A Modified XG Boost Classifier Model for Detection of Seizures and Non-Seizures

RAVEENDRA KUMAR T. H.[1], NARAYANAPPA C. K.[2], RAGHAVENDRA S.[3], POORNIMA G. R.[4]
[1]Ramaiah Institute of Technology, VTU Research Centre, Bengaluru, Karnataka, INDIA
[2]Department of Medical Electronics, Ramaiah Institute of Technology, Bengaluru, Karnataka, INDIA
[3]Department of CSE, School of Engineering & Technology, CHRIST Deemed to be University, Bengaluru, INDIA,
[4] Department of ECE, SVCE, Bengaluru, Karnataka, INDIA

Abstract: Diagnosis of Epilepsy is immensely important but challenging process, especially while using traditional manual seizure detection methods with the help of neurologists or brain experts' guidance which are time consuming. Thus, an automated classification method is require to quickly detect seizures and non-seizures. Therefore, a machine learning algorithm based on a modified XGboost classifier model is employed to detect seizures quickly and improve classification accuracy. A focal loss function is employed with traditional XGboost classifier model to minimize mismatch of training and testing samples and enhance efficiency of the classification model. Here, CHB-MIT SCALP Electroencephalography (EEG) dataset is utilized to test the proposed classification model. Here, data gathered for all 24 patients from CHB-MIT Database is used to analyze the performance of proposed classification model. Here, 2-class-seizure experimental results of proposed classification model are compared against several state-of-art-seizure classification models. Here, cross validation experiments determine nature of 2-class-seizure as the prediction is seizure or non-seizure. The metrics results for average sensitivity and average specificity are nearly 100%. The proposed model achieves improvement in terms of average sensitivity against the best traditional method as 0.05% and for average specificity as 1%. The proposed modified XGBoost classifier model outperforms all the state-of-art-seizure detection techniques in terms of average sensitivity, average specificity.

Keywords: Epilepsy, Seizure detection, XGboost Classifier, CHB-MIT dataset, EEG data.

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1 Introduction:

Currently, one of most general and deadliest chronic disorder of brain is Epilepsy which causes due to the unexpected and unusual transient disorders of brain neurons. Epilepsy affects at least 1% of total population of world [1]. Epilepsy is a temporary neuronal disease of brain which can last up to several months or years. Epilepsy word is taken from 'epilepsia' which is a Latin and Greek word. The real meaning of the word 'epilepsia' is 'seizure' or 'to seize upon'. Furthermore, An Epileptic seizure also known as seizure which is caused due to sudden uncontrolled electrical activity between brain cells (also called neurons or nerve cells) that causes abnormalities in muscle tone or movements (stiffness, twitching or limpness), behaviors, sensations or states of awareness which lasts for only a limited period of time. The term epilepsy can be dated back to the Babylonian text on medicine (3000 years ago).Epilepsy effects not only humans but also other species of mammals as well ex. Dogs, Elephants etc., it is one of the most common neurological disorder that affects more than 50 million people worldwide [2].

Furthermore, Seizures can be of two types, provoked and unprovoked i.e., some seizures can be provoked due to a temporary event such as low blood sodium, low blood sugar etc., and unprovoked seizures are those which starts without a known cause. Unprovoked seizures are likely to be triggered by stress, diseases of the brain or lack of sleep. When there has been at least one seizure and a long term risk of further seizures is known as epilepsy. Epilepsy is a chronic non-communicable disease. Epilepsy accounts for 0.5% of the global burden of disease. Provoked seizures occur in about 3.5 per 10,000 people a year while unprovoked seizures occur in about 4.2 per 10,000 people a year. After one seizure, the chance of experiencing a second is about 50%. Epilepsy affects about 1% of the population at any given time with about 4% of the population affected at some point in time. Nearly 80% of those with epilepsy live in developing countries.

One of the common way to determine the onset of a seizure before it manifests completely is by using the analysis of the scalp electroencephalogram (EEG) a noninvasive(not involving the introduction of instruments into the body), multi-channel recording of the brain's electrical activity. Although invasive electrodes are sometimes used, as in electrocorticography, sometimes called intracranial EEG. EEG is most often used to diagnose epilepsy, which causes abnormalities in EEG readings. Clinical EEG recording is usually for about 20–30 minutes (plus preparation time). Furthermore, EEG is utilized for the identification of electrical activities of the brain which can be done by attaching electrodes (metal discs) to the scalp. Usually, EEG is employed to diagnose brain disorders by detecting disturbances or changes in brain activities, especially, in case of epilepsy or another especially epilepsy or another seizure disorder. EEG characteristics vary among patients. EEG of a patient with seizure may show same patterns in the EEG of another patient. Some EEG monitoring can last up to few hours or even days and because of this when someone interprets the data i.e., human intervention it is prone to errors and a lot of time is wasted.

