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Comparative Analysis of Deep Learning Models for the Detection of Epileptic Seizure

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Abstract--Electroencephalogram (EEG) is used to detect epilepsy, a common neurological disorder. Neurologists visually examine EEG results to make the diagnosis. Researchers have suggested automated technologies to diagnose the seizure because traditional method are lengthy and there is a dearth of professionals everywhere. The common symptoms of seizures, which are characterized by aberrant brain activity brought on by an epileptic disease, include bewilderment, loss of awareness, and strange behaviour. Sometimes it becomes very difficult to identify the seizure in persons. So, for determining seizures there are many deep learning models have been designed. Among those, three models have been chosen and compared in this paper. These three models are, Convolutional neural network-long short-term memory (CNN-LSTM), convolutional neural network-recurrent neural network (CNN-RNN), and convolutional neural network-gated recurrent unit (CNN-GRU) whose comparison study have been discussed in this paper by using three different types of optimizers, namely Rmsprop, Adam, and Nadam. After that the result of deep learning models have been compared with some previous machine learning work for the detection of epileptic seizure. Mainly three parameters such as accuracy, sensitivity and specificityof the models are found and compared to predict which model as well as which optimizer among Rmsprop, Adam and Nadam is best. For efficient removal of the features from an EEG sequence data, one dimensional convolutional neural network (CNN) is created. For further extraction of temporal characteristics, the features extracted are processed by the CNN-LSTM model's LSTM layers, CNN-RNN model's RNN layers, and CNN-GRU model's GRU layers. The last epileptic seizure recognition step involves feeding the output characteristics into a number of fully connected layers. I

Index Terms-- Convolutional neural network (CNN), Electroencephalogram (EEG), Epileptic Seizure, Gated Recurrent Unit (GRU), Long Short-term Memory (LSTM), Recurrent Neural Network (RNN).

I. INTRODUCTION

ACCORDING to World Health Organization (WHO) statistics, epileptic seizures are one of the most prevalent brain illnesses, affecting more than 50 million individuals globally [1],[2]. Epilepsy is a brain disease which is caused by occurrence of unwanted number of seizures in the brain. The brain activity that results in epilepsy causes symptoms likebewilderment, lack of awareness, jerky, erratic movements, and many others. Patients who are suffering from epilepsy experience are also affectedby negativeeffectson both physical as well as mental health, and in very severe cases, their lives may even be in danger. It is very difficult to anticipate when somebody could experience a seizure. Most epileptic episodes occur suddenly. and therefore, it becomes difficult for experts to figure out how to predict one before it happens. As a result, it is crucial and necessary to offer timely protective measures to those who have epilepsy for betterment of their quality of life.

Deep learning techniques have been adopted significantly in recent years and is now utilized extensively across many industries, particularly in the analysis of images and natural language [3]. Convolutional neural network(CNN) is famous among all deep learning models, because they can extract a variety of characteristics by applying different number of filters and neurons in the convolutional, pooling, normalizing, and fully connected layers, which boost the effect of diverse tasks [4]. But CNN is unable to remember past time series patterns, which makes it difficult for CNN to immediately identify the most important and representative characteristics from time series of EEG data directly. As a result, CNN has trouble to establish a precise correlation between the raw EEG data and the outcomes of the seizure detection.In this paper the data set is pre-processed already by a University of California Irvine machine learning repository (UCI) [5],[6].This paper mainly discusses about the three model CNN-LSTM, CNN-RNN and CNN-GRU which are used for detecting epileptic seizure and tried to find which model is best among three. The rest paper is divided into following sections Literature Review, Dataset Information, Work Done, Comparison Result and Conclusion.

II. LITERATURE REVIEW

J. S.Kumaret al., 2012, [7], presented a paper showing analysis of EEG signal and its categorization. This paper

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mainly discusses about what is EEG and how EEG helps in measuring the different kind of signals in brain. From this paper it is known that there are mainly five kind of brain signals with different frequency range i.e., delta having frequency range between 0 to 4 Hz, theta having frequency range between 4 to 8 Hz, alpha with 8 to 13 Hz, beta with 13 to 30Hz and gamma with 30 to 100 Hz. EEG device comprised of electrodes, conductive gel, amplifier and analog to digital converter. The electrodes arranged here are by the10-20electrode placement technique.

