Mapana – Journal of Sciences
2024, Vol. 23, No. 2, 65-82
ISSN 0975-3303|https://doi.org/10.12723/mjs.69.4

Adaptive Bi-LSTM-based Epileptic Seizure Prediction from EEG Signals Using Deep Learning Algorithm

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Abstract

Millions of people worldwide who suffer from epilepsy are severely impacted by frequent, erratic seizures. Preventing seizures from occurring could greatly enhance patient care and safety. This paper presents an approach to real-time epileptic seizure prediction utilizing a unique kind of neural network known as Bidirectional Long Short-Term Memory (Bi-LSTM). The existing multidimensional CNN deep neural network models have average accuracy for multi-channel EEG data in predicting seizures. The proposed model was selected for its excellent ability to interpret complex seizure patterns from both historical and prospective data. We took advantage of a big dataset of real-time EEG recordings of brain activity. The testing yielded the results with the approach of 98% accuracy in predicting seizures. Using the Bi-LSTM model in real-time systems has shown that it can make precise predictions quickly, offering hope for improving the lives of those with epilepsy.

Keywords – Epileptic seizure, Bi-LSTM, Electroencephalogram (EEG), convolutional neural network (CNN)

1. Introduction

Millions of people worldwide suffer from epilepsy, a neurological condition that is chronic and severely interferes with daily life. Epilepsy, which is characterized by repeated, erratic seizures, can

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cause a variety of practical, psychological, and social challenges. The ability to predict seizures in advance holds considerable promise for enhancing patient care and safety. In this regard, we offer a ground-breaking study that focuses on the creation of an epileptic seizure prediction system that is accurate and dependable using advanced deep learning algorithms.

The main goal of this study is to improve epileptic seizure prediction through the use of Bi-LSTM techniques. We intend to extract meaningful features and create a model capable of identifying modest pre-seizure patterns by utilizing a broad dataset made up of multi-modal physiological signals, such as electroencephalogram (EEG), electrocardiogram (ECG), and accelerometry data. The ultimate objective is to develop a reliable and effective tool that may be incorporated into monitoring systems or wearable technology, enabling prompt interventions and enhancing the general quality of life for people with epilepsy.

The research relies heavily on the usage of a Bidirectional Long Short-Term Memory (Bi-LSTM) neural network model. The use of the Bi-LSTM architecture is made possible by its exceptional capacity to capture both forward and backward temporal dependencies in time-series data, a vital component in simulating the intricate patterns connected to epileptic episodes. We extract and normalize pertinent characteristics from the EEG signals using exact preprocessing approaches. The data must be prepared in this step in order for the Bi-LSTM model to be trained later.

An extensive training process is applied to the Bi-LSTM model using a portion of the preprocessed data. To effectively understand and reflect the underlying patterns suggestive of an imminent seizure, the model's parameters must be optimized during the training process. The model's performance is further assessed using a thoroughly thought-out cross-validation scheme, assuring its resilience and generalizability. The outcomes of our studies show an astounding accuracy of 98% in anticipating epileptic episodes, which is very positive. This outstanding performance highlights the effectiveness of the suggested strategy and establishes it as a major development in the field of epilepsy therapy.

1. Related Work

Xiaojun Cao (2022) reports in paper [1] that the multidimensional deep network model's average accuracy for multi-channel EEG data is approximately 94%.Larger and more varied EEG datasets may be obtained and incorporated into future research to further validate the suggested approach across a range of patient groups and recording circumstances. A 99.47 percent classification accuracy is achieved on average by Ranjan Jana (2021) in paper [2]. The ultimate goal should be to develop a seizure prediction technique that is patient-independent and effective for all epilepsy patients in the future.

Ahmed M. Abdelhameed (2021) reported an average sensitivity of 94.45% in paper [3]. Predictions could be made even more precisely and consistently by broadening the dataset to cover a wider variety of patients and improving the system's patient-specific features.

Manhua Jia1. (2022) reports in paper [4] that the model's average AUC is 0.92. Provide a real-time monitoring system that is capable of analyzing EEG data constantly and acting quickly to intervene or issue notifications when a seizure is anticipated.

