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Effect of Input Channel Reduction on EEG Seizure Detection

***Abstract**. In this study, the effectiveness of six machine learning and eight deep learning algorithms in analyzing electroencephalogram (EEG) signals for detecting epileptic seizures has been investigated. The study utilizes 14 channels in the EMOTIV EPOC+ device which is based on international 10-20 system. To find out the most informative and sensitive channel, one of the 14 channels has been dropped one at a time. The accuracy values were determined for all the methods using two different publicly available datasets: the Guinea-Bissau epilepsy dataset and the Nigeria epilepsy dataset. In case of machine learning models, the performance of SVM classifier performs best with maximum accuracy of 83.2% (Guinea-Bissau) and 77% (Nigeria) without excluding any channels. No significant performance degradation has been observed for single channel exclusion of this classifier. Among the deep learning models, the four best performing models in terms of accuracy are CNN-LSTM (92.5%), IC-RNN (91.8%), ChronoNet (91.1%) and C-DRNN (88.6%). After excluding one channel at a time and investigating their effect on the performance of the four DL models, it has been observed that the most significant and most sensitive channels lie within the frontal and parietal zone. This finding will be very useful in practice as it indicates that the electrodes in the frontal and parietal zone should be placed with absolute precision for accurate diagnosis of the diseases. In addition, this study also explore the effectiveness of the selected classifiers in detecting seizure in case of failure of any particular EEG signal channel.*

Streszczenie.** W tym badaniu zbadano skuteczność sześciu algorytmów uczenia maszynowego i ośmiu algorytmów głębokiego uczenia się w analizie sygnałów elektroencefalogramu (EEG) w celu wykrywania napadów padaczkowych. W badaniu wykorzystano 14 kanałów w urządzeniu EMOTIV EPOC+ opartym na międzynarodowym systemie 10-20. Aby znaleźć najbardziej pouczający i wrażliwy kanał, usuwano jeden z 14 kanałów na raz. Wartości dokładności określono dla wszystkich metod przy użyciu dwóch różnych publicznie dostępnych zbiorów danych: zbioru danych dotyczących padaczki w Gwinei Bissau i zbioru danych dotyczących padaczki w Nigerii. W przypadku modeli uczenia maszynowego wydajność klasyfikatora SVM jest najlepsza przy maksymalnej dokładności 83,2% (Gwinea Bissau) i 77% (Nigeria) bez wykluczania jakichkolwiek kanałów. Nie zaobserwowano znaczącego pogorszenia wydajności w przypadku wykluczenia pojedynczego kanału tego klasyfikatora. Wśród modeli głębokiego uczenia się cztery modele o najlepszych wynikach pod względem dokładności to CNN-LSTM (92,5%), IC-RNN (91,8%), ChronoNet (91,1%) i C-DRNN (88,6%). Po wykluczeniu jednego kanału na raz i zbadaniu ich wpływu na działanie czterech modeli DL zaobserwowano, że najważniejsze i najbardziej czułe kanały znajdują się w strefie czołowej i ciemieniowej. Odkrycie to będzie bardzo przydatne w praktyce, gdyż wskazuje, że elektrody w strefie czołowej i ciemieniowej powinny być umieszczone z absolutną precyzją, aby umożliwić trafną diagnostykę schorzeń. Ponadto w badaniu tym zbadano również skuteczność wybranych klasyfikatorów w wykrywaniu napadów w przypadku awarii dowolnego konkretnego kanału sygnałowego EEG.* (Wpływ redukcji kanału wejściowego na wykrywanie napadów EEG***)

Keywords: EEG, Seizure, Classifier, Channel Selection
Słowa kluczowe: EEG, drgawki, klasyfikator, wybór kanału

Introduction

EEG (electroencephalogram) is a widely used technique for monitoring and diagnosing various neurological conditions, including epilepsy. EEG measures brain activity and enables the identification of disease states, such as epilepsy, Parkinson's disease, Alzheimer's disease, sleep apnea, insomnia, and many others [1]. Epilepsy is a chronic neurological disorder characterized by recurrent seizures, which are sudden and abnormal bursts of electrical activity in the brain. Abnormal activity of the brain, recurrent convulsions, and unconsciousness are some of the major effects due to such seizures. Studies have also shown that epilepsy can also lead to serious injuries, and even death in some cases. Epilepsy defined as the most common brain disorder [2]. In recent times, researchers have identified about 50 million epilepsy patients among which the most impact are observed among adults aged 65-70 years and children [3,4]. EEG seizure detection plays a crucial role in diagnosing and managing epilepsy patients, as it helps in understanding the characteristics of seizures and monitoring their frequency and severity. Efficient and timely diagnosis epileptic seizures can be controlled in 80% of cases. [4, 5].