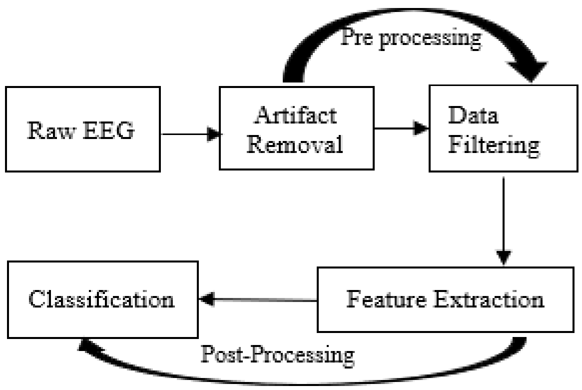

Fig. 1. Processing Stages of EEG Signals

For the analysis of EEG signal firstly raw signal from the scalp of the brain collected then preprocessing will take place and after that post processing will take place [7].

J. Fiaidhiet al.,2020, [8], presented a paper showingbinary classification methods employing brain signals using machine learning. In this UCI Machine Learning Repository dataset is used which comprises of five class. So, for binary classification 5 classes is convertedbetween two classes such as the seizure and non-seizure classes. But after converting into two class the dataset is unbalanced means they are having 80% non seizure data and 20% seizure data. For balancing the data sub sampling technique. After sub-sampling balanced data achived and by using balanced data feature extraction is done directly as the data set is already a pre processed data. After that five basic classifier used i.e.,Random Forest, K-nearest neighbor(KNN), Gradient boosting, Support vector machine(SVM) and Extra trees classifier have been used for the classification purpose. For comparing the classification result of these five machine learning techniques parameter such as accuracy, specificity, precision and recall was used. Among the five classifier Extra tree and SVM classifier are best [8].

W. Mardiniet al.,2020, [9], presented a paper showing improved EEG signal seizure detection for epileptic seizures in combinationwith machine learning classifier. In this paper Bonn data set is used which include five set data with173.6 Hz sampling frequency. The data set is not pre-processed so firstly data set pre-processed using band pass filter. After pre-processing feature extraction taken place. This paper mainly proposed a framework using 54 Discrete wavelet transformsmotherwavelet examining the EEG signalutilising a genetic algorithm in conjunction with 4 machine learning classifiers, namely support vector machine, K-nearest neighbour, Artificial neural network, and Naive Bayes. After classificiation accuracy, sensitivity, and specificity were calculated and compared to see which of these four classifiers was the best. After the classification it was found that Artificial neural network classifier was best. In this paper total 11 features were considered which include mean, average power, standard deviation, variance, mean absolute value, skewness, entropy, maximum, minimum, normalized SD and energy. Forextracting the fearure DWT was used. After feature extraction feature accuracy was calculated then genetic algorithm was applied on all the extracted features [9].

A. Rahmanet al., 2021, [10], presented a paper showingmachine learning techniques with hyperparameter optimisationare used to identify epileptic seizures from EEG signal data. This work also used the UCI Machine Learning Repository dataset. Here thedatset is preprocessed but for binary classification label encoding performed along with that scaling of the the inputs were performed by the help of standard scaler. In this paper no particular features extracted instead it considered all the features. Training and testing data are used in the ratio of 75:25. Finally classification was done using some machine learning technique such as Gaussian naïve bayes, K-nearest neighbour (KNN), ADA boost, Support vector machine(SVM), Gradient boosting, Multilayer perceptron and XGboost. After the calssification from these machine learning techniques. Then confusion matrix for this classifier were found and with the help of that performance parameter that is accuracy, precision, sensitivity, specificity were found. In this paper once again after hyperparameter tunning classificationwas performed and performance parameter were found then finally performance parameter were compared before tuning and after tunning. And finally, they have concluded that after hyperparameter tunning SVM performs better than all other machnie learning techniques [10].

From all the above paper it might be therefore said that machine learning models have some major disadvantages such as in machine learning model's person need to specify that what shorts of features need to be extracted particularly or it will consider all the features for classification but in case of deep learning models it will extract only those features that will be suitable for classification. Other than this in machine learning for better result they required balanced data that means if binary classification is performed then both the cases should have equal number of data.