According to Abhijeet Bhattacharya's study [5] from 2021, the network achieved an average sensitivity of 97.746% and a false positive rate (FPR) of 0.2373 per hour. Subsequent research endeavors may entail the integration of heterogeneous EEG datasets acquired from different patient populations. This would assist in evaluating the generalizability and robustness of the model.

Ziwei Tian (2023) reports in paper [6] that utilizing CNN's transition histogram to predict epileptic seizures from EEG signals results in 99.1% accuracy. In order to close a significant gap in portable and practical seizure classification methods, an effective and highly accurate feature extraction method for epilepsy detection from EEG signals is needed. This method is ideal for wearable medical devices with limited resources.

Mrutyunjaya Sahani et al. (2021) report in paper [7] that the accuracy achieved using RDCNN is 97.26%. Using both multichannel and single-channel EEG inputs, the integration of RDCSAE and KRVFLN for epileptic seizure recognition provides increased accuracy, computational efficiency, and model generalization.

Banu Priya Prathaban mentions that SVD creates a better accuracy of 98.% in the paper [8]. The investigation of further optimization or adaptation options for real-time application of these advanced dimensionality reduction techniques (SPPCA & SUBXPCA), taking into account pragmatic limitations and any difficulties that might occur when applying the suggested approach in a clinical context.

An article [9] by S. Raghu et al. (2019) reported that the results showed that the sigmoid entropy value was lower for epileptic activity as compared to normal EEG. In order to address issues like handling noisy data and improving its dependability for realistic clinical deployment, this study aims to explore the model's adaptability to various seizure types and its potential integration with real-time monitoring systems.

Asmaa Hamad et al. (2018) show how to improve accuracy using the Grasshopper Optimization Algorithm and SVM in paper [10].To investigate how well the model performs in cases that are noisy or unclear, as well as how well it can be used in real-time, in order to guarantee accurate and useful seizure detection in a larger variety of clinical circumstances.

This research [11] by Zheng Zhang et al. describes a proposed one-step semi-supervised seizure detection method using recorded EEG signals (2019). This might occur when using the suggested semi-supervised strategy to analyze EEG data gathered from patient groups with varying demographics and when creating strategies to minimize any possible biases without sacrificing effectiveness.

In a work published in 2021, Youghua Yang et al. show an average specificity of 92% and an average detection sensitivity of 88% for all patients [12]. In order to improve the system's resilience and reliability in real-time seizure detection settings, more research is required to comprehend the system's performance constraints and potential causes of false positives/negatives.

Using data-driven linear-phase finite impulse response filters as pre-processors, Kosuke Fukumori et al. (2022) present a novel neural network strategy for automated EEG diagnoses in epilepsy paper [13]. To examine the effects of alternative passbands and filter topologies on the neural network's performance, addressing the trade-offs between sensitivity and specificity for diverse types of seizures other than spike waves.

According to the results, the recommended approach produces high recognition accuracies of 99.39% & 82.00%, as stated in the publication [14] by Gaowei Xu et al. (2020). Testing the robustness and generalizability of the suggested 1D CNN-LSTM model using a wider variety of EEG datasets, such as information gathered from different clinical settings and patient demographics.

Cao Xiao et al. (2021) discuss a two-level feature extraction strategy and patient-specific pattern libraries in paper [15]. Using several adaptive prediction approaches across 10 epileptic patients, the researchers achieved significant prediction accuracy of 79-82%. To enhance the practical value of the approach and its possible inclusion into epilepsy management regimens, it would be beneficial to validate its reliability, sensitivity, and specificity during prolonged monitoring periods.

Using deep learning techniques, the current study [16] suggests a seizure prediction system. This approach entails preprocessing scalp EEG inputs, automated feature extraction via convolution neural networks, and vector machine-assisted categorization. After using the suggested approach on 24 participants from the CHBMIT scalp EEG dataset, an average sensitivity and specificity of 92.7% and 90.8%, respectively, were effectively attained.

Using data from several subjects, [17] we propose two patient-independent deep learning architectures with distinct learning algorithms that can learn a global function. End Results: On the CHB-MIT-EEG dataset, the suggested models perform at the cutting edge for seizure prediction, with accuracy levels of 88.81% and 91.54%, respectively.

In this paper [18], employing a convolutional neural network (CNN), we present an end-to-end deep learning solution. In the max-pooling and early-stage convolution layers, one- and two-dimensional kernels are used, respectively. Kaggle intracranial and CHB-MIT scalp EEG datasets are used to assess the proposed CNN model.