Over the years, researchers and scientists have worked on in building automated systems to detect epilepsy from enormous number of patients, thus reducing the complexity of labour and time associated with detecting significant seizures by human experts. Machine and deep learning with their advanced state of art techniques have gained much popularity in building these automated systems. Deep learning gained considerable interest in the field of feature learning in recent years and is emerging as an efficient machine learning paradigm [6, 7, 8].

In this paper, a total of fourteen machine-learning (ML) and deep-learning (DL) based approaches have been investigated. Among which, the six ML approaches are Logistic Regression (LR), Decision Tree (DT), Gaussian Naïve Bayes (GNB), Random Forest Tree (RFT), K-Nearest Neighbour (k-NN), Support Vector Machine (SVM). The eight DL based approaches are Vanilla Neural Network (VNN), Convolutional Neural Network (CNN), Gated Recurrent Neural Network (RNN), Inception Convolutional gated Recurrent Neural Network (IC-RNN), Convolutional gated Recurrent Neural Network (C-RNN), Convolutional Densely Connected Gated Recurrent Neural Network (C-DRNN), ChronoNet, and Convolutional Neural Network-long short-term memory (CNN-LSTM). The investigation has been carried out firstly to find the most efficient model and secondly to identify most and least significant EEG channels. The most efficient model has a high accuracy with a moderate complexity and hence cheaper. The least significant channels may be dropped but the most significant channels should be placed with absolute precision.

Logistic regression (LR) is a widely used statistical tool for binary classification problems. LR focuses on estimating the possibility that an input will belong to one of two classes. Although Linear Regression gained much popularity due to its simplicity but Logistic Regression seems to be more effective as the data points are arranged in line rows resulting in more accuracy in some cases. The best regression coefficient in the regression formula is determined by a training classifier in logistic regression using the optimization algorithm [9, 10].

Decision tree (DT) is another prominently used Machine Learning algorithm that performs classification as well as regression tasks with its relatively simple structure ensuring robustness and efficiency by building decision trees from data. Random Forest termed as an ensemble learning technique where multiple trees are combined, and a different subset of the training data are used for each one's training with a random subset of features. [11]. Another popular efficient classifier namely Naïve Bayes classifier derived simply from Naïve Bayes falls among top ten algorithms for data mining. Bayesian classifiers operate under two presumptions and are based on the Bayesian rule and probability theorems. Firstly, attributes are conditionally independent given the class label and secondly, label prediction process is unaffected by latent attributes as well.

Gaussian naive Bayes (GNB) classification is derived from the existing naive Bayes method assuming attribute values possess a Gaussian distribution given the class label. [12,13,14]. Another simple yet effective non-parametric classification method is K-Nearest Neighbours (k-NN). The process of this classification method involves retrieving the k nearest neighbours for a data record t. Typically, a majority vote among the data records in the neighbourhood, with or without distance-based weighting, determines the classification for t. [15, 16]. SVM utilized for supervised learning is a mathematical entity, an algorithm that maximizes a specific mathematical function with respect to a given set of data [17]. Non-linear classification problems can be approached using SVM through the help of kernel functions.

In a vanilla neural network (VNN), the basic building block is a dense layer. Here data is given as input to the first layer, which is then passed through one or multiple hidden layers composed of dense layers. Neurons of every single layer are connected to every neuron of the following layer.

In Convolutional Neural Networks (CNNs), instead of neurons being connected to every neuron in former layers like VNN, these are only connected to the neurons close to it. The network consist of a convolutional layer, pooling layer and a fully connected layer. More complex features are produced by subsequent convolutional layers, covering larger portions of the processed data [18, 19]. CNNs use a parameter sharing scheme to regulate and decrease the number of parameters. Few trainable parameters and computation of a pooling layer is designed to control overfit and reduce the spatial size of data [20].

By maintaining a recurrent hidden state whose activation at each time is dependent on that of the previous time step, RNNs are capable of processing variable-length sequential data. RNNs are susceptible to the vanishing and exploding gradient problem, which occurs when the gradients either become too small (vanishing) or too large (exploding) during the backpropagation process. Gated recurrent unit (GRU) [21] and Long Short-Term Memory (LSTM) [22,23,24] are two noteworthy models for classification. ChronoNet is a deep learning model that is designed to perform time-series forecasting tasks, such as predicting future values of a time-series based on its historical data. It is a recurrent neural network architecture [25]. The ChronoNet model processes sequential time-domain data using multiple layers of GRU.

The following is a summary of the paper's structure: In section II methodology has been discussed. Section III gives a brief comparison of models applied and section IV contains a conclusion.