III.DATASET DESCRIBITION

The data set taken in the model is taken from UCI machine learning repository [5],[6]. Total dataset of 500 persons is available. Each person has 23 seconds of recorded data where each second consists of 178 samples representing a row. So total number of rows=23×500=11500. And total number of

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columns is 179 in which 178 columns consist of data and last column consists of label y, which represents five numbers from 1 to 5, which represent five different following classes:

1- data recorded from the seizure activity
2- data recorded from the area where tumour was located
3- data recorded from non-tumour area
4- data collected when the eyes were closed
5- data collected when the eyes were opened

To show a model detecting epileptic seizure for binary classification, we have changed the five classes into two classes seizure and non-seizure, where 1 represent the data from seizure class and rest 4 cases considered as data taken from normal class and represented by 0. So that the model finally has to classify 0 and 1.

IV. WORK DONE

In this paper three models CNN-LSTM, CNN-RNN, CNN-GRU considered to be able to detectthe epileptic seizures. CNN is made up of three layers i.e., convolutional layer, pooling layer and fully connected layer, which is also known as dense layer. Convolutional layer creates a feature map using a filter, which is also known as kernel [11].RNN stands for recurrent neural network. It is mainly used in collecting past information in time scale which helps in performing temporal task quite well. It is also very useful in handling temporal sequence of arbitrary length.Long short-term memory is referred to as LSTM.This is a more sophisticated RNN. In general, RNN gradient approaches to zero, but in some cases, it may become very large and get overflowed. Hence to reduce that problem LSTM is used which includes memory blocks to get rid of the mentioned problems [12].GRU stands for gated recurrent unit which is the LSTM in a modified form [2]. It is very useful and gives accurate result for small datasets. The cost of computing for the third model is less as compared to previous two models.Each model uses three optimizer one at a time i.e., Rmsprop, Adam, Nadam and finds which optimizer gives the best result. After that all three models CNN-LSTM, CNN-RNN and CNN-GRU are compared with each other and the best among them is considered. All the three models consist of one input layer with input value 178×1, four convolutional layers each consisting of 64,128,256 and 512 number of kernels respectively with kernel shape 3×1 and two maxpooling layers with pooling window 2 for extracting high number of features. Then all three models consist of one dense layers or fully connected layers with number of neurons as 256. After that CNN-LSTM model consists of two LSTM layer, CNN-RNN model consists of two simpleRNN layer and CNN-GRU model consists of two GRU layer for supporting sequence prediction in all three models. Again, all three models also consist of three fully connected layers with number of neurons 256,128 and 64 respectively. At last, three models are then given a softmax output layer with number of neurons as 2 for the purpose of final recognition. In all layer's activation used are 'relu' except LSTM, RNN and GRU layer in which the activation used are 'tanh'.

A. *Model Output Summary*

All the three models are simulated using python coding in Google Colab. Model summary is nothing but the showing the details of the layer used and after using the layer what all outputs are getting. The stimulating model's summary have been shown in Fig.2. In the model summary there are three things i.e., layer, output shape and parameters. In the layer it is mentioned about types of layers used. Output shape mainly shows about number of features passed in next layer except last dense layer where 2 represent for final classification as seizure and non-seizure. Parameters is required by the model during the time of making prediction.

For convolutional layer output shape is given as (Output, Number of kernals used).

To calculate the output and parameters of convolutional layers, the formula used are as follows:

$$\text{Output} = \frac{\text{input size} - \text{kernal size} + 2\text{padding}}{\text{Number of strides}} + 1 \qquad (1)$$

$$\text{Parameter} = (\text{height} \times \text{width} \times \text{NL} + 1) \times \text{NC} \qquad (2)$$

For Maxpooling layer output shape is given as (Output, Number of kernals used in previous convolutional layer).For pooling layer, parameter is 0 and output value is given by

$$\text{Output} = \frac{\text{LO} - \text{pool dimension}}{\text{Number of strides}} + 1 \qquad (3)$$

Here,height= height of filter, width= width of filter andLO= last layer output

TABLE I

Model summary of CNN-LSTM

Layer	Output Shape	Parameter
Convolutional Layer	(176, 64)	256
Maxpooling Layer	(88,64)	0
Convolutional Layer	(86, 128)	24704
Maxpooling Layer	(43, 128)	0
Convolutional Layer	(41, 512)	197120
Convolutional Layer	(39, 1024)	1573888
Dense Layer	(39, 256)	262400
Dropout Layer	(39, 256)	0
LSTM Layer	(39, 64)	82176
LSTM Layer	128	98816

