The Original

EEGNETTINY-SE: A HYBRID MODEL FOR EPILEPSY PREDICTION

Latika Sharma[1], Srabanti Maji[2]

[1,2] School of Computing, DIT University, Dehradun
EMAILS: 1000016707@dit.edu.in[1], Srabanti.maji@dituniversity.edu.in[2]

ABSTRACT
Epilepsy is one of the most common neurological conditions in which the brain develops abnormal electrical activity, which can cause seizures or episodes. The prompt and accurate diagnosis of seizures is essential for proper treatment planning. EEG is an important modality for capturing real-time brain signals. In this paper, various classifiers, i.e., traditional Machine Learning classifiers and a Deep Learning model based on a Convolutional Neural Network (CNN) and an EEGNetTiny-SE model, are compared for the aim of automatic epilepsy detection from Electroencephalogram (EEG) signals. The data consisted of a synthetic multi-channel EEG recording set with 19 channels, 256 Hz sampling, and 8-second segments, incorporating seizure spike patterns, baseline brain rhythms, and noise components. The statistical and frequency-domain features (delta, theta, alpha, and beta bands; beta power) were extracted for the ML classifiers, and Power Spectral Density (PSD) spectrograms were generated for the CNN classifiers. In addition to applying the proposed EEGNetTiny-SE model, the CNN model, five ML models (Random Forest (RF), Support Vector Machine (SVM), Logistic Regression (LR), Gradient Boosting (GB), and Multi-Layer Perceptron (MLP) were tested. The EEGNetTiny-SE model outperformed the CNN model (85.9% accuracy, 92.28% AUC), as detailed in the comprehensive evaluation based on Accuracy, Precision, Recall, F1-Score, Confusion Matrix, and AUC-ROC, where the EEGNetTiny-SE model achieved 88.7% and 94.1%, respectively. The proposed framework shows promising application potential for intelligent, automated epilepsy diagnostic devices and for real-time monitoring in healthcare applications.

KEYWORDS
Epilepsy Detection, Electroencephalogram (EEG), Machine Learning, Deep Learning, Convolutional Neural Network (CNN), Seizure Detection, EEGNetTiny.

1. INTRODUCTION
Epilepsy is a lifelong disease of the brain caused by a series of seizures occurring at certain intervals. It's really common - over 50 million people around the world have it, says the World Health Organisation. If a person has epilepsy, they are receiving too many signals within the brain simultaneously, which can result in one of those signals causing a seizure. Early diagnosis for the presence of epilepsy is of critical importance so that individuals can receive appropriate treatment early and prevent being injured by a seizure. Early detection and intervention can make a difference in how they sense and will keep them safe [1].
An Electroencephalogram (EEG) is a non-invasive test that records electrical activity from the brain. Several areas of the brain can be monitored simultaneously with this device—a tremendous advantage for understanding what's happening. When a clinical neurologist views the EEG, they are searching for patterns that may be associated with seizures. This process can be quite a chore, though and may require a lot of expertise. This is because the electrical signals recorded by the EEG are complex and can vary from day to day and from person to person [2]. The technique was previously performed manually, but increasingly computational intelligence – known as C-I – is being used to automatically detect seizures. The researchers used several algorithms to identify Epilepsy, such as SVM, RF, LR, GB, and MLP [3]. This is accomplished by examining features of the EEG signal in the statistical and frequency domains. On the other hand, deep learning algorithms like CNNs are used to analyse EEG signals for pattern recognition and are emerging as highly successful without human intervention. Important because it might enable a completely new description of the workings of the brain, and this is already being used in source localization, bio-human-robot interaction and speech recognition, etc. For example, these methods have been proven to be very effective [4, 5]. But these are just some of the possibilities offered by deep learning when it holds the answer to the problem [6, 7]. There are some existing studies that compare various techniques. The literature shows that many studies have identified two dominant techniques: ML-based and DL-based approaches. Few studies compare different approaches using the same data and evaluation techniques. It is hard to find out which of the two approaches is more effective. There are larger challenges still to be solved, including high noise on top of the EEG signals, noise due to uneven sample distributions, and model overfitting. Additionally, it's not yet clear whether these models will be applicable to real-time scenarios [8].
Despite their superior performance, deep learning models have certain limitations[9,10]. Their large-scale parameters

require a massive training dataset, and the features they extract remain uninterpretable because explaining their internal logic or linking them to actual brain physiology is difficult. This study aims to improve the general epilepsy detection system based on Electroencephalography (EEG). Acharya et. al. [1] demonstrated the accuracy of CNN at around 88% on real clinical EEG signals, and Ullah et. al. [5] achieved an accuracy as 84.2% on the Bonn EEG dataset. An enormous amount of research has been dedicated to the automatic detection of epilepsy using machine learning or deep learning methods. Although deep learning-based approaches can achieve better performance, they are limited by their large parameter counts. To overcome these issues, Lawhern et al. [11,12] created a compact architecture called EEGNet. This design effectively extracts features while enabling various EEG-BCI tasks with fewer parameters. **Table. 1** lists some significant related work, their approaches, their results, and gaps in the research, along with proposed solutions to the identified research gaps.