Methodology

A. Data Preparation

Fig. 1 shows the placement of electrodes in Emotiv Epoc+. There are total 14 electrodes or channels named: AF3 (Anterior Frontal electrode on the left side), AF4 (Anterior Frontal electrode on the right side), F3 (Frontal electrode on the left side), F4 (Frontal electrode on the left side), F7, F8, FC5 (Frontocentral electrode on the left side), FC6 Frontocentral electrode on the right side, O1 (Occipital electrode on the left side), O2 (Occipital electrode on the right side), P7 (Parietal electrode on the left side), P8 (Parietal electrode on the right side), T7 (Temporal electrode on the left side), and T8 (Temporal electrode on the right side).

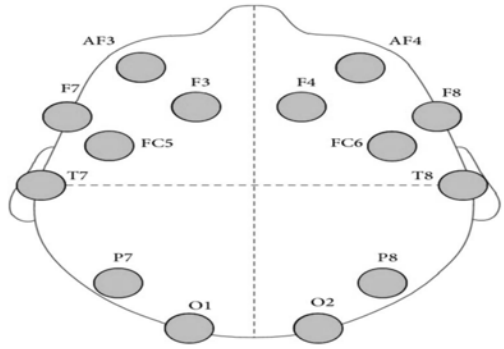

Fig. 1. The electrode locations of the 14 channel Emotiv EEG headset [26]

The study has involved 97 participants from Nigeria and 97 participants from Guinea-Bissau. At first, they were all subjected to a 14-channel EEG test keeping bit resolution-16 and sampling rate of 128 Hz.

The electrodes were positioned following International 10-20 system, covering the Antero frontal, front central, occipital, parietal, and temporal regions.

A band pass filter was applied to extract features within the 1 Hz-30 Hz range, as this is where the relevant information is found, including delta (0.5-1Hz), delta (1-2 Hz), delta (2-4 Hz), theta (4-8 Hz), alpha (8-16 Hz), and beta (16-32 Hz) bands [27, 28]. After that, 1 channel out of 14 channels has been excluded repeatedly and the above steps were followed.

B. Machine Learning Models

At first 14 or 13 channels from each sample have been used for pre-processing data. These have been labelled as 0 and 1 for healthy person and patient respectively. Welch Power Spectrum method has been used to find the power spectral densities of the signals which are the features of the machine learning classification model. Scikit-learn module has been used for machine learning classifiers.

For Logistic Regression, tolerance and maximum iterations have been set as 0.0001 and 100 respectively. In DT and RFT, minimum samples split = 2 and minimum samples lead = 1 has been used. In k-NN, 5 neighbours and uniform weights have been fixed.

In GNB, among all features taken in the sample, a part of the largest variance which is added to variances is set to 1e-9. For SVM, tolerance has been set as 0.001 and no limit in maximum iterations.

C. VNN

Welch Power Spectrum method has been used to find the power spectral densities of the signals which are the features of the model as ML models. The VNN consisting of 3 densely connected layers; each containing 16 neurons and rectified linear unit (ReLU) as activation function.

For the output layer, an S-shaped rectified linear activation function (Sigmoid) function was used. Learning rate = 0.001 and batch size = 512 have been used. The model has been fit for 100 epochs.

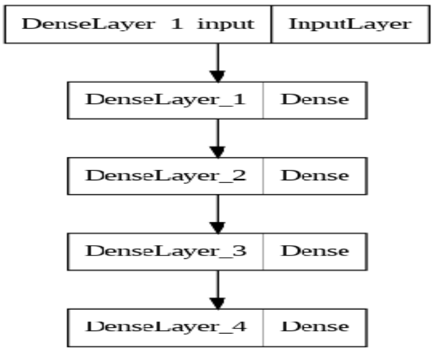

Fig. 2. Vanilla Neural Network

D. CNN

Fig. 3 represents the CNN model used in this work. Each one dimensional convolutional layer contains 5 filters, kernel size = 3, and strides = 1. For maxpooling layers, pool size = 2 and strides = 2. Dropout rate = 0.2 has been used.

Sigmoid activation function has been used for output layer. Learning rate = 0.0006 and batch size = 32 have been used. The model has been fit for 100 epochs.