Dense Layer	256	33024
Dense Layer	128	32896
Dense Layer	64	8256
Dense Layer	39	130

TABLE II
Model summary of CNN-RNN

Layer	Output Shape	Parameter
Convolutional Layer	(176, 64)	256
Maxpooling Layer	(88,64)	0
Convolutional Layer	(86, 128)	24704
Maxpooling Layer	(43, 128)	0
Convolutional Layer	(41, 512)	197120
Convolutional Layer	(39, 1024)	1573888
Dense Layer	(39, 256)	262400
Dropout Layer	(39, 256)	0
SimpleRNN Layer	(39, 64)	20544
SimpleRNN Layer	128	24704
Dense Layer	256	33024
Dense Layer	128	32896
Dense Layer	64	8256
Dense Layer	2	130

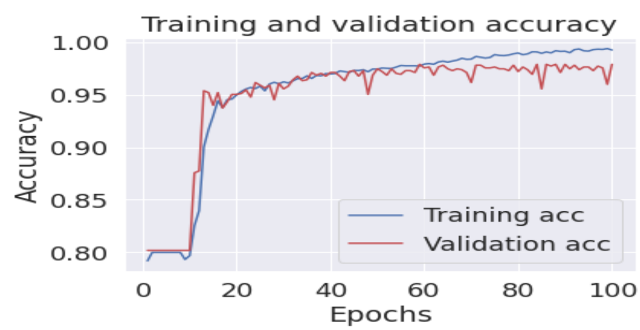
TABLE III
Model summary of CNN-GRU

Layer	Output Shape	Parameter
Convolutional Layer	(176, 64)	256
Maxpooling Layer	(88,64)	0
Convolutional Layer	(86, 128)	24704
Maxpooling Layer	(43, 128)	0
Convolutional Layer	(41, 512)	197120
Convolutional Layer	(39, 1024)	1573888
Dense Layer	(39, 256)	262400
Dropout Layer	(39, 256)	0
gru_1 (GRU)	(39, 64)	61824
gru_2 (GRU)	128	74496
Dense Layer	256	33024
Dense Layer	128	32896
Dense Layer	64	8256
Dense Layer	2	130

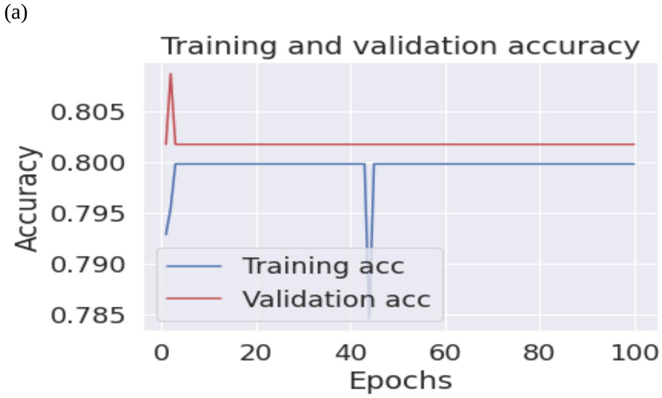
B. Training and Validation Accuracy Plot

The labelled dataset used to instruct a model is referred to as training data. Examples are given, together with the relevant goal labels and input attributes. The model gains knowledge from this data by spotting patterns, connections, and rules that let it correctly forecast or categorise fresh, unobserved data.On the other hand, validation or testing data is a different dataset used to assess how well a machine learning model that has been trained performs. It includes instances without labels in which simply the input features are given. In order to determine the model's accuracy, generalisation ability, and resilience, it applies its learnt information to forecast the target labels for the testing data. These predictions are then compared to the actual labels. In our model we have taken training and validation data ratio as 9:1 i.e., 90% data are used for training the model whereas 10% data are used for validation of model. The models have been simulated in Google Colab using python coding taking 100 epochs and ‘Rmsprop’, ‘Adam’, ‘Nadam’ as three different optimizers.

