, move data
                to the current device.
                Zero the gradients of the
                optimizer.
                Forward propagate through
                the model
                Calculate loss using the
                criterion
                If in training phase,
                backpropagate errors and
                update model weights
    Evaluate the proposed model:
        Calculate accuracy and loss over the validation set
        Compare against the best model and update if the
    current model performs better
        end for
    Load the best model weights after training
```

III. Results and Discussion

A. Datasets

The TUH Abnormal EEG Corpus [46] consists of a total of 2993 EEG signal files. This dataset has a train set and a validation set. The train set consists of 2717 EEG signal files, and the validation set has 276 EEG signal files. The EEG signals in each file were recorded from an array of 24 up to 36 channels with sampling rates ranging from 250 Hz to 512 Hz, indicating a rich diversity in the channel composition of the dataset. However, some channels were not consistently presented across the recordings, which required padding with zeros, and any channels with zero values were removed as they did not provide informative content.

Thus, the dataset needs pre-processing to standardize it before being fitted into the deep learning for training. There are 21 channels present in the EEG signals files without zero values across the dataset. These channels were resampled to a uniform sampling rate to 250 Hz to ensure consistent signal quality across the dataset. Each file performed segment extraction for 60 seconds, equivalent to 15,000 time steps, and saved as a NumPy file. After extracting the EEG signals, the dataset was split into a training set, a validation set, and a testing set for the model. The training set has 2095 EEG signal files, the validation set includes 598 EEG signal files, and the testing set contains 300 EEG signal files. The training set consists of 70% of the dataset, the validation set has 20% of the dataset, and the testing set has 10% of the dataset.

B. Model Setting

The training is implemented in Pytorch [47]. The model was trained with 100 epochs using a batch size of 32. The learning rate is set to 0.0001, using cross-entropy loss [48] for optimization and Adaptive Moment Estimation (Adam) [49] for parameter updates. An early stopping mechanism is used with patience of 25 epochs, stopping the training if no improvement is found after 25 consecutive training.

C. Evaluation Metrics

A comprehensive evaluation metric is crucial for assessing the model's performance in classifying EEG signals into ‘normal’ and ‘abnormal’ categories. This study uses accuracy, precision, recall, and F1 score metrics. Accuracy measures the ratio of correct prediction, both true positive (‘abnormal’ correctly predicted) and true negative (‘normal’ correctly predicted) predictions out of all predictions. Precision measures the proportion of ‘abnormal’ predicted that are actual ‘abnormal’ cases. Recall measures the proportion of actual ‘abnormal’ that are correctly predicted by the model. The F1 score is a balanced measure of the model’s robustness to accurately classify the EGG signals, calculated as the harmonic mean of precision and recall.

D. Comparisons with State-of-the-Art Models

The performance of the proposed model is compared with the other state-of-the-art model such as standalone model (LSTM, RNN, GRU, 1D-CNN), hybrid model (1D-CNN+LSTM, 1D-CNN+RNN, 1D-CNN+GRU) and hybrid model with SE block (1D-CNN+SE+LSTM, 1D-CNN+SE+RNN, 1D-CNN+SE+GRU, 1D-CNN+SE). The training and testing phase are conducted on an NVIDIA GeForce RTX 2080 Ti GPU (11GB).

E. Findings and Discussion

The performance metrics of various models, including standalone models (LSTM, RNN, GRU, 1D-CNN), hybrid models that combine 1D-CNN and SE with other recurrent layers, and the NNF architecture, were evaluated. The models were evaluated based on accuracy, precision, recall, F1 score, and training time (in minutes) to assess each model's efficiency and effectiveness in classifying the EEG signal as normal or abnormal. The results showed the importance of integrating convolutional and recurrent layers with SE blocks to improve classification results. Table 2 shows the result of the experiment.