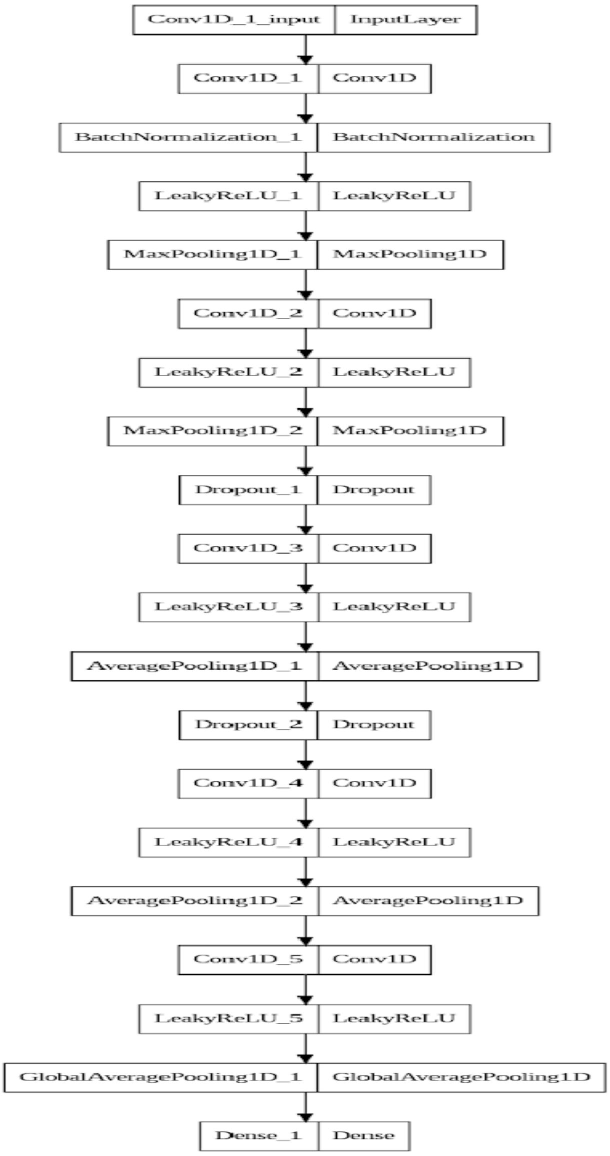

Fig. 3. Convolutional Neural Network

E. RNN

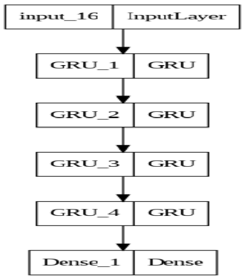

Fig. 4. Deep Gated Recurrent Neural Network [24]

The RNN model used in this study is shown in Fig. 4. Each of the four GRU layers contains 32 units with hyperbolic-tangent (tanh) activation.

The first 3 layers return sequences as well. Sigmoid activation function has been used for output layer. Learning rate = 0.001 and batch size = 128 have been used. The model has been fit for 50 epochs.

F. C-RNN

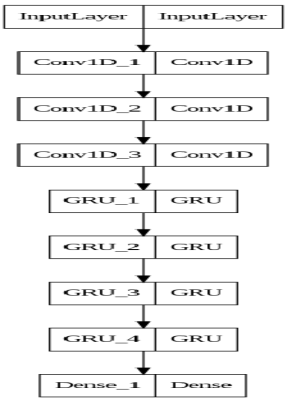

Fig. 5. Convolutional gated Recurrent Neural Network [24]

C-RNN model used in this research is given in Fig. 5. Similar GRU layers of the RNN model has been used here.

Each convolutional layer contains 32 filters, kernel size = 4 and strides = 2 with ReLU activation function. Learning rate = 0.0006 and batch size = 512 have been used. The model has been fit for 50 epochs.

G. C-DRNN

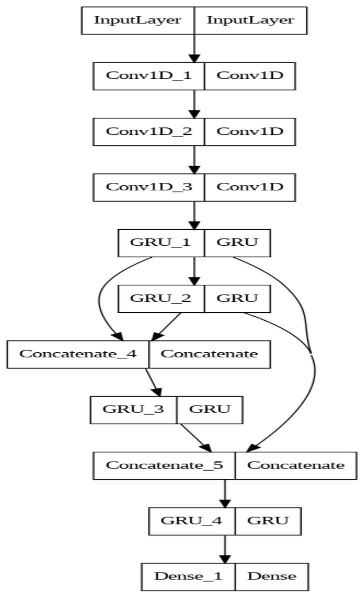

Fig. 6. Convolutional Densely Connected Gated Recurrent Neural Network [24]

Fig. 6 shows the C-DRNN model. It's a modification to IC-RNN. Only 2 concatenation layers have been introduced in between the GRU layers. Learning rate = 0.0006 and batch size = 512 have been used. The model has been fit for 50 epochs.

H. ChronoNet

The ChronoNet model shown in Fig. 7 is a clever combination of IC-RNN and C-DRNN. Learning rate = 0.0006 and batch size = 512 have been used. The model has been fit for 100 epochs.

