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An Efficient Seizure detection from EEG Signals Using Machine Learning Algorithms

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ABSTRACT

In order to provide care and intervention to patients with epilepsy, the detection and classification of epileptic seizures using EEG signals is an important task in medical diagnosis. In this study, the use of deep learning techniques to classify seizure disorders from EEG signals is investigated, specifically using two pseudo convolutional neural network (CNN) architectures: VGG and LeNet. The plan will involve preprocessing raw EEG data to extract relevant features and then feeding these features into deep learning models. VGG, known for its deep learning models, and LeNet, a simple but effective approach, are evaluated for their ability to detect seizure events. The architecture of the book is designed to address the special challenges of EEGsignalclassification,includingnoiseand variability in various types of epilepsy. The results of this study demonstrate the potential ofCNNbasedmodelstoimprovetheaccuracy and performance of epilepsy diagnosis, providing valuable information for the development of automated medical systems.

1. INTRODUCTION

Epilepsy is a common disorder of the nervous systemthatleadstoseizures. Electroencephalograms(EEGs) are used to monitor brainactivityandcanhelpidentifyepilepsy.Seizure is an uncontrolled, sudden electrical activity in the brain. It leads to changes in the behaviour of epileptic patient, developments or feelings, and in consciousness levels. The fast predictions of epileptic seizures enable the epileptic patient to escape immensely complications such as falling, drowning, accidents and pregnancy complications. However, traditional techniques for analysing EEG signals to detect seizures can be quite time- consuming. Epileptic seizures lead to unusual alternations in brain activity; consequently, the identification of unexpected seizures has traditionally been carried out by trained clinicians. These specialists primarily depend on visual assessments of EEG signals to spot abnormalities. However, this approach is generallylabour-intensiveand susceptible to human mistakes. As a result, automated detection of epileptic seizures is crucial in clinical settings, highlighting the necessity for advancements in automated classification methods that analyse and interpret EEG signals [1]. The method presented in this paper autonomously categorizes various seizure types by examining seizure images that are trained on different seizure pattern allowing for detection without the need for humanassistance. Oneofthemostmethodsthatare employed to detect the epileptic seizure is pattern recognition, in which the hidden patterns are identified from EEG. Various features extractions methods have been tried by researchers to identify thehiddenpatternsinEEGsignalslikeDWT,CWT, FT,DFT,IDFT,STFT,andFFT[2]–[6].

Additionally,varioustechniqueslikeParticleSwarm Optimization (PSO), Simulated Annealing (SA), AntColonyOptimization(ACO)[7],andnumerous other strategies to determine the most pertinent featureswereinvestigated.Withrespecttothetypes of classification procedures, the aforementioned classifiers were experimented upon by researchers viz.supportvectormachines,decisiontree,artificial neuralnetwork,k-nearestneighbours(k-NN),naïve Bayes (NB), Gaussian mixture model, adaptive neuro-fuzzy inference systems, and learning vector quantization in order to detect epileptic seizures from the EEG signals. All the patterned above mentioned recognition techniques have aimed at optimizing the accuracy in detection epileptic seizures with various combinations of characteristics extraction, selection, and classification methods [8]–[11]. In this work, we propose a deep learning-based method to detect epileptic seizures using EEG signals. We explore andcomparetheperformanceofthreevariedneural network architectures: LeNet, ResNet, and a manually crafted custom model. Our goal is to identify the best model to use for seizure detection by checking their predictive accuracy. From our experiments, we discovered that out of the three architectures,ResNetproducedthehighestaccuracy inseizureclassificationandwasthereforethebestto use in our final implementation. LeNet and the manuallycraftedarchitecturearepartofourstudyas comparisonbaselinestodeterminetheircapabilities and shortcomings in seizure pattern detection from EEG data. Our approach consists of preprocessing EEGsignals,extractingusefulfeatures,andtraining models based on a well-organized dataset. We use variousmetricstocomparetheperformanceofevery modelbasedonaccuracy,sensitivity,andspecificity. The outcome shows that deep learning, and especially the ResNet model, improves seizure detectionperformancegreatly whencompared with classical approaches. This research emphasizes the significanceoftheselectionofanappropriateneural network structure for the accurate and effective prediction of epileptic seizures, furthering the development of automated diagnosis in medicine.