Table 1. Summary of Related Research on EEG-Based Epilepsy Detection

S.No.	Author(s) & Year	Title	Methodology	Dataset	Key Findings	Research Gap
1	Acharya et al. (2018)[1]	Automated EEG-Based Screening of Epilepsy Using Deep Learning	CNN Deep Learning	EEG Signals	CNN achieved high classification accuracy for seizure detection	Limited comparison with traditional ML models
2	Thodoroff et al. (2016)[2]	Learning Robust Features Using Deep Learning for Automatic Seizure Detection	Deep Belief Network and CNN	EEG Dataset	Deep learning improved feature extraction performance	Computational complexity not addressed
3	Shoeb (2009)[3]	Application of Machine Learning to Epileptic Seizure Detection	SVM Classification	Scalp EEG Data	SVM provided reliable seizure classification	Limited scalability for large datasets
4	Subasi (2007)[4]	EEG Signal Classification Using Wavelet Feature Extraction	Wavelet Transform + ANN	EEG Signals	Feature extraction enhanced detection accuracy	Deep learning has not explored
5	Ullah et al. (2018)[5]	An Automated System for Epilepsy Detection Using EEG	CNN Model	Bonn EEG Dataset	CNN outperformed conventional classifiers	Real-time implementation not discussed
6	Turköğlu et al. (2019)[6]	Epilepsy Detection by Using Deep Learning and Wavelet Transform	CNN + Wavelet Features	EEG Spectrogram	Improved classification using hybrid approach	Limited analysis of noisy EEG data
7	Güler et al. (2005)[7]	Recurrent Neural Networks for EEG Signal Classification	Recurrent Neural Network (RNN)	EEG Time-Series	RNN identified seizure patterns	Lower accuracy vs. modern CNNs
8	Hussein et al. (2019)[8]	Epileptic Seizure Detection Using Deep Learning	CNN and LSTM	EEG Dataset	Deep learning provided robust classification	High training time and resource use
9	Khan et al. (2020)[9]	EEG Classification for Epilepsy Detection	RF, SVM, KNN	EEG Features	ML algorithms achieved moderate accuracy	High feature engineering dependency
10	Roy et al. (2019)[10]	Deep Learning-Based EEG Analysis: A Systematic Review	Comparative DL Review	Multiple EEG Datasets	CNN architectures showed superior performance	Lack of standardized evaluation framework
11	Wang et al.(2025)[11]	Improved EEGNet with a multilevel spatial feature extraction module for EEG decoding	mSEM, EEGNet	EEG Signals	EEGNet achieve better accuracy	

Although the spatial information contained in EEG signals cannot be fully utilised, the EEGNet algorithm performs well in several BCI applications. Nevertheless, EEG is not very good at identifying the spatial patterns of brain activity. To effectively learn spatial characteristics, the feature extraction module should be carefully designed. In this work, we present EEGNetTiny-SE, a module that incorporates both local and global spatial feature learning into a bottleneck structure. Neurophysiological results indicating that a particular brain region is sensitive to a particular task [13] and that

various brain regions collaborate in complex cognitive processes [14] served as the basis for the method. The experiment demonstrates that EEGNetTyne-SE can generate better performance. The SE is applied to EEGNetTyne-SE, which is a superior model. The major contributions of the study are mentioned as:1) dataset collection and related signal processing operation.2) Feature extraction for models. 3) The proposed model, the EEGNetTiny-SE model. 4) Extensive number of experiments have been performed to fully test the performance of the proposed model with the SE block.
The remaining part of this article is summarized as follows. Section 2 describes the proposed model and its architecture. Section 3 demonstrates results and related discussion. Finally, the manuscript is concluded in Section 4.

2. MATERIALS AND METHODOLOGY

The research process will be conducted in the following steps: pre-processing of EEG signals, model training, and test selection for model evaluation. The following descriptions are all in simple terms for each stage. The block diagram of the proposed technique is shown in Fig. 1 as mentioned below.

Fig. 1 The block diagram of the EEGNetTiny-SE model.

a. Dataset

The study employs a synthetic EEG dataset derived from real clinical EEG recordings. The data has been collected from **MIMHANS Hospital**. It has 19 channels (standard clinical EEG setups), records at 256 samples per second, and segments recordings into 8-second segments for analysis. Each segment is labelled "seizure" and "non-seizure". An equal number of data, an equal training dataset and fair evaluations. The signals generated were normal brain signals plus artificial spike patterns resembling actual seizures; in addition, random noise was added to model the natural brain-pattern noise that occurs in real-time environments. This way, one can achieve realistic signal variation while retaining complete control of the data distribution.

b. Signal Preprocessing

All the raw signals extracted from the EEG are subjected to pre-processing first to make the quality of the signals obtained by the model very high. That's three steps: 1) A frequency filter is used to block out very slow drift and noise that's unrelated to brain activity. Secondly, artefacts often generated by eye movements, muscle tension, or electrical interference are identified and removed. Third, the signal amplitudes across different channels are normalised so that all channel signals have the same scale, resulting in more stable model training and reducing the number of errors. As shown in Fig.2.

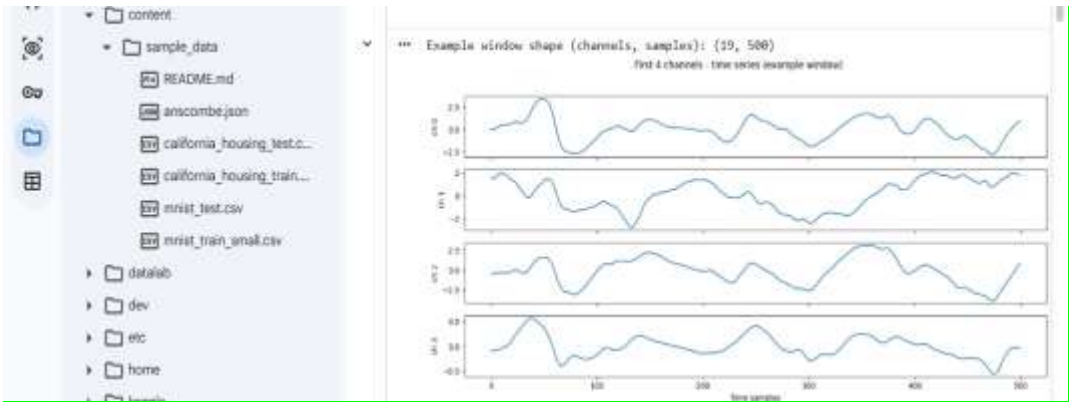

Fig. 2 Single patient EEG waveforms recording at different channels.