Fig. 2 shows the training and testing accuracy of the CNN-LSTM model for three different optimizers Rmsprop, Adam and Nadam respectively. Similarly, Fig. 3 and Fig. 4 shows the training and testing accuracy of optimizers Rmsprop, Adam and Nadam for CNN-RNN and CNN-GRU models respectively.



(a)



(b)

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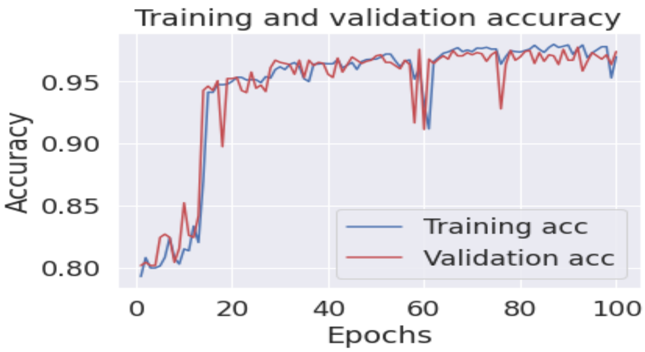
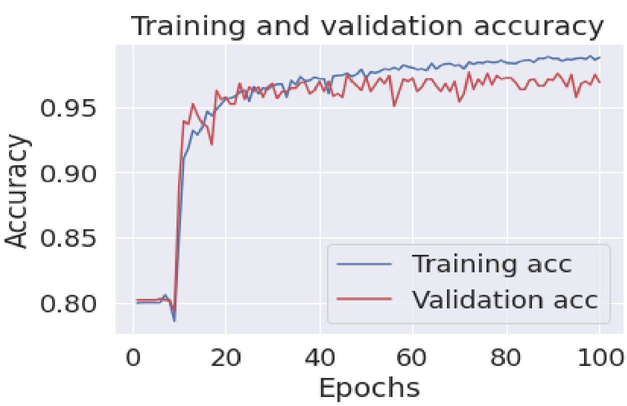
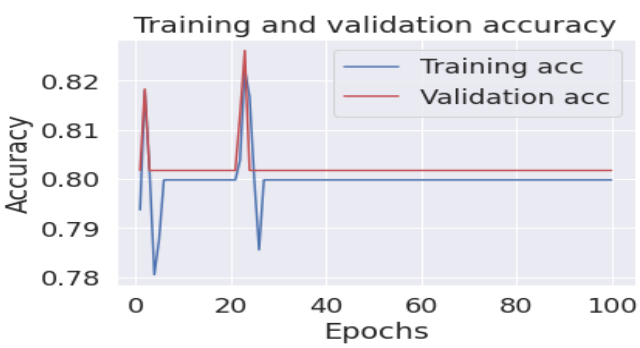


(c)

Fig. 2. Training and Validation Accuracy of CNN-LSTM using Optimizer (a)Rmsprop (b)Adam (c)Nadam



(a)



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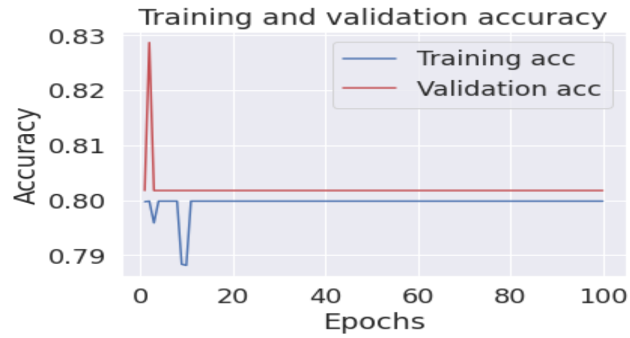
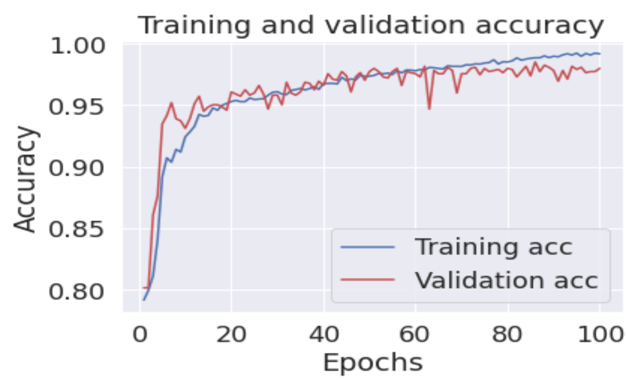
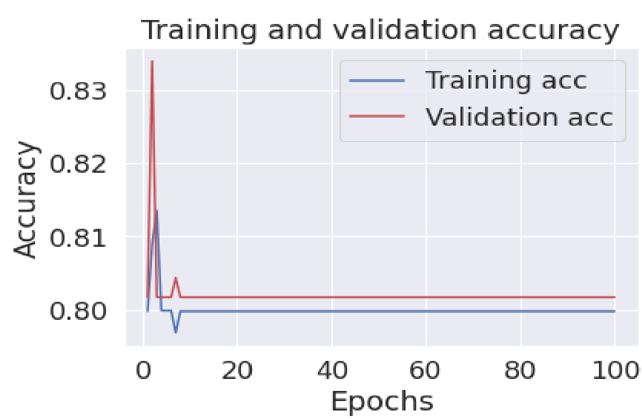