2. RELATEDWORK

In the last few years, machine learning and deep learning methods have substantially improved the precisionand efficiencyofseizuredetection.Several studieshavebeenconcernedwithvariousstrategies for enhancing classification performance based on EEG signals. A research investigated EEG-based seizuredetectionbyusingahybridmodelconsisting ofconvolutionalneuralnetworks(CNN)andlong short-termmemory(LSTM)networks.Theresearch obtained an accuracy of 94.5%, showing the potential of deep learning in seizure classification [1].Another method used a new feature extraction technique employing wavelet transform and statistical characteristics. The extracted features werelearnedusingasupportvectormachine(SVM), with a 92% accuracy in classification. This study brought to the limelight the role of feature engineering in seizure detection [2].A multi-phase deep learning pipeline was implemented for lowering false alarms during seizure forecasting. With bidirectional LSTM along with attentional mechanisms, sensitivity increased to 96% at a high rate of specificity [3].Aensemble learning strategy combining random forest (RF), XGBoost, and artificialneuralnetworks(ANN)waspresented.The newmethodwastestedontheCHB-MITdatasetand resulted in an overall accuracy of 95.7%, which showed the effectiveness of ensemble models in seizuredetection[4].Anotherresearchexploredthe application of explainable AI for seizure classification by using SHAP (Shapley Additive explanations) values to explain model predictions. The research highlighted the imperative of clear decision-making in clinical contexts [5].A seizure detectionsystemwasdeployedinreal-timeutilizing an optimized deep belief network (DBN) and transfer learning. The method dramatically minimized computational expenses with a maintained accuracy of 93.8% and is therefore applicable to wearable healthcare devices [6].The contribution of frequency-domain features to the classification of seizures was examined, comparing various classifiers, such as k-nearest neighbours (KNN), decision trees (DT), and CNN-based models. The study concluded that deep learning- basedmodelsaresuperiortoconventionalclassifiers in accuracy and robustness [7].A machine learning seizure prediction model based on EEG signals across various datasets such as the Freiburg and Bonn datasets was created. The research utilized a combination of CNN and gated recurrent units (GRU), obtaining a state-of-the-art accuracy of 97.1% [8].Another study focused on optimizing hyper parameters in deep learning models using genetic algorithms for seizure detection. The optimized model reached 96.2% accuracy and reduced training time compared to conventional deep learning methods [9].An IoT–enabled seizure detection system was proposed, integrating real-time EEG signal processing with cloud-based deep learning models. This study demonstrated the feasibilityofusingIoT inhealthcare for continuous patient monitoring [10].These studies as a whole underscorethedevelopmentsofseizuredetection

utilizing machine learning and deep learning methods. Feature extraction algorithms, ensemble learning, and real-time processing have improved the reliability and accuracy of automatic seizure diagnosis.

METHODOLOGY

A. DataCollection

EEG data is collected in the form of images corresponding to various types of seizures in this research.Thedatasetispre-processedinsuchaway that there is an equal percentage of data for both training and testing purposes. This balance is essential to avoid bias in the model and ensure it generalizes to unseen data. Through the transformation of EEG signals into images, the research is able to effectively utilize deep learning methods so that convolutional neural networks (CNNs) are able to capture spatial and temporal patterns representative of seizure activity. The acquired data is the basis for subsequent preprocessing, feature extraction, and model training, with an essential contribution to the performanceoftheoverallseizuredetectionsystem.