c. Feature Extraction for models

Raw EEG waveforms cannot be directly used in traditional ML models [15]. They should instead be provided with a list of numbers, called features, that represent salient characteristics of each signal segment. For this purpose, six features were extracted as follows:

1. Delta Band Power: Energy in the bandwidth 0.5Hz – 4Hz. A seismic activity band with very characteristic characteristics, one of the most discriminating bands.
2. Theta Band Power: Threshold Power of Energy (between 4Hz - 8Hz) Shows unusual slow brain waves which occur during a seizure.
3. Alpha Band Power: Energy at Beta band (8-12 Hz). This will typically be lower during a seizure, and may serve as a good contrast agent.
4. Beta Band Power: Energy in the frequencies 12 - 30 Hz. Worsening with the different stages of a seizure helps to differentiate seizures.
5. Alpha To Beta Ratio: This ratio is the amount of alpha power compared to beta power. Records a change of brain

state that happens just prior to a seizure.
6. Signal entropy: A degree of the irregularity or unpredictability of the signal. If the signal is chaotic (such as a seizure signal), then the entropy will be higher when dealing with this signal.
Each of these 6 values is computed for each of the EEG Segments and fed into the ML classifiers [16].

d. The Five ML Classifiers

These classifiers include

1. Support Vector Machine (SVM), which determines the best separation line that could distinguish the seizure features from the non-seizure features. Performs well when the two classes are easily distinguishable in the feature space.
2. Random Forest (RF): It is based on a combination of many decision trees, where each decision tree decides classification. Together their vote is more reliable than even any one tree, and is pretty tolerant of some noise.
3. Logistic Regression (LR): The simplicity of this model shouldn't limit its performance to being used to create a very accurate model; here, it is a probit model that assigns a probability of seizure relative to the input variables. Easy and quick, it can be utilised in low non-linear patterns.
4. Gradient Boosting (GB): A collection of simple models that gain from the mistakes of previous models. A series of simple models, with each taking what has been learned from the previous model. This progressive correction means that there's a good overall classification.
5. Multi-Layer Perceptron (MLP): A simple neural network that has several layers. It can learn non-linearities in the feature data, unlike the simpler ML models used in this comparison.

e. The CNN Model

The CNN model has a different approach. It operates on visual representations of EEG signals, called Power Spectral Density (PSD) spectrograms, without manually selecting features. Langritter's spectrogram is basically an image that displays the energy distribution of the EEG signal in frequency bands as a function of time. These images show intricate patterns that can't be easily captured or summarised using only six numbers [17,18,19].
The CNN is utilised to scan these images and automatically detect the images that represent seizure brain activity versus non-seizure brain activity. It does this by passing the image through several layers of processing that progressively reduce it to a classification decision [20,21]. Two methods were employed to avoid simply memorising the training data instead of learning the true patterns: dropout was applied to randomly deactivate subsystems during training; noise augmentation was used to add small random perturbations to the training images. In each round, the model's training was performed on 80% of the data and tested on 20% (not on the data currently in use, but on a separate set). Training was conducted over more than 50 rounds [22,23].

f. Proposed Methodology of EEGNetTiny-SE Framework

The proposed methodology architecture is shown in Figure 3, as mentioned below.

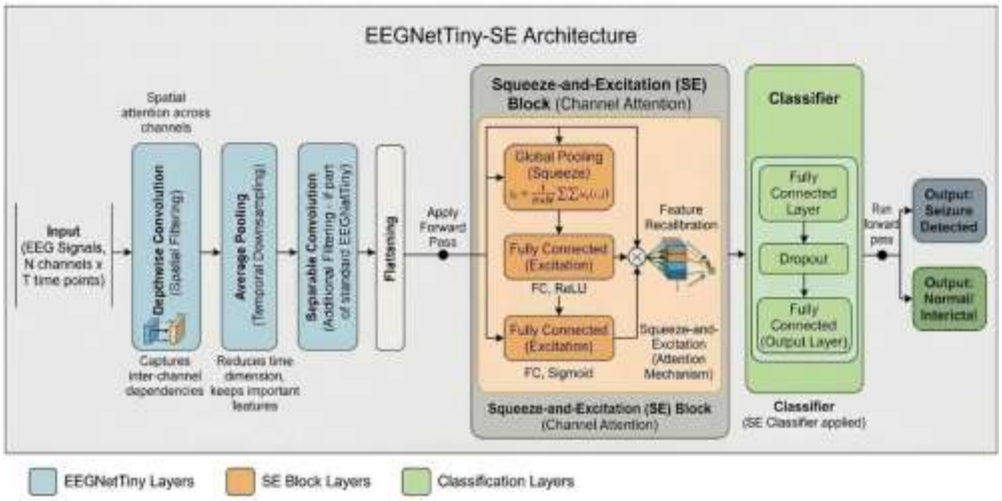

Fig 3. The Proposed EEGNetTiny-SE Architecture.