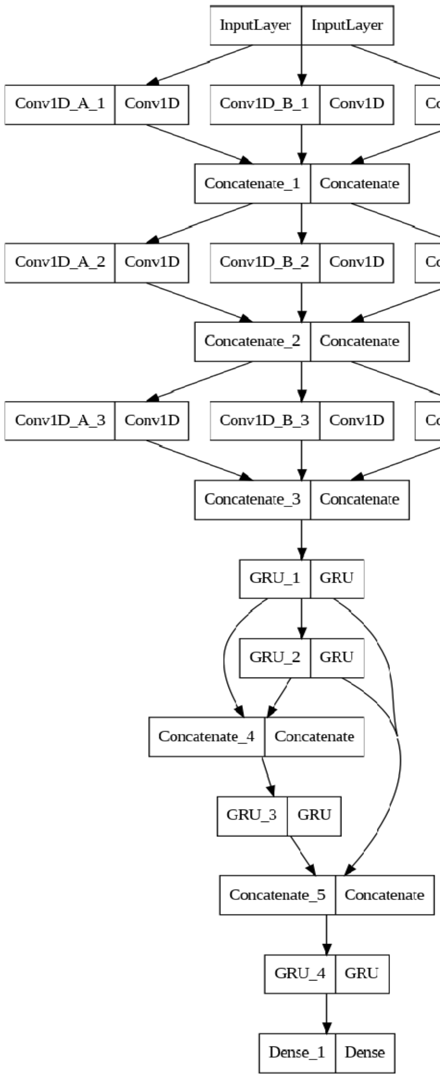

Fig. 7. ChronoNet [24]

I. IC-RNN

Fig. 8 represents the IC-RNN model. Same GRU layers of the RNN model has been used here. Before GRU layers, three similar blocks have been repeated. Each block contains three parallel convolutional layers followed by a concatenation layer.

All three convolutional layers have 32 filters and strides = 2. The kernel sizes for the three layers are 2, 4, and 8 respectively. Learning rate = 0.0006 and batch size = 512 have been used. The model has been fit for 40 epochs.

J. CNN-LSTM

Fig. 9 shows CNN-LSTM model. All the convolutional layers have 1 stride and kernel of size 3. The convolutional layers have 128, 512, 1024, and 256 filters respectively. The dropout rate is 0.5.

The dense layers have ReLU activation function and 256, 128, and 64 neurons respectively.

Both LSTM layers contain 64 units. The first one returns sequences as well as state additionally. Learning rate = 0.0006 and batch size = 128 have been used. The model has been fit for 60 epochs.

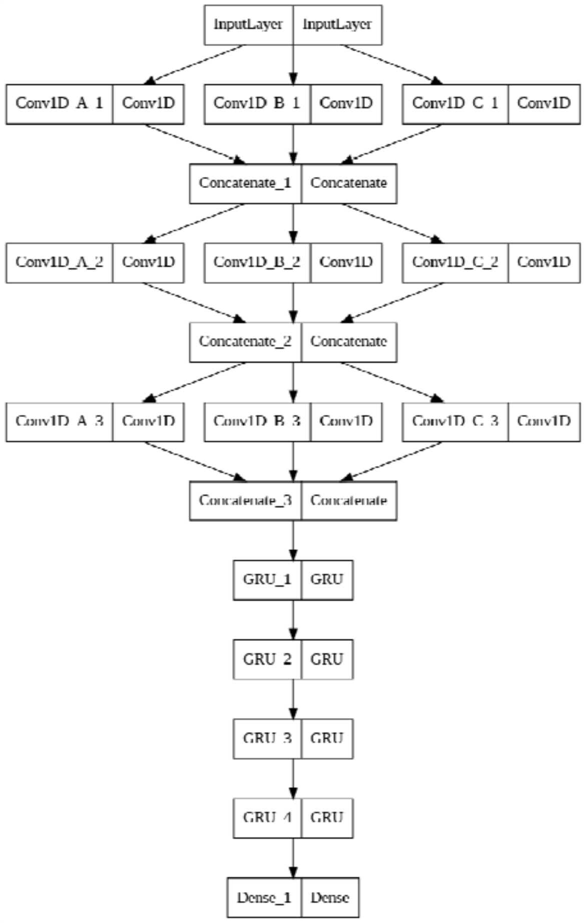

Fig. 8.Inception Convolutional gated RNN [24]

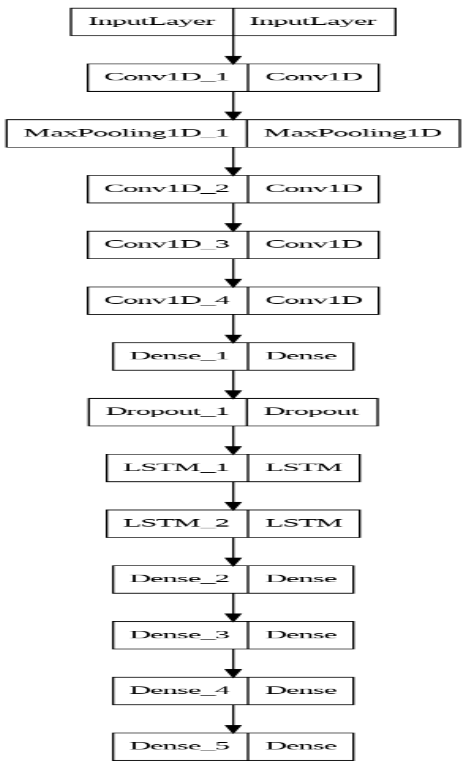

Fig. 9. Convolutional Neural Network-long short-term memory [29]