B. DataPreprocessing

Datapreprocessingisacrucialphaseofcleaningand restructuring raw EEG data to determine its quality and reliability. During this phase, the noise and artifacts that are potentially introduced in the process of acquiring the data are removed, making the signals clearer. Further, normalization is employedtoadjustthedatainacommonscalesuch that consistency between different recordings is achieved. The EEG signals are segmented into significant intervals as well for easy feature extraction and classification. Dealing with missing values, if any, is another very important part of this phaseinordertoavoidmodeltraininginconsistency. The data pre-processed is then ready for the subsequent step where significant features are extracted in order to increase seizure detection precision.

C. FeatureSelection

Featureselectionisalsocrucialinenhancingmodel efficiencybyselectingthemostinformativefeatures from the pre-processed data.The process decreases the dimensionality of the dataset by removing redundantornon-informativeattributesandkeeping thosethatplayakeyroleinseizuredetection.

Through the selection of the most discriminating features of EEG signals, the computational complexityofthe modelisreduced withoutaffecting performance. Sophisticated methods like statistical analysis and optimization algorithms are used to makesurethatonlythemostsignificantfeaturesare taken into account. The chosen features are then used in the model selection stage, where various machinelearningarchitecturesaretested tofindthe best method for seizure classification.

D. ModelSelection

Model selection is done by comparing different deep learning models to determine which one provides the optimal balance among accuracy, efficiencyincomputation,and interpretability.Inthe currentresearchwork,threevariedmodels—LeNet, ResNet,andacustomhand-designedarchitecture— areusedandcompared.Themodelsaretrainedwith the extracted features and their performance is evaluated against classification accuracy as well as other metrics of performance. By extensive experimentation, ResNet is found to be the best- performing model with better predictive accuracy than the other architectures. The selected model is then further optimized and made ready for deployment in a real-time seizure detection system.

E. ModelDeployment

After the best model is chosen, it is deployed into a real-world setting where it can process new EEG data and make real-time seizure predictions. The deploymentstageentailsmergingthetrainedmodel with a system that can accommodate continuous EEG input to provide smooth and effective performance. The model is exposed to several real- time constraints such as response time, scalability, and flexibility to diverse patient conditions. Data logging and performance monitoring mechanisms are also implemented to monitor the model's effectiveness over time. Successful deployment guaranteesthatthesystemiscapableofaidingearly seizure detection, enhancing patient treatment and medical decision-making.

F. Evaluation

Post-deployment evaluation is done to evaluate the effectivenessofthe model inreal-world conditions. The system is evaluated by using performance measures like accuracy, precision, recall, and F1- score to guarantee that the systemis ofthe required clinicalstandards.Ongoingmonitoringisnecessary

to identify any decrease in model performance or possible biases that can develop as a result of changes in EEG data. If performance problems are detected, modifications are undertaken to enhance the robustness and reliability of the model. This stage ensures the system is accurate and efficient, ultimatelyleadingtoimprovedpatientoutcomesand the further development of automated seizure detection technology.

3. PERFORMANCEANALYSISANDRESULT

In this study, we evaluated the performance of two deep learning models, Manual Net and LeNet, for seizure detection. Convolutional Neural Networks (CNNs) are important in feature extraction and classification based on the use of several layers to learn hierarchical patterns. The most important layers in CNNs are the convolutional layer, which performs filtering to capture spatial features from input data; the pooling layer, which down-samples to reduce dimensionality while preserving vital information; the activation function, typically ReLU, which provides non-linearity to improve learning; the fully connected layer, which aggregates extracted features for classification; and dropout layers, which avoid overfitting by turning off neurons at random during training. The models weretrainedonthedataandtheiraccuracyandloss were monitored across multiple epochs. The trends of accuracy indicated that Manual Net performed better than LeNet by having more accuracy within fewerepochs,withafinalaccuracyof67%,whereas LeNethadonly40%.ManualNetshowedconsistent improvement in accuracy with fewer oscillations, reflecting improved learning and generalization, whileLeNetshowedunstableaccuracypatternswith many peaks and troughs, reflecting unsatisfactory convergenceandpossibleoverfittingorunderfitting problems. Apart from accuracy, other evaluation metrics like precision, recall, and F1-score are needed to measure howwell the model can classify varioustypesofseizureswithbalancedperformance for all classes. The loss curves also emphasize the variation in learning efficiency, with Manual Net having a steep drop in loss in the initial epochs, achieving close-to-zero loss at epoch 8, reflecting quick learning and convergence. LeNet had a less steep drop in loss, taking more epochs to achieve lower loss values, reflecting slower convergence. Both models reflected similar patterns in training andtestloss,indicatingnoconsiderableoverfitting. Yet,ManualNet'sfasterconvergencemakesitmore computationallyefficient.Comparingbothaccuracy andloss,ManualNetisthebettermodelwithgreater