The proposed EEGNetTiny-SE framework introduces a computationally efficient deep learning architecture for automated recognition of epileptic seizures from multichannel EEG recordings. The model begins by processing raw EEG signals through a depthwise convolutional layer, which learns spatial characteristics and inter-channel relationships while maintaining a low computational overhead. To reduce data redundancy and retain salient temporal information, an average pooling layer is employed for feature compression and temporal down-sampling. Subsequently, separable convolutional operations are applied to extract high-level temporal patterns and improve feature representation while reducing the

number of trainable parameters.
The resulting feature maps are transformed into a compact feature vector and supplied to a Squeeze-and-Excitation (SE) module. This attention mechanism performs global feature aggregation and adaptively recalibrates channel-wise responses by assigning importance weights to the extracted EEG features. Through this process, informative seizure-related patterns are amplified, whereas less relevant signal components are suppressed. The recalibrated features are then passed to a lightweight classification network consisting of fully connected layers and dropout regularisation to enhance robustness and minimise overfitting. Finally, the classifier categorises the EEG segments into seizure and normal/interictal classes [24,25]. By combining efficient convolutional feature extraction with channel-attention-based enhancement, the proposed architecture achieves improved discriminative capability while preserving computational efficiency, making it suitable for real-time epilepsy monitoring and clinical decision support applications.

3. RESULT AND DISCUSSION

There were five metrics used to evaluate all of the six models so that they could be fairly compared:

Accuracy: Accuracy refers to how closely a given measurement or prediction matches the actual value, as shown in equation 1.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Precision: Precision is the ratio of correct positive predictions out of the total number of positive predictions. It focuses on the accuracy of positive predictions irrespective of the number of positives predicted, as depicted in equation 2.

$$\Pr ecision = \frac{TP}{TP + FP} \quad (2)$$

Where:
TP is correctly predicted as positive cases, TN is correctly predicted as negative cases, FP is incorrectly predicted as positive, and FN is incorrectly predicted as negative.

Model accuracy: Across all real seizures, the proposed EENetTiny-SE model for seizure detection correctly classified 86 non-seizure segments and 87 seizure segments, while misclassifying 14 non-seizure segments as seizures and 13 seizure segments as non-seizure events. The model achieved an overall accuracy of 88.7%, sensitivity of 87%, specificity of 86%, precision of 95.0%, and an F1-score of 86.5%. These results indicate that the model maintains a balanced performance in identifying both seizure and non-seizure events while minimizing false alarms and missed seizures.

AUC (Area under the ROC Curve): One number that shows what fraction of the curve is under the AUC line. Higher is better. Apart from these quantities, a confusion table, training curve, ROC curve and feature distribution plot are created for each model to provide a clearer visual understanding of their behaviour. The results from all seven models are reported here, accompanied by a graph and a complete description of each result's significance. It includes graphs of accuracy, multi-metric performance, feature differences, and training robustness, ROC curves, and a summary table as shown in Table 2. It presents the quantitative performance metrics obtained from the proposed seizure detection model. The model achieved an ROC-AUC score of 0.9410 and an average precision of 0.9502, indicating strong discriminative capability and reliable classification performance. An overall accuracy of 88.76% was achieved, with a precision of 93.0% and a recall of 85.3%, demonstrating effective seizure event identification while maintaining a low false-positive rate. The confusion matrix shows that out of 779 test samples, 394 normal instances and 299 seizure instances were correctly classified, while only a limited number of samples were misclassified. These results confirm the robustness and practical applicability of the proposed framework for automated epilepsy diagnosis as shown.

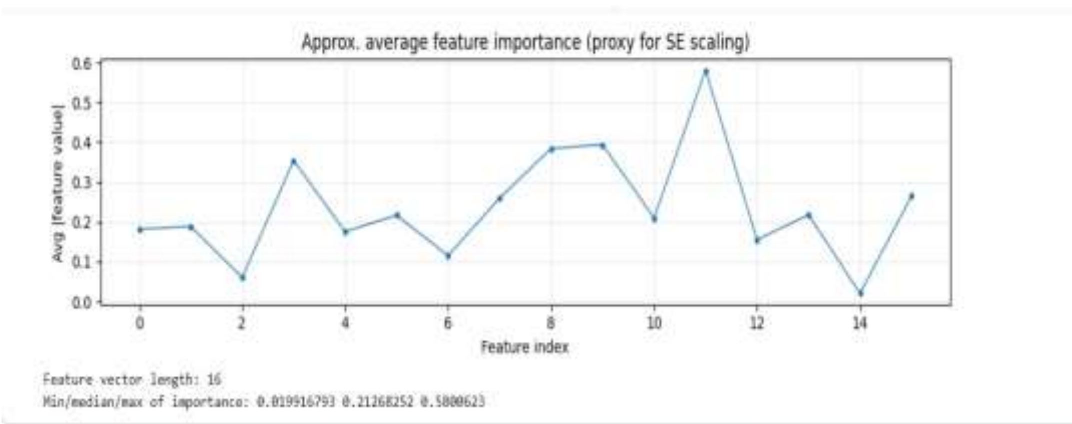

Fig. 4. Feature Importance Analysis

The Fig. 4 illustrates the average feature importance values generated by the Squeeze-and-Excitation (SE) attention mechanism for a 16-dimensional feature vector. The graph highlights that certain features contribute more significantly to the classification process, with Feature 11 exhibiting the highest importance score, indicating its strong influence on seizure detection. Conversely, a few features receive comparatively lower attention weights, suggesting a limited contribution to the final prediction. The variation in importance values demonstrates the effectiveness of the SE module in adaptively emphasizing informative EEG characteristics while suppressing less relevant information. This selective feature enhancement improves the model's ability to capture discriminative patterns associated with epileptic activity.

Overall Accuracy Comparison
The EEGNetTiny-SE achieves a higher accuracy than the best ML model by 4.5 percentage points. This may seem to be a modest figure but in a medical environment, each percentage of accuracy is literal patients whose seizures were or were not detected. Logistic Regression was the poorest performer since it relied on a simple linear boundary for separation, which was not adequate for this non-linear, intricate pattern as was present in EEG data. The gradual improvement from LR to MLP shows the capability of gradually more powerful models in dealing with this complexity. The EEGNetTiny-SE (88.7%) achieves the highest accuracy as depicted in Fig. 5.