TABLE II
THE RESULT OF THE EXPERIMENT

	Accuracy (%)	**Precision (%)**	**Recall (%)**	**F1 Score (%)**	**Duration (minutes)**
Standalone Model					
LSTM [29]	60.33	61.81	60.33	59.06	38.65
RNN [28]	48.00	47.81	48.00	46.86	41.19
GRU [32]	59.56	61.12	59.53	58.43	30.35
1D-CNN [30]	56.00	56.40	55.67	54.34	13.13
Hybrid Model					
1D-CNN +LSTM	66.00	69.05	66.00	64.58	18.89
1D-CNN +RNN	60.33	60.50	60.33	60.17	13.65

	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Duration (minutes)
1D-CNN +GRU	68.67	66.88	68.67	68.58	17.43
Hybrid Model with SE					
1D-CNN +SE	70.00	75.17	70.00	68.38	16.70
1D-CNN +SE+LSTM	72.00	73.51	72.00	71.54	18.89
1D-CNN +SE+RNN	67.33	67.34	67.33	67.33	21.09
1D-CNN +SE+GRU	71.33	71.58	71.33	71.25	18.82
NNF (Proposed)	75.33	76.39	75.33	75.08	16.88

The standalone model, LSTM, achieved the highest accuracy of 60.33%, a precision rate of 61.81%, a recall of 60.33%, and an F1 score of 59.06% with a training time of 38.65 minutes. The LSTM can archive these performances due to its ability to capture long-term dependencies in the EEG data. However, RNN underperformed, achieving the lowest accuracy of 48.00%, a precision of 47.81%, a recall of 48.00%, and an F1 score of 46.86% with the longest training time of 41.19 minutes. The 1D-CNN alone had an accuracy of 56.00%, which is lower than LSTM and GRU models, showing that 1D-CNN may not be as effective at modeling the temporal sequences in EEG data without the integration of recurrent layers. However, the 1D-CNN demonstrated its ability to compute efficiently as the training time is 13.13 minutes, indicating its potential as a core component in more complex architectures designed for EEG signal analysis. The 1D-CNN can process data quickly, making it a valuable component when combined with other mechanisms that cannot capture full temporal dynamics as effectively as recurrent layers.

The 1D-CNN framework with GRU has the highest accuracy of 68.67%, a recall of 68.67%, and an F1 score of 68.58%, with a training time of 17.43. The 1D-CNN framework with LSTM has the highest precision of 69.05%, while the 1D-CNN framework with RNN has the most computation efficiency, with a training time of 13.65 minutes compared to others.

The 1D-CNN+SE framework with LSTM has the highest accuracy of 72%, a precision of 73.51%, a recall of 72%, and an F1 score of 71.54%, outperforming the 1D-CNN+SE framework with RNN and GRU. The 1D-CNN+SE framework with GRU demonstrated the most computational efficiency, completing the training process in just 18.82 minutes compared to RNN and LSTM. This shows that the GRU's architecture gating mechanism offers significant gains in processing speed compared to LSTM. These models intergraded with the 1D-CNN+SE framework have shown improvement in feature extraction and deep analysis of temporal dependencies through recurrent layers.

The NNF network demonstrated superior performance across all metrics, resulting in an accuracy of 75.33%, a precision of 76.39%, a recall of 75.33%, and an F1 score of 75.08% with a training time of 16.88 minutes. This is a significant improvement over both the standalone model and other hybrid models. The integration of SE blocks into 1D-CNN architectures can make a considerable improvement from 56% to 70% accuracy, a precision from 56.40% to 69.05%, a recall from 59.53% to 70%, and an F1 score from 54.34% to 68.58%. The combination of recurrent layers with the 1D-CNN+SE framework has improved the performance, showing the effectiveness of the combination.

The combination of SE blocks, 1D-CNN, and the parallel fusion of recurrent layers with attention mechanisms has significantly improved EEG signal analysis. The NNF network outperformed the traditional and hybrid models, highlighting the importance of architectural innovation in improving neurological diagnostics.