(c)

Fig. 3. Training and Validation Accuracy of CNN-RNN using Optimizer (a)Rmsprop(b)Adam(c)Nadam



(a)



(b)

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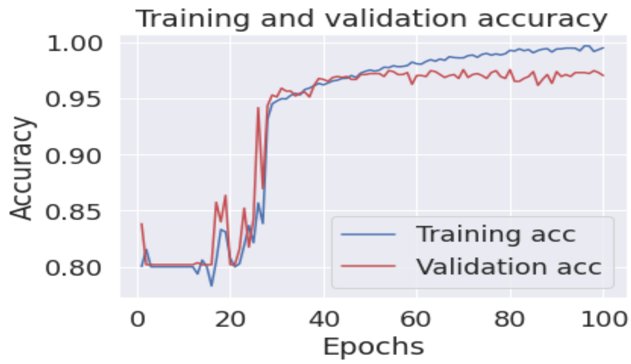

(c)

Fig. 4. Training and Validation Accuracy of CNN-RNN using Optimizer(a)Rmsprop (b)Adam (c)Nadam

C.Important Parameters

For comparing all the models from one another the following parameters have been calculated [13]:

Accuracy: It represents the proportion between the total of true positive and true negative to the total of all true positive, true negative, true positive, and false positive[14]. Its mathematical representation is given as

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

Sensitivity: The ratio of accurately anticipated positive instances to all positive cases is known as sensitivity.

$$\text{Sensitivity}=\frac{TP}{TP+FN} \quad (5)$$

Specificity:The ratio of accurately predicted negative cases to all negative cases is known as specificity.

$$\text{Specificity}=\frac{TN}{TN+FP} \quad (6)$$

Here,TP=True Positive, means the person is having seizure and correctly identified as a seizure,

TN=True Negative, means the person is healthy and also identified as healthy,

FP= False positive, means the person is healthy but identified as having seizure,

FN=False negative, means the person is having seizure but identified as a healthy.

V. COMPARISON RESULTS

Comparison for optimizers Rmsprop, Adam and Nadamfor CNN-LSTM, CNN-RNN and CNN-GRU models have been made in Table IV, V and VI respectively using parameter accuracy, sensitivity and specificity to find which optimizer is best. In Table VII by considering the best optimizer, comparison between three models have been made to find which model is best for detection of epileptic seizure and in table 7 also compare these three deep learning model with machine learning models.

TABLE IV
Comparison study of three optimizer of CNN-LSTM

Optimizer	Accuracy (%)	Sensitivity (%)	Specificity (%)
Rmsprop	97.91	92.54	99.24
Adam	80.17	0	100
Nadam	97.39	89.91	99.24

TABLE V
Comparison study of three optimizer of CNN-RNN

Optimizer	Accuracy (%)	Sensitivity (%)	Specificity (%)
Rmsprop	96.86	87.71	99.13
Adam	80.17	0	100
Nadam	80.17	0	100

TABLE VI
Comparison study of three optimizer of CNN-GRU

Optimizer	Accuracy (%)	Sensitivity (%)	Specificity (%)
Rmsprop	98.17	93.85	99.24
Adam	80.17	0	100
Nadam	97.04	90.78	98.59