In this paper [19], we present an accurate deep learning-based IoT platform for epileptic seizure prediction. The suggested method applies raw EEG signals without any preprocessing, hence reducing computation complexity by combining the feature extraction and classification phases into a single integrated system. In order to extract significant spatio-temporal information from the non-stationary and nonlinear EEG data, we created a model based on Convolutional Neural Networks (CNNs).

In this research [20], we propose the Binary Single-dimensional Convolutional Neural Network (BSDCNN), a hardware-friendly network designed for epileptic seizure prediction. 1D convolutional kernels are used by BSDCNN to enhance prediction performance. With the exception of the first layer, all parameters are binarized to minimize the amount of processing and storage needed.

The main conclusions of the literature review are outlined in this part, along with the unmet research needs. By contrasting CNN and Bi-LSTM algorithms and using texture, shape, and intensity-based characteristics to predict epileptic seizures, it draws attention to the significance of the suggested method as well as some of its distinctive qualities.

2. Methodology

a. Dataset Description.

A collection of data that a deep learning system uses as input is called an input data set. The function loads the "Epileptic Seizure Detection.csv" dataset. There are 180 attributes altogether and 11501 rows in the data collection. 80/20 train and test sets are formed when the dataset is divided into its characteristics and target. The UCI and Kaggle sources provided the data set.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
11480	X3.V1.554	452	470	401	291	163	83	20	-32	-61	-83	-98	-109	-111	-115	-112	-105	-93	-86	-74
11481	X16.V1.35	62	68	75	75	75	77	81	85	82	81	77	72	71	70	69	63	60	55	53
11482	X13.V1.26	26	33	31	26	31	40	49	61	61	41	12	-1	-1	10	24	36	45	35	23
11483	X8.V1.444	-86	-101	-115	-129	-139	-147	-154	-159	-165	-170	-178	-173	-161	-142	-134	-139	-158	-177	-189
11484	X8.V1.904	-121	4	104	185	269	352	405	421	392	369	348	346	364	405	477	548	582	575	551
11485	X1.V1.902	7	30	16	10	17	23	42	31	34	39	35	35	43	40	36	17	-2	10	70
11486	X13.V1.58	-18	-12	-5	-4	-3	-9	-16	-27	-35	-49	-62	-71	-82	-90	-94	-94	-85	-67	-51
11487	X7.V1.81	-27	-8	-22	-48	-75	-99	-109	-105	-99	-82	-55	-54	-54	-56	-44	-37	-39	-38	-33
11488	X15.V1.60	7	-28	-46	-45	-31	2	17	12	-2	-34	-73	-106	-101	-85	-78	-53	-15	-1	-7
11489	X17.V1.87	98	107	121	143	166	184	185	174	153	132	120	112	87	28	-50	-113	-141	-124	-96
11490	X20.V1.49	267	409	450	416	334	248	173	113	67	30	0	-22	-50	-75	-107	-121	-132	-126	-131
11491	X7.V1.51	90	83	69	41	31	40	58	75	82	79	55	29	19	16	6	-5	-21	-42	-43
11492	X14.V1.40	-22	-64	-121	-201	-292	-336	-398	-527	-773	-1069	-1219	-1186	-941	-661	-420	-254	-153	-96	-94
11493	X20.V1.88	102	137	158	158	128	92	60	56	63	63	77	75	74	68	57	52	43	40	47
11494	X13.V1.62	-27	-53	-84	-104	-131	-171	-199	-203	-177	-142	-111	-105	-102	-90	-67	-36	-8	2	4
11495	X23.V1.71	-136	-137	-138	-135	-130	-123	-116	-118	-119	-119	-115	-111	-106	-97	-91	-98	-105	-108	-108
11496	X21.V1.76	-39	-16	-13	-14	-68	-84	-92	-61	-89	-86	-86	-59	-11	-22	-39	-95	-139	-153	-135
11497	X22.V1.11	-22	-22	-23	-26	-36	-42	-45	-42	-45	-49	-57	-64	-73	-79	-76	-70	-63	-57	-57
11498	X19.V1.35	-47	-11	28	77	141	211	246	240	193	136	78	8	-66	-132	-180	-210	-227	-225	-212
11499	X8.V1.28	14	6	-13	-16	10	26	27	-9	4	14	-1	-10	14	44	77	61	42	32	29
11500	X10.V1.93	-40	-25	-9	-12	-2	12	7	19	22	29	22	6	1	-28	-37	-35	-35	-45	-64
11501	X16.V1.21	29	41	57	72	74	62	54	43	31	23	13	11	-3	-5	-9	-14	1	27	60
11502																				