Results and Analysis

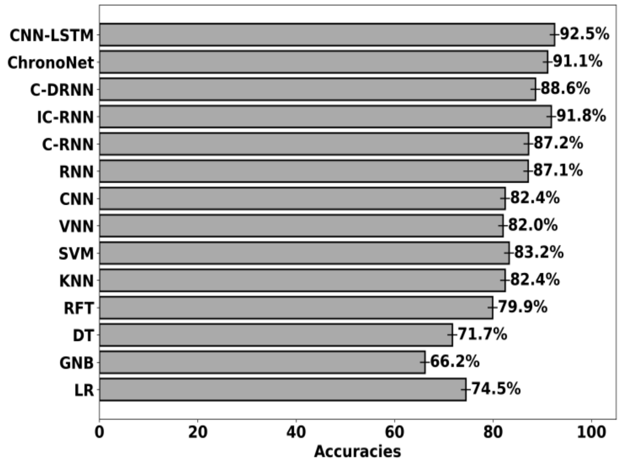

Fig. 10. Accuracies for Guinea-Bissau dataset with 14 channels

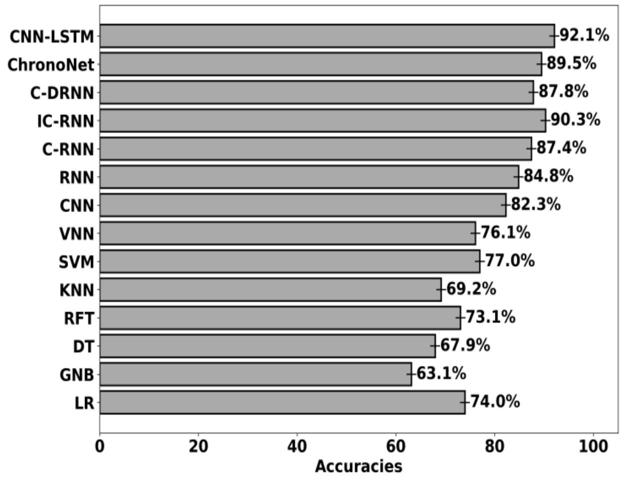

Fig. 11. Accuracies for Nigeria dataset with 14 channels

From Fig. 10 and Fig. 11, it can be found that the models work better on Guinea-Bissau dataset than Nigeria Dataset. Maximum accuracies: 92.5% and 92.1% have been achieved for Guinea-Bissau and Nigeria dataset respectively by CNN-LSTM model. IC-RNN model has also achieved over 90% accuracy in both dataset. Among the 6 ML models, SVM has performed the best in both dataset. Fig. 12 and Fig. 13 shows the accuracies found using SVM for Guinea-Bissau and Nigeria dataset respectively.

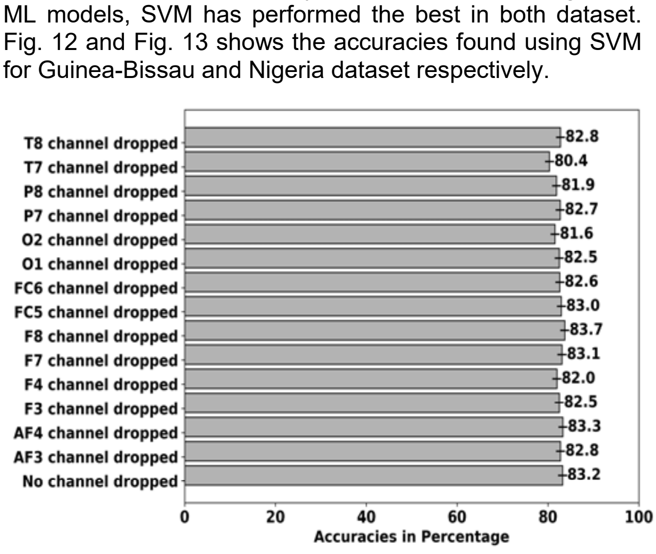

Fig. 12. Accuracies for Guinea-Bissau dataset using SVM model

From Fig. 12, it is visible that for all the cases accuracies are almost same which are between 80.4% and 83.7%.