TABLE VII
Comparison of best deep learning models withmachine learning models

Work	Model	Accuray (%)	Sensitivity (%)	Specificity (%)
[8]	Extra Tree Classifier	96.8	94.5	97.3
[9]	ANN	97.82	99.12	96.47
[10]	SVM	97.86	93.40	98.98
This study	CNN-LSTM	97.91	92.54	99.24
This study	CNN-RNN	96.86	87.71	99.13
This study	CNN-GRU	98.17	93.85	99.24

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By comparing the first three tables and by seeing the accuracy plot, Rmsprop optimizer is the most suitable one. From the fourth table CNN-GRU model with Rmsprop optimizer is giving best result with accuracy=98.17%, precision=96.83%, sensitivity=93.85%, specificity=99.24%.

VI. CONCLUSION

In thispaper, three optimizers Rmsprop, Adam, and Nadam, with accuracy, sensitivity, and specificity are tested and compared. Also, three classification techniques CNN-LSTM, CNN-RNN, and CNN-GRU is compared with some machine learning models to find which model performs the best in detecting seizures and the comparison results show that the CNN-GRU model using Rmsprop optimizer is best among the three deep learning and three machine learning models and can be used for the detection of epileptic seizure.

VII. REFERENCES

[1] M.Sameer, & B.Gupta, "CNN based framework for detection of epileptic seizures,"*Multimedia Tools and Applications*, vol. *81*, no. 12, pp.17057-17070, Mar 2022.

[2] S.S. Talathi, "Deep recurrent neural networks for seizure detection and early seizure detectionsystems,"arXiv preprint arXiv:1706.03283, June 2017.

[3] Y.LeCun, Y.Bengio, &G.Hinton, "Deep learning,"nature, vol. *521*, no. 7553, pp. 436-444, May 2015.

[4] F.Radenović, G.Tolias&O.Chum, "Fine-tuning CNN image retrieval with no human annotation," *IEEE transactions on pattern analysis and machine intelligence*, vol. 41, no. 7, pp.1655-1668, July 2019.

[5] G. R. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David,&C. E. Elger, "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state," *Physical Review E*, vol. 64, no. 6, 061907, Nov 2001.

[6] W. Qiuyi and F. Ernest, "Epileptic Seizure Recognition,"*UCI Machine Learning Repository*, May 2017.

[7] J. S. Kumar&P. Bhuvaneswari,"Analysis of electroencephalography (EEG) signals and its categorization- a study," *Procedia engineering*, vol.38,pp. 2525-2536, Jan 2012.

[8] T. Wadiwala, V. Trikha,&J. Fiaidhi, "Machine learning approaches for binary classification using brain signals".

[9] W. Mardini, M. M. B. Yassein, R. Al-Rawashdeh, S. Aljawarneh, Y. Khamayseh,&O. Meqdadi, "Enhanced detection of epileptic seizure using EEG signals in combination with machine learning classifiers," *IEEE Access*, vol. 8, pp. 24046-24055, Jan 2020.

[10] A. A. Rahman, F. Faisal, M. M. Nishat, M. I. Siraji, L. I. Khalid,M. R. H. Khan,&M. T. Reza, "Detection of epileptic seizure from EEG signal data by employing machine learning algorithms with hyperparameter optimization,"*4th International Conference on Bio-Engineering for Smart Technologies (BioSMART)*, Dec 2021, pp. 1-4.

[11] G. Swapna, K. P. Soman,&R. Vinayakumar,"Automated detection of cardiac arrhythmia using deep learning techniques," Procedia *computer science*, vol. 132, pp.1192-1201, June 2018.

[12] S. Hochreiter, &J. Schmidhuber, "Long short-term memory," *Neural computation*, vol. *9*, no. 8, pp.1735-1780, Nov 1997.

[13] A. Baratloo, M. Hosseini, A. Negida,& G. Ashal, "Part 1: simple definition and calculation of accuracy, sensitivity and specificity,"*Emergency*, vol. 3, no. 2, pp. 48-49, 2015.

[14] A. Gon, A. Mukherjee, "FPGA-Based Low-Cost Architecture for R-Peak Detection and Heart-Rate Calculation Using Lifting-Based Discrete Wavelet Transform,"Springer Circuits Systems and Signal Processing, vol. 42, no. 1, pp. 580–600, Jan 2023.

VIII. BIOGRAPHIES

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