Fig. 1 Epileptic Seizure dataset

b. Proposed System

The suggested study approach is creating an all-inclusive seizure detection system. The CNN and Bi-LSTM algorithms are both used by the system.

The first step was to compile a large dataset of physiological signals from people with epilepsy, including EEG data. To ensure representation across all seizure types and patient demographics, this dataset underwent careful curation. In order to extract useful features from these multi-modal inputs, preprocessing was essential. To improve the model's capacity to recognize minor pre-seizure patterns, signal normalization and feature extraction approaches were used.

The capacity of the Bi-LSTM design, a kind of recurrent neural network (RNN), to detect temporal dependencies in sequential data was a deciding factor in its selection. The Bi-LSTM's ability to examine sequences in both forward and backward orientations, in particular, allows for a more thorough comprehension of the underlying patterns. This is especially helpful when replicating the intricate and dynamic character of epileptic convulsions.

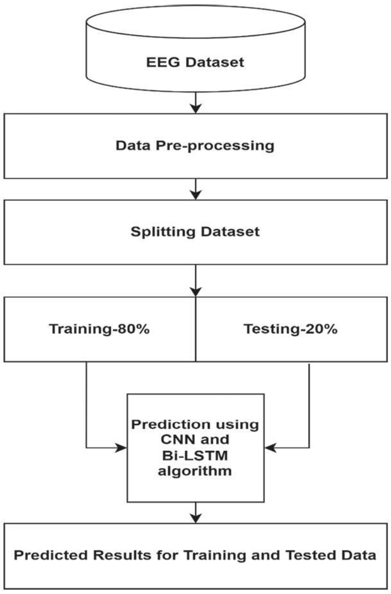

Fig.2 Proposed System Work Flow

The initial step in Figure 2 is data pre-processing. The data is then divided into train and test sets. Two algorithms are used to train the model: CNN and Bi-LSTM. When calculating accuracy, the optimal method is applied to get the desired outcome after calculating accuracy for both algorithms.

b. Dataset Pre-Processing

Checking for missing values in the dataset completes the preprocessing stage, however, the provided code sample has a small syntax issue (data.isnull.sum() should be fixed to data.isnull().sum()). This extensive preparation guarantees that the dataset is clean of missing values and formatted correctly, preparing it for further analysis and modeling.

i. Data Cleaning: Standardizing the representation of missing data in datasets requires replacing “NA” values with “NaN” through data replacement techniques. This guarantees data handling consistency and interoperability with different analysis libraries. Mathematical errors can be prevented by changing “NA” to “NaN,” and deep learning models perform better when missing values are handled correctly. Preprocessing is essential in general for preserving data integrity and enabling precise modeling and analysis.

ii. Data Imputation: To improve data handling, the code uses a data replacement technique, replacing "NA" values with "NaN". This is crucial because computations or the process of fitting models can be hampered by missing values. Potential mistakes are reduced by guaranteeing homogeneity through this substitution, resulting in smoother analyses and more dependable modeling outputs.

iii. Splitting the data set: A foundational framework for predictive modeling is established by the code by splitting the dataset into features and target variables. This separation makes it easier to discover underlying linkages by identifying input features that affect the target variable. The model may identify patterns and generate precise predictions by using features to represent input data and the target variable to indicate the desired result. This critical stage defines the input-output relationship in the data, laying the foundation for efficient deep-learning algorithms.

iv. Creating test and train sets from the dataset: To assess the performance of the model, test and train sets must be created from the dataset. While the training set is utilized for model training, the test set functions as an impartial dataset to evaluate how effectively the model generalizes to new data. This separation allows the model to learn from one set and assess its performance on another, which helps prevent overfitting. This stage directs additional refining and offers insightful information about the model's efficacy by mimicking real-world circumstances.

v. Load Training Data and Validation: Data using the mean of the appropriate column to fill in any missing values, the software loads a dataset of epileptic seizures. Following the division of the dataset into training and testing sets, the CNN and Bi-LSTM classification models are trained and compared, and the accuracy of each model is plotted using StandardScaler. Using Matplotlib, the code also displays the two models' accuracy.