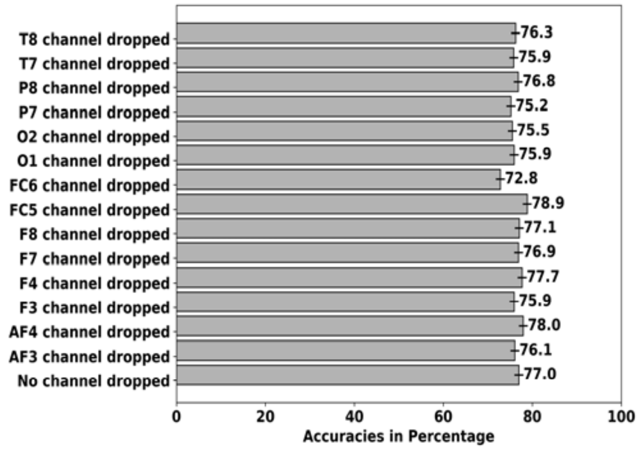

Fig. 13. Accuracies for Nigeria dataset using SVM model

Table 1. Worst accuracies with best performing models

Models	**Minimum Accuracy (GB)**		**Minimum Accuracy (N)**	
	Acc %	*Channel Excluded*	*Acc %*	*Channel Excluded*
IC-RNN	88.9	AF3	84.1	AF4
C-DRNN	87.6	P7	86.1	F3
ChronoNet	88.3	F8	82.1	P8
CNN-LSTM	84.2	F8	46.9	F7

From Table 1, it can be noticed that dropping AF3, AF4, F7, F8, F3, P7, and P8 have resulted in significant drop in accuracies. So, these channels are the most significant and cannot be dropped. These channels should be placed accurately.

Conclusion

From the experimental results, it can be stated that the implemented deep Learning models work fairly well than machine learning models. Guinea-Bissau dataset have higher accuracies than Nigeria dataset in almost all the models. Maximum accuracy achieved for Guinea-Bissau and Nigeria dataset are 92.5% and 92.1% respectively using CNN-LSTM model. In case of machine learning models, the performance of SVM classifier performs best with maximum accuracy of 83.2% (Guinea-Bissau) and 77% (Nigeria) without excluding any channels. No significant performance degradation has been observed for single channel exclusion of this classifier. Among the deep learning models, the four best performing models in terms of accuracy are CNN-LSTM (92.5%), IC-RNN (91.8%), ChronoNet (91.1%) and C-DRNN (88.6%). After excluding one channel at a time and investigating their effect on the performance of the four DL models, it has been observed that the most significant and most sensitive channels lie within the frontal and parietal zone. This finding will be very useful in practice as it indicates that the electrodes in the frontal and parietal zone should be placed precisely for accurate diagnosis of the diseases. In addition, this study also explores the effectiveness of the selected classifiers in detecting seizure in case of failure of any particular EEG signal channel.

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REFERENCES

[1] Duraj, Agnieszka, and Łukasz Chomątek. "Outlier detection in EEG signals." *Przeglad Elektrotechniczny* 99, no. 1 (2023).

[2] Blume, W. T., H. O. Lüders, E. Mizrahi, C. Tassinari, W. van Emde Boas, and J. Engel Jr. "Glossary of descriptive terminology for ictal semiology: report of the ILAE task force on classification and terminology." Epilepsia 42, no. 9 (2001): 1212-1218.

[3] Lasefr, Zakareya, Sai Shiva VNR Ayyalasomayajula, and Khaled Elleithy. "Epilepsy seizure detection using EEG signals." In 2017 IEEE 8th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference (UEMCON), pp. 162-167. IEEE, 2017.

[4] Hassan, Fatima, Syed Fawad Hussain, and Saeed Mian Qaisar. "Epileptic Seizure Detection Using a Hybrid 1D CNN-Machine Learning Approach from EEG Data." Journal of Healthcare Engineering 2022 (2022).

[5] Gandhi, Tapan, Bijay Ketan Panigrahi, and Sneh Anand. "A comparative study of wavelet families for EEG signal classification." Neurocomputing 74, no. 17 (2011): 3051-3057.

[6] Yao, Xinghua, Qiang Cheng, and Guo-Qiang Zhang. "A novel independent rnn approach to classification of seizures against non-seizures." arXiv preprint arXiv:1903.09326 (2019).

[7] Yao, Xinghua, Xiaojin Li, Qiang Ye, Yan Huang, Qiang Cheng, and Guo-Qiang Zhang. "A robust deep learning approach for automatic classification of seizures against non-seizures." Biomedical Signal Processing and Control 64 (2021): 102215.

[8] Ke, Hengjin, Dan Chen, Xiaoli Li, Yunbo Tang, Tejal Shah, and Rajiv Ranjan. "Towards brain big data classification: Epileptic EEG identification with a lightweight VGGNet on global MIC." IEEE Access 6 (2018): 14722-14733.