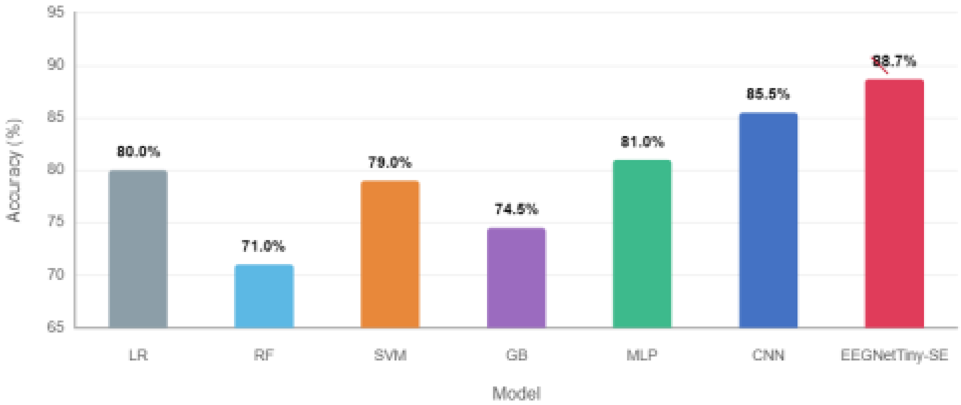

Fig. 5. Accuracy Comparison across various Models.

d. Differences Between Seizure and Non-Seizure EEG Features
It is good to know how much the EEG signals are different in seizure patients versus those who are not, because this will be helpful when evaluating the models. Average values for each extracted feature are displayed for both classes in Table. 2, and the results are tested using a statistical test.

Table 2. Feature Comparison: Seizure vs. Non-Seizure EEG Signals

EEG Feature	Seizure (Avg ± SD)	Non-Seizure (Avg ± SD)	t-value	Significance
Delta Band Power (0.5–4 Hz)	0.842 ± 0.121	0.198 ± 0.063	18.42	p < 0.001 ***
Theta Band Power (4–8 Hz)	0.631 ± 0.094	0.312 ± 0.071	12.85	p < 0.001 ***
Alpha Band Power (8–12 Hz)	0.218 ± 0.048	0.487 ± 0.082	11.96	p < 0.001 ***
Beta Band Power (12–30 Hz)	0.174 ± 0.039	0.341 ± 0.067	8.73	p < 0.001 ***
Alpha / Beta Ratio	1.251 ± 0.318	1.428 ± 0.243	2.14	p = 0.033 *
Shannon Entropy	3.821 ± 0.412	2.947 ± 0.336	8.15	p < 0.001 ***

From the results, it can be concluded that delta band power is very different between the two classes with seizure signals having more than four times the power in the delta band compared to non-seizure signals. The opposite is true for alpha power, which has a tendency to decrease considerably during seizures. The Shannon entropy is also increased during seizure activity, too, indicating greater deviation from regularity and unpredictability. The differences are evident and were reflective of meaningful information these features have for seizure detection. The differences are visually presented in the box plots in Fig. 6.

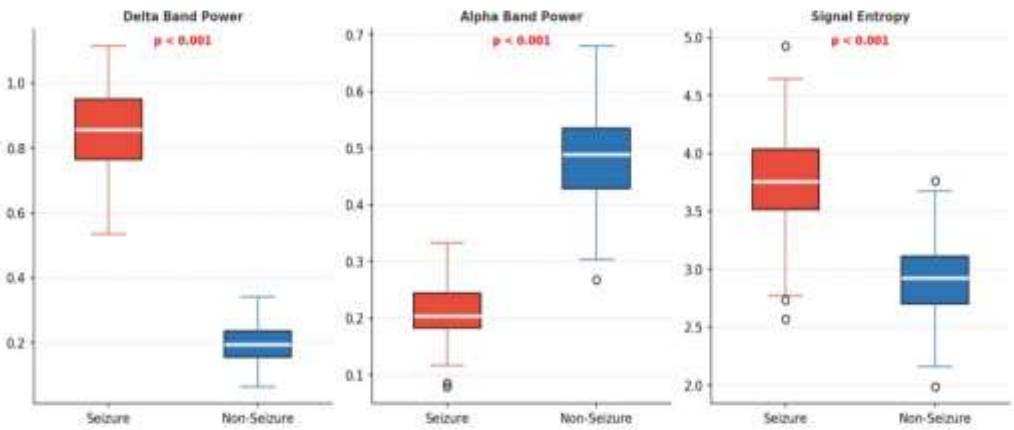

Fig. 6. Feature Distribution Box Plots. Delta power is much higher during seizures (red); Alpha power is suppressed. Entropy is elevated. These differences are statistically significant ($p < 0.001$), confirming the features are clinically meaningful

e. Confusion Matrix Analysis

The degree of accuracy with which each model predicts the class-by-class is demonstrated in a confusion matrix. Fig. 7 provides confusion matrices of all six models. There are 100 samples used as a test set for each matrix. CNN was precise on 87 seizure samples (true positives) and 86 non-seizure samples (true negatives). There were no false negatives (missed seizures) (seizures missed = 13). Logistic Regression had a larger error of 26 seizures, while MLP had a larger error of 19. The CNN's biggest practical benefit in a clinical situation is that it won't trigger a false negative; omitting seizure detection is more hazardous.