4. Modelling

a. Convolutional Neural Networks (CNNs)

CNNs are powerful for extracting spatial features from structured data like images. In the context of epileptic seizure prediction, we apply CNNs to process electroencephalogram (EEG) data. The CNN layers are responsible for learning spatial patterns and identifying distinctive features in EEG signals that are indicative of pre-seizure states.

Data preprocessing involves noise removal and segmentation, leading to the extraction of relevant features. The CNN architecture is specifically designed for multi-channel EEG data, allowing the model to automatically learn discriminative patterns. Using labeled datasets, optimization algorithms are used to fine-tune the model's weights and biases. Real-time prediction capabilities are achieved by monitoring incoming EEG data and triggering alerts based on the CNN's predictions.

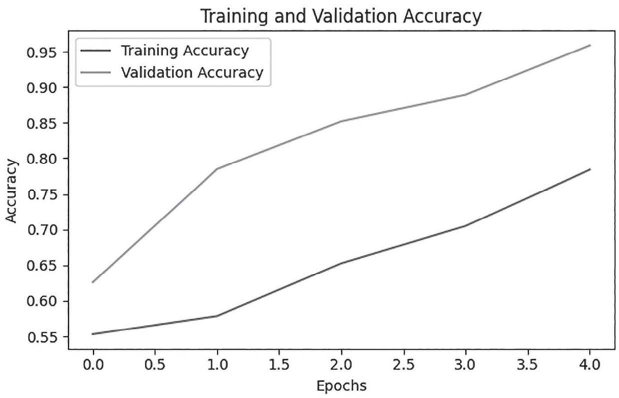

Fig.3 Representation of CNN's Accuracy

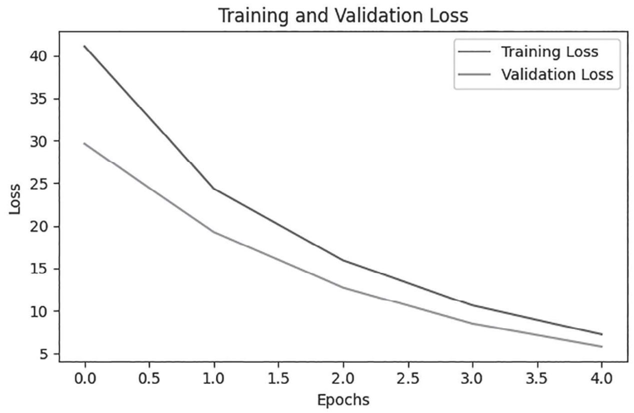

Fig.4 Representation of CNN's Loss

b. Bidirectional Long Short-Term Memory (Bi-LSTM)

Bi-LSTM networks are well-suited for modeling temporal dependencies in sequential data. In this case, we utilize the Bi-LSTM to capture the temporal dynamics of EEG signals. By processing data bi-directionally, the Bi-LSTM effectively captures long-term dependencies and contextual information crucial for predicting epileptic seizures. The below steps state the working of BiLSTM in predicting seizure attacks,

Step 1: In the input layer, the input is pre-processed with an EEG dataset from Epileptic Seizure Detection.csv.

Step 2: The BiLSTM layers are added, and each layer will consist of a forward LSTM and a backward LSTM, allowing the network to understand temporal dependencies in both directions.

Step 3: The dense layer is fully connected to interpret the features learned by BiLSTM layers.

Step 4: Finally, the output layer makes the binary classification of whether the seizure occurs or not.

The CNN component processes the EEG data to extract spatial features, which are then fed into the Bi-LSTM network as sequential input. This integration allows the model to benefit from both spatial and temporal information. The combined features are then passed through fully connected layers for final prediction.

During training, the model parameters are optimized jointly using backpropagation. The loss function is chosen to be suitable for the binary classification task (seizure or non-seizure). The optimizer adjusts the weights to minimize the classification error.