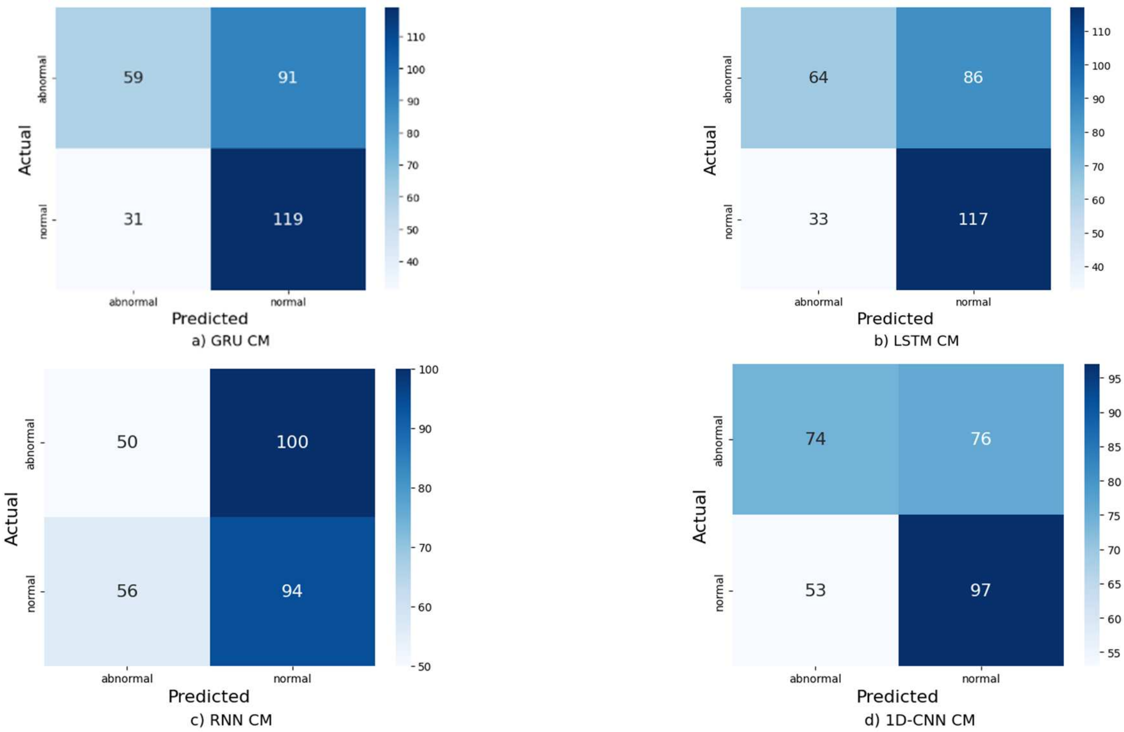

Fig. 3 The confusion matrix of the standalone model

The confusion matrix can provide insight into each model's predictive capabilities to assess their robustness in EEG signal classification critically. The section presents the confusion matrix for the standalone, hybrid, hybrid model with SE block and the proposed NNF network. Figure 3 shows the confusion matrix of the standalone model. The confusion matrix of the GRU model shows that 59 abnormal signals are correctly classified as true positives while 31 are misclassified as normal (false negatives). Additionally, the GRU correctly classified 119 normal signals as true negatives, but 91 signals were misclassified as abnormal (false positives). The confusion matrix of the LSTM model shows that there are 64 true positives and 33 false negatives. There are 86 misclassified signals as false positives, while 117 normal signals are classified as true negatives. The confusion matrix of the RNN model shows that there are 50 true positives and 56 false negatives. There are 100 misclassified signals as false positives, while 94 normal signals were classified as true negatives. The confusion matrix of the 1D-CNN shows that there are 74 true positives, 53 false negatives, 76 false positives, and 97 true negatives. Table 3 shows the results based on the confusion matrix of the standalone model.