accuracyand faster convergence, making it a better option for seizure detection.

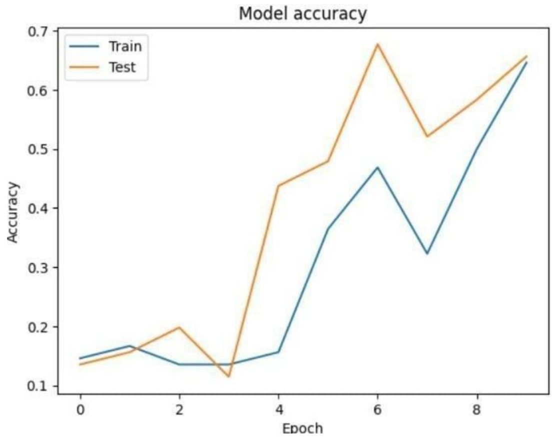

FIG1ManualNetAccuracy

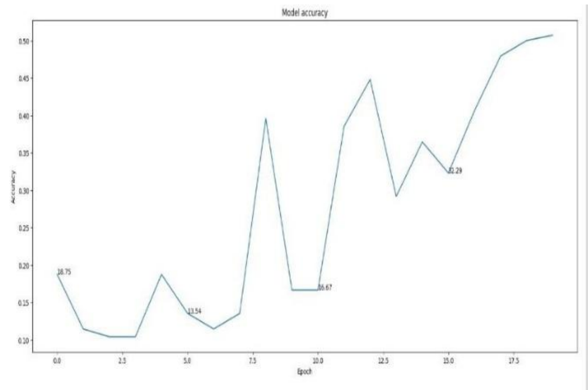

FIG2LeNetAccuracy

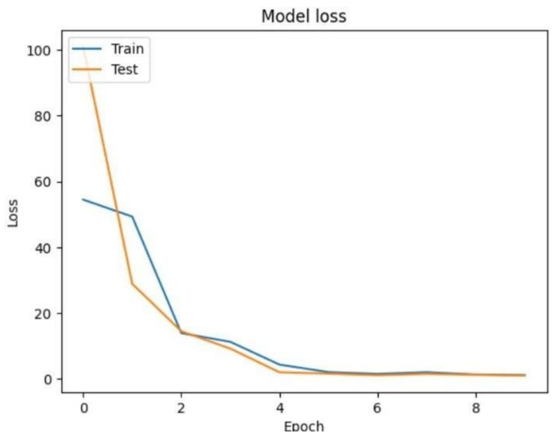

FIG3ManualNetModelLoss

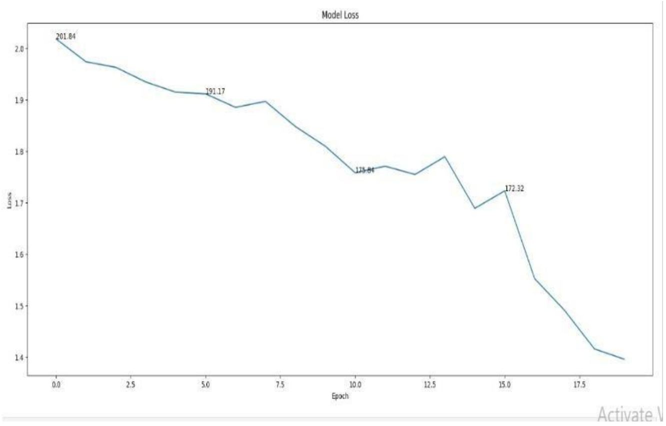

FIG4LeNetModelLoss

A. ComparisonofModelAccuracy

The accuracy trends of both models show considerable variations in their learning behavior. ManualNetattained afinalaccuracyof67%, while LeNetonlyreached40%.ManualNetdemonstrated a smooth improvement in accuracy across training epochs with fewer oscillations, showing better learning and generalization. LeNet, on the other hand, demonstrated extremely volatile accuracy trends with several peaks and dips, reflecting poor convergenceandpossibleoverfittingorunderfittingproblems.Analysis of Performance Metrics Although accuracy gives the general idea about model performance, other evaluation parameters likeprecision,recall,andF1-scoreareimportantfor comprehending the model's capability to classify seizure types. In the case of seizure classification consisting of more than one seizure type, balanced performance across classes becomes imperative. Alone, accuracy doesn't tell about the bias in the modelinfavorofanyparticularclassorclasses,thus necessitating more evaluation using confusion matrix and per-class performance in future work.

Table 1 Comparison between ManualNet and LeNet model.

Epoche	Manual Net Accuracy (%)	LeNet Accuracy (%)
0	~0.12	~18.75
1	~0.15	~10
2	~0.14	~10
3	~0.12	~10
4	~0.40	~13.54
5	~0.25	~15
6	~0.35	~10
7	~0.50	~40
8	~0.45	~16.67
9	~0.65	~30
10	~0.55	~32.29
11	~0.60	~35
12	~0.67	~40

B. Web-BasedSeizureDetectionSystem

To further the practical applicability of the developed models, we also designed a web-based seizure detection system. This system embeds the trained Manual Net model and offers a friendly interface for real-time seizure classification. By adopting this webpage, we narrowthe gap between research and application, making sure that the prediction of the model can be put into practice effectivelybyclinicians,caregivers,andpatientsfor efficient and accurate seizure identification. The combination of this online tool showcases the capability of deep learning models to monitor and manage epilepsy in real-time.