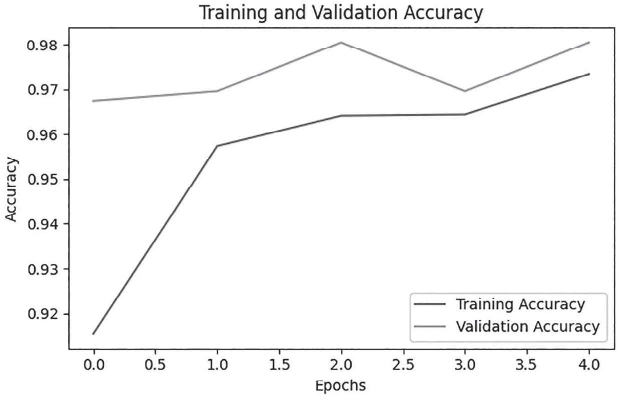

Fig.5 Representation of Bi-LSTM's Accuracy

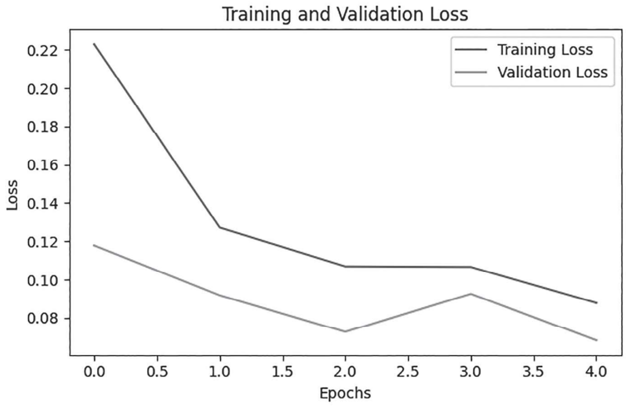

Fig.6 Representation of Bi-LSTM's Loss

5. Performance Analysis

When a classifier's performance is analyzed, its accuracy is usually assessed in relation to the demands and particular tasks. An outline of these performance metrics is provided below:

a. Accuracy: The classifier's overall prediction accuracy is ascertained by calculating the ratio of successfully classified cases to all instances.

Accuracy = (TP + TN) / (TP + FP + FN + TN)

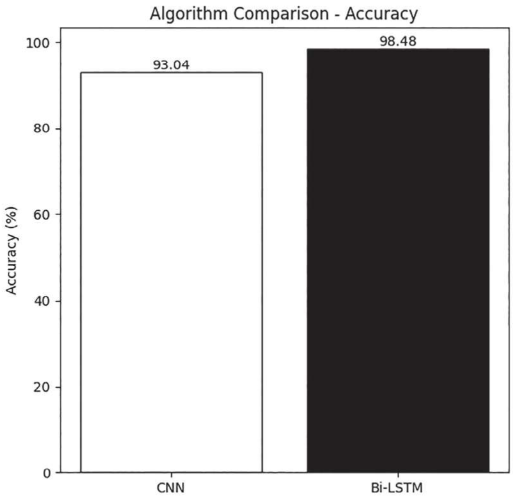

Fig.7 Accuracy Score

b. Precision: True positives, or the percentage of all expected positive cases that are correctly predicted to be positive, are known as precision cases. Its primary goal is to assess how well optimistic forecasts work and how well the classifier can weed out false positives.

Precision=TP/ (TP+FP)

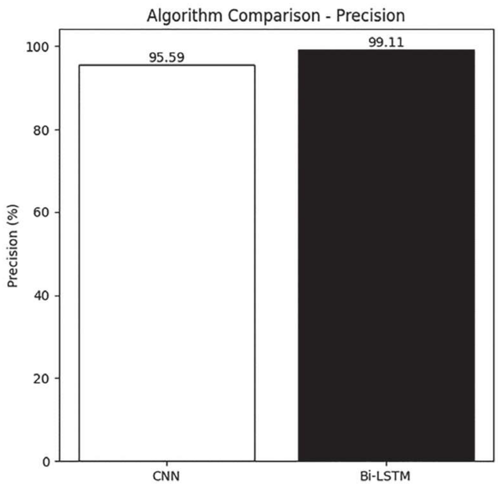

Fig.8 Precision Comparison

c. Recall: Recall is the ratio of all actual positive instances to all accurately predicted positive events. On rare occasions, it is also referred to as the true positive rate or sensitivity. It evaluates the classifier's inclination to recognize positive examples and avoid false negatives.