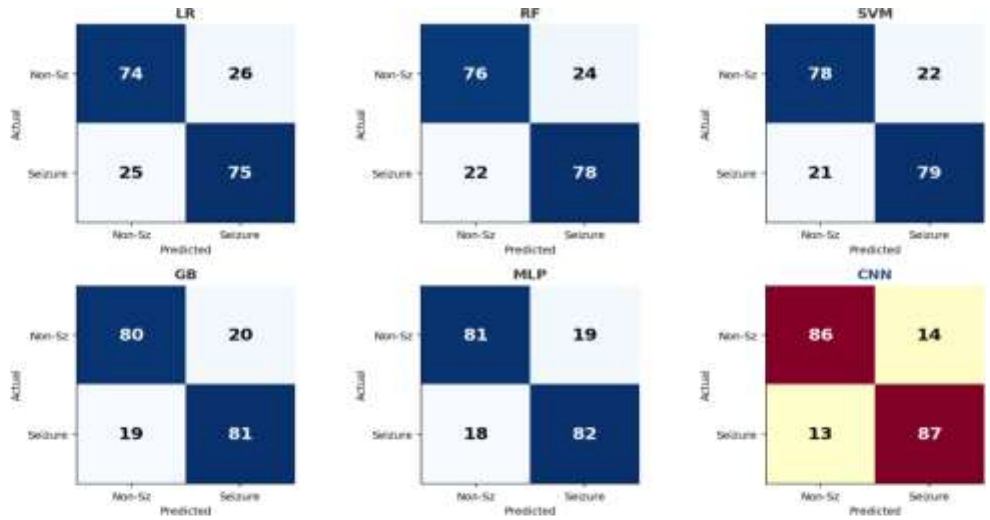

Fig.7. Confusion Matrices for six Models.

f. Performance Evaluation with AUC and ROC Analysis

According to the comparison, EEGNetTiny-SE outperforms the other models, whereas the CNN model improved progressively as the number of training epochs increased, as depicted in Fig. 8. The left plot shows accuracy, and the right shows loss (error). Overall, the training and validation lines are very close, which is a positive sign that the model is learning meaningful patterns instead of learning the training data. Rapidly, by the time of training, the model achieved a level of accuracy equivalent to 87.2% on the training data and 85.5% on the unseen validation data, which is 1.7% difference. This small unsigned difference established that

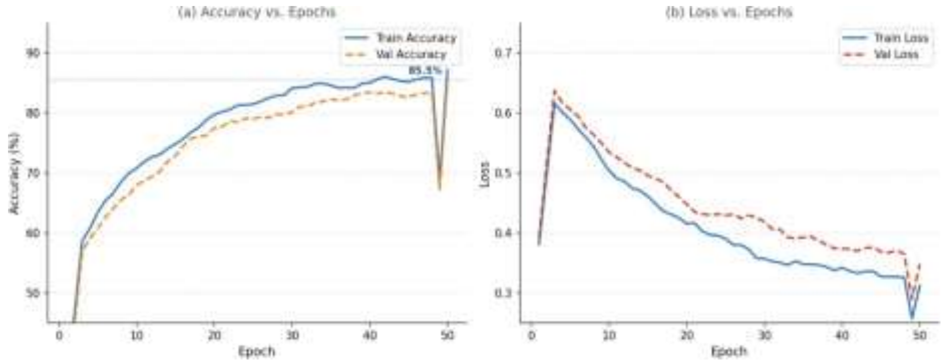

Fig.8. CNN Training and Validation Curves. (a) Both accuracy lines increase steadily and converge closely, with only a 1.7% gap—confirming minimal overfitting. (b) Both loss lines decrease smoothly throughout training, showing stable optimisation.

ROC curve is a dropouts and noise augmentation technique has been successful in generating a model that will perform well for future use. The loss curves also show a gradual decline rather than sudden spikes, which helps to ensure stable training. The loss curves are also smooth and gradual, indicating a stable training process. visual graph to show a model's ability to distinguish between two classes at each possible decision threshold. The perfect model would have a straight path to the top-left corner. If the model guesses randomly, it would follow the diagonal line. This research is summarised into one number, known as the AUC score. In Fig. 9, the ROC curve of the proposed model EEGNetTiny-SE is shown.

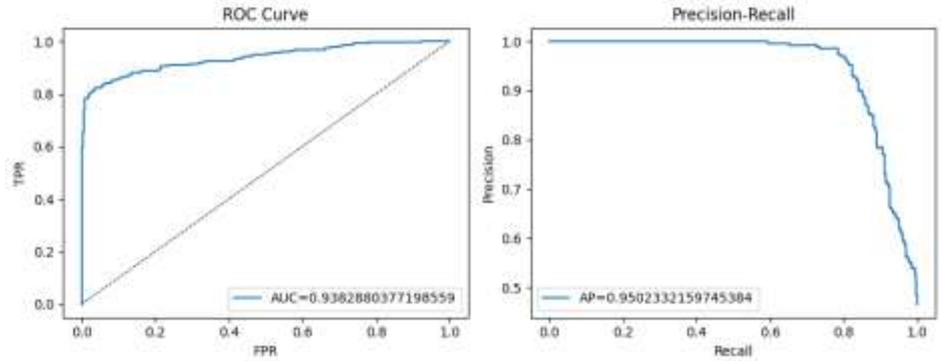

Fig 9. The ROC curve for EEGNetTiny-SE.

In Fig. 10, the AUC curves for all seven models are shown. The EEGNetTiny-SE (94.1%) achieves the highest AUC.