[9] Zou, Xiaonan, Yong Hu, Zhewen Tian, and Kaiyuan Shen. "Logistic regression model optimization and case analysis." In 2019 IEEE 7th international conference on computer science and network technology (ICCSNT), pp. 135-139. IEEE, 2019.

[10] Z. Qian, Meng. Deyu, Xu. Zongben, "$L_{1/2}$ Regularized Logistic Regression," Pattern Recognition and Artificial Intelligence, vol. 25(05), pp. 721-728, 2012.

[11] Breiman, Leo. "Random forests." Machine learning 45 (2001): 5-32.

[12] Jahromi, Ali Haghpanah, and Mohammad Taheri. "A non-parametric mixture of Gaussian naive Bayes classifiers based on local independent features." In 2017 Artificial intelligence and signal processing conference (AISP), pp. 209-212. IEEE, 2017.

[13] Wu, Xindong, Vipin Kumar, J. Ross Quinlan, Joydeep Ghosh, Qiang Yang, Hiroshi Motoda, Geoffrey J. McLachlan et al. "Top 10 algorithms in data mining." Knowledge and information systems 14 (2008): 1-37.

[14] John, George H., and Pat Langley. "Estimating continuous distributions in Bayesian classifiers." arXiv preprint arXiv:1302.4964 (2013).

[15] Guo, Gongde, Hui Wang, David Bell, Yaxin Bi, and Kieran Greer. "KNN model-based approach in classification." In On The Move to Meaningful Internet Systems 2003: CoopIS, DOA, and ODBASE: OTM Confederated International Conferences, CoopIS, DOA, and ODBASE 2003, Catania, Sicily, Italy, November 3-7, 2003. Proceedings, pp. 986-996. Springer Berlin Heidelberg, 2003.

[16] Hand, David J. "Principles of data mining." Drug safety 30 (2007): 621-622.

[17] Noble, William S. "What is a support vector machine?." Nature biotechnology 24, no. 12 (2006): 1565-1567.

[18] Ismaeel, Ghassan Ahmad, "Machine Learning to Diagnose Breast Cancer", , *Przeglad Elektrotechniczny,* vol. 1, pp. 10, 2022.

[19] Wiszniewski P, Kołodziej M, Majkowski A, Rysz A. Detection of epileptic seizures with the use of convolutional neural networks. Przegląd Elektrotechniczny. 2023;99:51–55.

[20] Zhou, Mengni, Cheng Tian, Rui Cao, Bin Wang, Yan Niu, Ting Hu, Hao Guo, and Jie Xiang. "Epileptic seizure detection based on EEG signals and CNN." Frontiers in neuroinformatics 12 (2018): 95.

[21] Cho, Kyunghyun, Bart Van Merriënboer, Dzmitry Bahdanau, and Yoshua Bengio. "On the properties of neural machine translation: Encoder-decoder approaches." arXiv preprint arXiv:1409.1259 (2014).

[22] Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." Neural computation 9, no. 8 (1997): 1735-1780.

[23] Graves, Alex. "Generating sequences with recurrent neural networks." arXiv preprint arXiv:1308.0850 (2013).

[24] Roy, Subhrajit, Isabell Kiral-Kornek, and Stefan Harrer. "ChronoNet: a deep recurrent neural network for abnormal EEG identification." In Artificial Intelligence in Medicine: 17th Conference on Artificial Intelligence in Medicine, AIME 2019, Poznan, Poland, June 26–29, 2019, Proceedings 17, pp. 47-56. Springer International Publishing, 2019.

[25] Ismail Fawaz, Hassan, Germain Forestier, Jonathan Weber, Lhassane Idoumghar, and Pierre-Alain Muller. "Deep learning for time series classification: a review." Data mining and knowledge discovery 33, no. 4 (2019): 917-963.

[26] Balasubramanian, Sangeetha, Shruti Shriya Gullapuram, and Abhinav Shukla. "Engagement estimation in advertisement videos with eeg." arXiv preprint arXiv:1812.03364 (2018).

[27] Vincent van Hees, & Wim Otte. EEG data collected with Emotiv device in people with epilepsy and controls in Guinea-Bissau and Nigeria (1.0) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.1252141. (2018).

[28] van Hees, Vincent T., Eric van Diessen, Michel RT Sinke, Jan W. Buitenhuis, Frank van der Maas, Lars Ridder, and Willem M. Otte. "Reliable and automatic epilepsy classification with affordable, consumer-grade electroencephalography in rural sub-Saharan Africa." BioRxiv (2018): 324954.

[29] Xu, Gaowei, Tianhe Ren, Yu Chen, and Wenliang Che. "A one-dimensional cnn-lstm model for epileptic seizure recognition using eeg signal analysis." Frontiers in neuroscience 14 (2020): 578126.