Recall=TP/ (TP+FN)

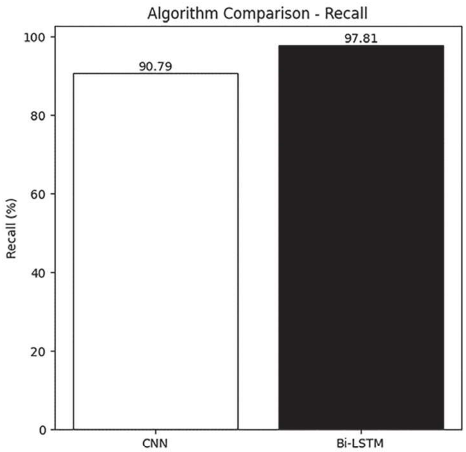

Fig.9 Recall Comparison

d. F1Score: The F1 score provides a single statistic that balances recall and precision because it is the harmonic mean of these two criteria. It is particularly helpful when recall and precision are equally significant or when the class distribution is asymmetrical.

F1-score=2*(recall*precision)/ (recall+precision)

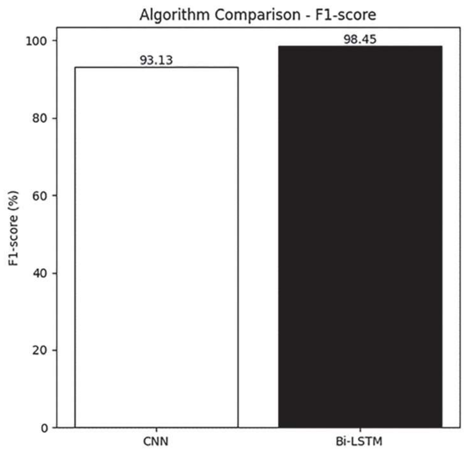

Fig.10 F1-score Comparison

6. Results And Discussion

Model	CNN	Bi-LSTM
Accuracy	93.04%	98.48%
Precision	95.59%	99.11%
Recall	90.79%	97.81%
F1-Score	93.13%	98.45%
Sensitivity	90.79%	97.81%
Specificity	95.48%	99.14%

Table 1 Comparison of 2 Classifiers

Both CNN and Bi-LSTM classification models are trained and evaluated using the accuracy score. At the end are graphs showing the accuracy of the two models.

The performance comparison between CNN and Bi-LSTM is displayed in Table 1 above. Using two popular categorization models, the software provides a straightforward implementation of model evaluation and data pre-processing. It is possible to enhance the code to incorporate more complex pre-processing procedures.

7. Conclusion and Future Work

With an outstanding accuracy rate of 98%, the trial showed great potential in anticipating epileptic episodes. With respect to the field's current methods, this high sensitivity and low false alarm rate represent a major improvement. The enhanced performance of the model is ascribed to the implementation of a new technique that utilizes the Bidirectional Long Short-Term Memory (Bi-LSTM) algorithm in combination with multi-modal physiological information. With its more accurate and dependable prognostic tool, this novel strategy marks a significant leap in the treatment of epilepsy.

The model's success creates additional research opportunities. Increasing the model's resilience and predictive power could be achieved by further refining its architecture. In order to increase the model's generalizability and accuracy across a variety of patient populations, it is imperative to expand the datasets utilized for training and validation.

Furthermore, this predictive model's integration with wearable technology has the potential to completely transform ongoing monitoring and assistance for epileptic patients. Real-time data from wearable technology can power the model, enabling it to run constantly and quickly notify patients or caregivers of oncoming seizures. With this integration, the model's usefulness as a management tool for epilepsy would be improved in routine clinical settings.

The ultimate goal of these projects is to improve seizure prediction systems' clinical contexts' usability and effectiveness. By concentrating on improving the model, growing the datasets, and incorporating wearable technologies in real time, scientists and medical professionals can endeavor to offer more dependable and efficient assistance to people with epilepsy. This development signifies a noteworthy advancement in enhancing the standard of living for those impacted by this illness.

Declaration of Conflicting Interests:

The authors hereby declare no potential conflicts of interest with respect to the research, funding, authorship, and/or publication of this article.

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