TABLE III
THE RESULT BASED ON THE CONFUSION MATRIX OF STANDALONE MODEL

Model	Precision	Specificity	Recall	F1 Score
GRU	39.33	56.67	65.56	49.17
LSTM	42.67	**57.64**	**65.98**	51.82
RNN	33.33	48.45	47.17	39.06
1D-CNN	**49.33**	56.07	58.27	**53.43**

Based on Table 3, the 1D-CNN model has the highest precision of 49.33% and an F1 score of 53.43, and the RNN has the lowest precision of 33.33% and an F1 score of 39.06%. The LSTM has the highest specificity of 56.57% and a recall of 65.98%. The 1D-CNN model can robustly classify the EEG signal with balanced precision and recall.

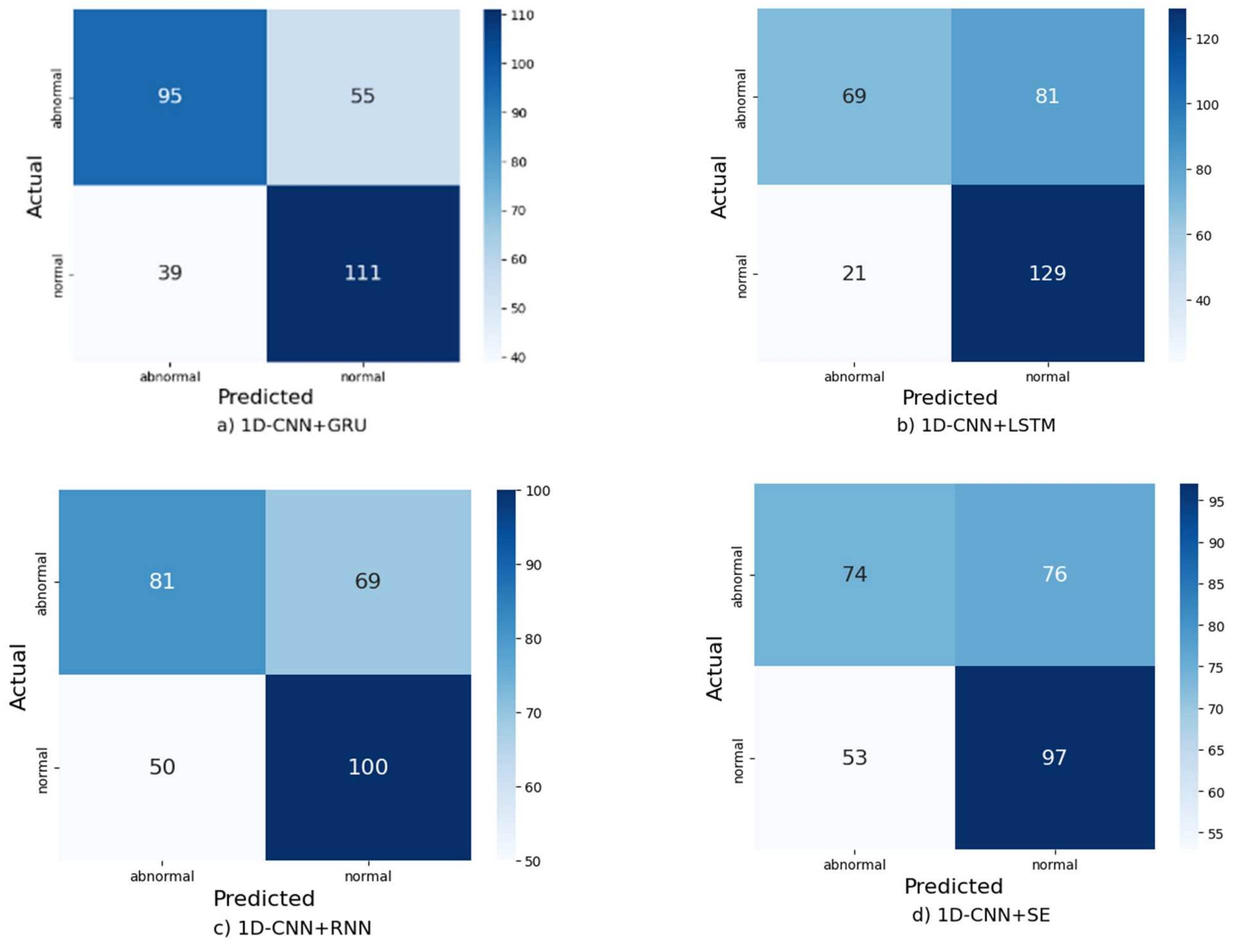

Fig. 4 The confusion matrix of the hybrid model

The performance of the hybrid model is assessed by its confusion matrix. Figure 4 shows the confusion matrix of the hybrid model. The 1D-CNN+GRU has 95 true positives, 55 false positives, 39 false negatives, and 111 true negatives. The 1D-CNN+LSTM has 69 true positives, 81 false positives, 21 false negatives, and 129 true negatives. The 1D-CNN+RNN has 81 true positives, 69 false positives, 50 false negatives, and 100 true negatives. The 1D-CNN+SE has 71 true positives, 79 false positives, 31 false negatives, and 139 true negatives. Table 4 shows the hybrid model's precision, specificity, recall, and f1 score. Based