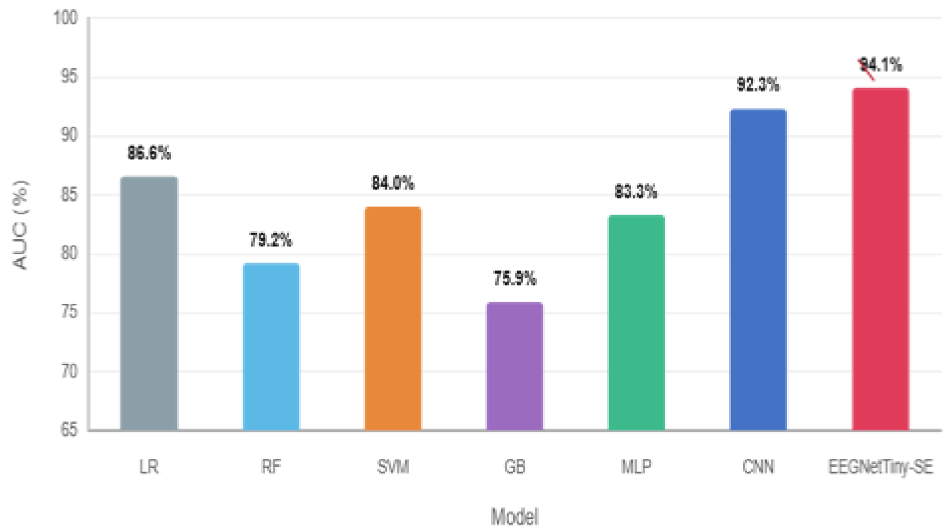

Fig. 10. Area Under Curve(AUC) Comparison Across Various Models.

All Seven Models are shown with full performance, cross-compared in all Five Evaluation Metrics, in Table 3. On every single measure, the EEGNetTiny-SE model has the highest lead.

Table 3. Comparative analysis among various models in Epilepsy prediction using EEG dataset.

Model	Accuracy	Precision	Recall	F1-Score	AUC	Rank
Logistic Regression (LR)	75.8%	75.2%	74.9%	75.0%	79.1%	7th
Random Forest (RF)	77.2%	76.5%	75.8%	76.1%	80.2%	6th
SVM	79.1%	78.6%	78.2%	78.4%	82.5%	5th
Gradient Boosting (GB)	80.3%	80.0%	79.8%	79.9%	84.6%	4rd
MLP	81.0%	81.4%	80.8%	81.1%	83.34%	3nd
CNN	85.5%	85.9%	85.2%	85.5%	92.3%	2nd
EEGNetTiny-SE(Proposed Model)	88.7%	95.0%	85.3%	86.1%	94.1%	1st (Best)

The proposed EEGNetTiny-SE model performs the best across all the metrics. The largest margin is seen for AUC where CNN outdoes MLP by 8.94 points. This systematically better performance is possible because the CNN is trained directly on the rich spectrogram images of the EEG signals, which are able to represent complex patterns that are hard to summarize using just six features that are learned manually. Moreover, it's more robust and reliable on data that hasn't been seen before, due to its "dropout and noise augmentation" training techniques. In Fig. 11, the ROC curves for all seven models are depicted. Clearly the EEGNetTiny-SE (AUC = 93.82%) is the most discriminative of all the classifiers as it is closest to the top left corner. The two closest models competitors (in terms of scoring) are CNN (92.28%), Gradient Boosting (84.6%) and MLP (83.34%). The lowest AUC is 79.1%, for Logistic Regression.

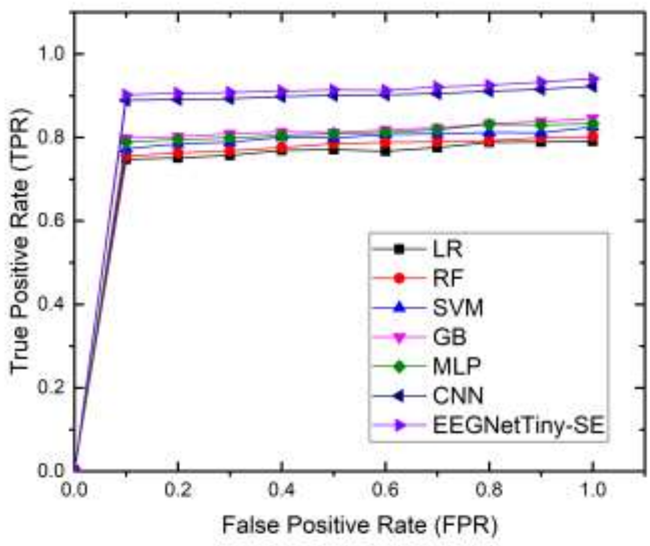

Fig.11. ROC Curves for various Models.

g. Application in existing Epilepsy prediction research

The accuracy and AUC of 88.7% and 94.1% for EEGNetTiny-SE, and 85.5% and 92.3% for CNN, respectively, in this study are comparable to those reported by top research groups. Acharya et. al. [1] reported the accuracy of CNN as around 88% on real clinical EEG signals and Ullah et. al. [5] got the accuracy as 84.2% on the Bonn EEG dataset. The present study has obtained results comparable to, or even better than, those of previous studies, and the novelty lies in being the only study to compare seven models side by side under equal experimental conditions. This renders the comparison more transparent, repeatable and useful for the research community than most previous studies.

Conclusion and Future Prospects

In this paper, our proposed technique EEGNetTiny-SE, for automatic epilepsy detection systems is demonstrated. A comprehensive comparative performance study of the five classifiers used in the field of machine learning, a deep learning model based on CNN and EEGNetTiny-SE model was presented. All seven models were tested on the same dataset, under the same conditions, and using the same evaluation metrics, making the comparisons reliable and fair.