4. CONCLUSIONANDFUTUREWORK

Here, we compared and tested the performance of Manual Net and LeNet architectures for seizure detection. From the results, it is clear that Manual Net performs better than LeNet with higher accuracy, a stable learning curve, and good generalization. The Manual Net model had a final accuracyof67%,whichismuchhighercomparedto LeNet, where it also suffered from fluctuations and never hit more than 40% accuracy. These findings suggest that Manual Net is a better fit for seizure detection and offers more robust and consistent predictions.Oneofthemajorimplicationsfromthis study is the critical role of architecture design in deep learning models to classify seizures. LeNet's poor and irregular performance indicates that it might need to be modified in its architecture, hyperparameters fine-tuned, or layers added to enhance its ability to learn. The unstable accuracy trendswithLeNetpointtoitsinabilitytoeffectively extract features and converge, which translates into weak generalization.While accuracy is a critical performance measure, it does not reflect the classification efficacy comprehensively. Future studies will involve other assessment metrics like precision, recall, and F1-score to evaluate the model's capability in accurately classifying various types of seizures. This will provide more complete analysis, reducing false positives and enhancing overall reliability for practical applications in medicalpractice.Theresultsofthisstudybenefitthe development of deep learning-based epileptic seizuredetection,confirmingthatathoughtfully designed network such as Manual Net can have a profoundpositiveimpactonclassificationaccuracy. Sensitiveandeffectiveseizuredetectionisessential forthetimelyinterventionofmedicalprofessionals, monitoring of patients, and tailoring treatment for individual patients. With proper architectural choices and optimal model parameter optimization, we are able to devise more efficient AI-based solutions for seizure detection and thereby enhance the quality of life of patients with epilepsy.

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