on Table 4, the 1D-CNN+GRU model has the highest precision of 63.33%, a specificity of 66.87%, and an F1 score of 66.90%, while the 1D-CNN+RNN has the lowest specificity of 59.13%. The 1D-CNN+SE has the highest recall of 86.59%, while 1D-CNN+LSTM has the lowest precision of 46% and an F1 score of 57.70%. The 1D-CNN+GRU model can robustly classify the EEG signal with balanced precision and recall.

TABLE IV
THE RESULT BASED ON THE CONFUSION MATRIX OF HYBRID MODEL

Model	Precision	Specificity	Recall	F1 Score
1D-CNN +GRU	**63.33**	**66.87**	70.90	**66.90**
1D-CNN +LSTM	46.00	61.43	76.67	57.50
1D-CNN +RNN	54.00	59.17	61.83	57.65
1D-CNN +SE	47.33	63.76	**86.59**	61.21

Fig. 5 shows the confusion matrix of the hybrid model with SE block and the NNF network. The 1D-CNN+SE+GRU has 99 true positives, 51 false positives, 35 false negatives, and 125 true negatives. The 1D-CNN+SE+LSTM has 89 true positives, 61 false positives, 23 false negatives, and 127 true negatives. The 1D-CNN+SE+RNN has 100 true positives, 50 false positives, 48 false negatives, and 102 true negatives. The NNF has 98 true positives, 52 false positives, 22 false negatives, and 128 true negatives. Table 5 shows the hybrid model's precision, specificity, recall, and f1 score with SE block and the proposed network.