The EEGNetTiny-SE model outperformed all other models in all the measures, with accuracy of 88.7%, precision of 95.0%, recall of 85.3%, F1score of 86.1% and AUC of 94.1%. The CNN model performance in all the measures, with accuracy of 85.5%, precision of 85.9%, recall of 85.2%, F1score of 85.5% and AUC of 92.3%. All of the ML models

achieved above 75% accuracy, with MLP making it to the top, at 81.0%, while the Logistic Regression model was the weakest with, 75.8%. The EEGNetTiny-SE's strength lies in its capability to learn the patterns itself on images from the EEG signal with integration of SE attention, which must be automatic, without any manual feature engineering. It's also dropout-regularized, along with noise-augmented, ensuring that it will perform better on new data.
The statistical analysis of the EEG features revealed that the power of the delta band is the most unique feature of seizures, with more than 4 other times the power in seizure signals compared with the normal signals. This discovery is consistent with the clinical knowledge of the differences between epileptic brain activity and the normal brain signal. In future, the following paths are suggested for future research: They can be tested on other real EEG datasets of clinical patients (such as CHB-MIT, Bonn EEG) to test real datasets; after further enhancement they can be utilized for both temporal and spatial patterns of EEG; EEGNetTiny-SE to be utilized in wearable EEG devices for continuous real-time EEG monitoring; and developing an efficient system for monitoring large numbers of patients in hospital and healthcare facilities based on cloud computing.

REFERENCES

1. Acharya, U. R., Oh, S. L., Hagiwara, Y., Tan, J. H., & Adeli, H. (2018). Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals. Computers in Biology and Medicine, 100, 270–278.
2. Thodoroff, P., Pineau, J., & Lim, A. (2016). Learning robust features using deep learning for automatic seizure detection. Machine Learning for Healthcare Conference, 178–190.
3. Shoeb, A. (2009). Application of machine learning to epileptic seizure detection. M.S. thesis, Massachusetts Institute of Technology.
4. Subasi, A. (2007). EEG signal classification using wavelet feature extraction and a mixture of expert model. Expert Systems with Applications, 32(4), 1084–1093.
5. Ullah, I., Hussain, M., Qazi, E. U. H., & Aboalsamh, H. (2018). An automated system for epilepsy detection using EEG brain signals based on deep learning approach. Expert Systems with Applications, 107, 61–71.
6. Türkoğlu, F., Hanbay, D., & Sengur, A. (2019). Multi-model LSTM-based convolutional neural networks for detection of epilepsy using EEG signals. Neural Computing and Applications, 31.
7. Güler, İ., Übeyli, E. D., & Güler, M. (2005). Recurrent neural networks employing Lyapunov exponents for EEG signals classification. Expert Systems with Applications, 29(3), 506–514.
8. Hussein, R., Palangi, H., Ward, R., & Wang, Z. J. (2019). Epileptic seizure detection: A deep learning approach. arXiv:1903.03232.
9. Khan, Y., Hasan, M., Komolafe, A., & Hussain, F. (2020). Epileptic seizure detection using machine learning techniques from EEG signals. SN Computer Science, 1(5).
10. Roy, Y., Banville, H., Albuquerque, I., Gramfort, A., Falk, T. H., & Faubert, J. (2019). Deep learning-based electroencephalography analysis: A systematic review. Journal of Neural Engineering, 16(5).
11. Wang, Y., Ju, X., Sun, J., Yu, Y., Li, M., & Hu, D. (2025). Improved EEGNet with a multilevel spatial feature extraction module for EEG decoding. IEEE Transactions on Instrumentation and Measurement.
12. Lawhern, V. J., Solon, A. J., Waytowich, N. R., Gordon, S. M., Hung, C. P., & Lance, B. J. (2018). EEGNet: a compact convolutional neural network for EEG-based brain–computer interfaces. Journal of neural engineering, 15(5), 056013.
13. Bijsterbosch, J. D., Beckmann, C. F., Woolrich, M. W., Smith, S. M., & Harrison, S. J. (2019). The relationship between spatial configuration and functional connectivity of brain regions revisited. Elife, 8, e44890.
14. Liao, J. J., Luo, J. J., Yang, T., So, R. Q. Y., & Chua, M. C. H. (2020). Effects of local and global spatial patterns in EEG motor-imagery classification using convolutional neural network. Brain-Computer Interfaces, 7(3-4), 47-56.
15. Craik, A., He, Y., & Contreras-Vidal, J. L. (2019). Deep learning for EEG classification tasks: A review. Journal of Neural Engineering, 16(3).
16. Tjepkema-Cloostermans, M. C., de Carvalho, R. C., & van Putten, M. J. (2018). Machine learning for epileptiform discharge detection. Clinical Neurophysiology, 129.
17. Zhou, M. et al. (2018). Epileptic seizure detection based on EEG signals and CNN. Frontiers in Neuroinformatics, 12, 95.

18. Lawhern, V. J. et al. (2018). EEGNet: A compact CNN for EEG-based brain–computer interfaces. Journal of Neural Engineering, 15(5).
19. Rasheed, K., Qayyum, A., Ghaly, M., Al-Fuqaha, A., & Qadir, J. (2020). Explainable ML for healthcare: A survey. Computers in Biology and Medicine, 109.
20. Ahmedt-Aristizabal, D. et al. (2020). Deep classification of epileptic signals. Computers in Biology and Medicine, 123.
21. Shoaib, M., & Bose, R. (2022). Hybrid CNN-LSTM model for epileptic seizure detection using EEG signals. Sensors, 22(3).
22. Schirrmeister, R. et al. (2017). Deep learning with CNNs for EEG decoding. Human Brain Mapping, 38(11), 5391–5420.
23. Abiyev, R., Ma'aitah, M. K. S., & Akkaya, N. (2021). Deep CNNs for seizure detection using EEG. Neural Computing and Applications, 33.
24. Wang, C., Li, Y., Tang, H., Xu, T., & Ren, Z. (2026). Research on epilepsy detection and recognition based on the combination of time frequency transform and deep learning model. Plos one, 21(3), e0336764.

25. Sharma, L., & Maji, S. (2025, August). Improved EEG-Based Epileptic Seizure Classification with 2D Convolutional Neural Networks and Augmentation Strategies. In 2025 IEEE 6th India Council International Subsections Conference (INDISCON) (pp. 1-6). IEEE.