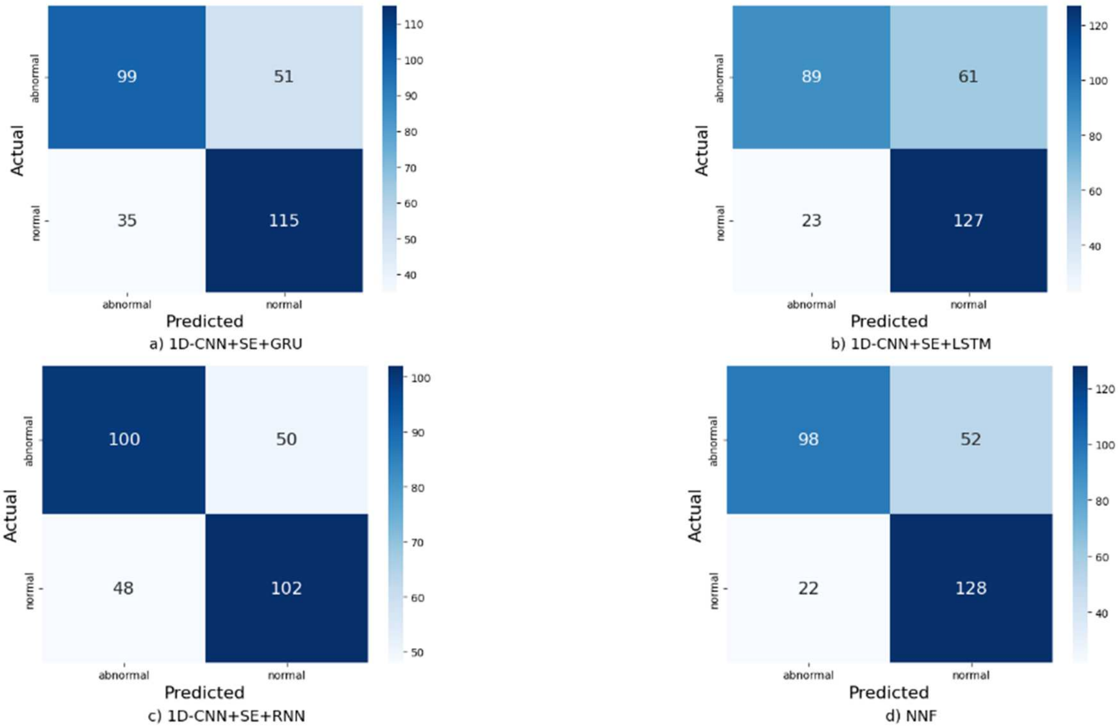

Fig. 5 The confusion matrix of the hybrid model with SE block and the NNF network

Based on Table 5, The 1D-CNN+SE+LSTM has the highest precision of 66.67% but achieved the lowest specificity of 67.11%, a recall of 67.57%, and an F1 score of 67.11%, while the 1D-CNN+SE+RNN has the lowest precision of 59.33%. The NNF has the highest specificity of 71.11%, a recall of 81.67%, and an F1 score of 72.59%. The NNF has demonstrated its robustness in classifying the EEG signal and outperforming all the models in the experiment.

TABLE V
THE RESULT BASED ON THE CONFUSION MATRIX OF HYBRID MODEL WITH SE BLOCK AND THE NNF NETWORK

Model	Precision	Specificity	Recall	F1 Score
1D-CNN +SE +GRU	66.00	69.28	73.88	69.72
1D-CNN+SE +LSTM	**66.67**	67.11	67.57	67.11
1D-CNN +SE +RNN	59.33	67.55	79.46	67.94
NNF	65.33	**71.11**	**81.67**	**72.59**

However, this work could be improved. The EEG signals may contain noise, and obtaining large datasets can be very challenging. The network's performance is dependent on the given dataset. Thus, data augmentation can increase the quantity of EEG signals. The proposed network's training time is longer than the existing state-of-the-art. Thus, it is possible to implement knowledge distillation to reduce the model size, which can decrease the computational resource.

IV. CONCLUSION

The NNF network has demonstrated a novel approach for classifying EEG signals. It is designed to extract and analyze temporal features from EEG signals using 1D-CNN combined with SE blocks and parallel processing fusion of RNN, LSTM, and GRU layers. The NNF architecture can capture the temporal features and accurately classify the EEG signal as normal or abnormal.

Combining 1D-CNN, SE blocks, and the parallel processing fusion of LSTM, GRU, and RNN layers with multi-head attention mechanisms has improved the accuracy of EEG signal classification. This work has provided valuable insights and highlighted the potential of deep learning architectures in EEG signal analysis. Future work could investigate the capabilities of the NNF network to classify EEG signals with the combination of real-time monitoring systems for the immediate detection of abnormalities.

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