However, identification of seizures manually is very challenging and critical due to it requires large period of time for precise analysis of EEG signals through visual inspection. Usually, an approximate of 1.20 GB of data is produced by an 18-channel, 36-h digital recorder and is almost equal to 20 thousand pages of traditional paper EEG data and it becomes difficult to review the huge amount of data and its get even more complicated when the number of channel increases. Furthermore, EEG contains certain artifacts (electrical activities arising from sites other than the brain) and these cause errors by visual inspection of EEG by experts. Hence automatic methods are being developed to detect and predict the seizure and is in high demand for clinical application.

Therefore, in this article, a machine learning algorithm is employed to detect seizure quickly and with high accuracy when compared to the previous methods of seizure detections. The main goal of this paper is to discover the seizure and epilepsy status using the prediction algorithm on the test results received from patient medical reports. Furthermore, the timely detection of seizures can automatically play an important part in epilepsy diagnosis. The identification of seizures and non-seizures in patients and seizure status knowledge can provide great helps towards future neurological applications. Therefore, a novel seizure detection algorithm is presented. This novel algorithm utilizes modified XGboost classifier which is modified by using focal loss function to give better accuracy and results when compared to the other state-of-art-classification techniques. Here, seizures are detected for some specific patients from the available dataset for few seconds. The number of non-seizure patients are more in contrast to their counterpart seizure patients. The focal loss function is utilize to reduce discrepancy between seizures and non-seizures in classification process. Here, focal loss function can easily handle the differences of binary classification operations. Here, machine learning techniques make implementation of proposed modified XGboost classifier faster and efficient. Moreover, the performance results are evaluated for several patients and compared with various state-of-art-techniques in terms of sensitivity, specificity and classification accuracy.

This paper is presented in the following manner. Section 2, describes about the related work presented regarding automated detection of seizures and detection issues and how those issues can be handle with the help of the proposed epilepsy model based on machine learning techniques. Section 3, discusses about the methodology proposed for the effective implementation of proposed epilepsy model for the classification analysis of epilepsy. Section 4 discusses about the simulation results and their comparison with state-of-art classification algorithms and section 5 concludes the paper.

2 Related Work:

There are various application of machine learning in different fields of engineering and a significant development can be seen on health sector and can be applied on biological data sets for better outcomes[1][2].Machine learning is also used to find insights and patterns from different datasets from different domains[3][4].Applications of machine learning can also be seen on brain datasets for seizure detection, epilepsy lateralization, differentiating seizure sates, and localization [5][6][7][8].

In paper [9-11], feature extraction was not used and the data was further processed for deep learning models which was trained with raw EEG signals. Feature extraction is an important step which can ease the way to give input to the classifier, but in the mentioned papers they skipped the process of classification due to its complexity and fed the raw data samples to the classifiers. One of the main difficulties of seizure detection or prediction is that to find the correlation that is to which EEG timestamp to be input to the classifier but this process had it major downside was even with feature extraction ambiguity it didn’t recognize the patterns of the temporary signal.

Many machine learning methods for determining epilepsy collect the emotional condition from the brain by using an algorithm called as bayes classifier which contains 1902 statistical and 23 EEG signals people of age between 10-15 were collected. Moreover[12] by using wavelet DB Four shanon’s entropy researches extracted unique features from the subjects and the method consisted of 4 levels and when the signal was obtained the features from it was extracted and a new software was developed called so which was pre trained to record the changes in the brain action and by this process the accuracy was around 75% but this process had it drawbacks such as that the features were not universal for classification because there was difference in individual signals.

Seizure prediction is mainly dependent on 2 components one is extracting the requires features and classifying them and features plays an important role because we need to differentiate the various EEG signal patterns and by this well get better classification results on EEG signals based on this [13] proposed a model which was divided into 2 domains spectral and temporal domain features. This method is useful even though it differs from various involving technology.

An algorithm which depends on univariate features and uses it for machine learning known as ASPPR(Advanced seizure Prediction via Pre-lctal Relabeling) [14] and in this process 34 features were used considering its non-liner dynamics and energy in which 14 of the features were used to compare algorithms which in the past used these features and the rest 20 were constructed on EEG statistical descriptors and spectral band power which is calculated over the standard EEG bands and spectral frequency, "time in advance predictive model" was introduced and this model used to learn during training and used to predict the seizure only drawback of this model was the prediction time was not accurate and overall accuracy was not satisfying .

In this paper [15], spectral features of intracranial EEG is patient specific and further trained using machine learning algorithms a total of 18 patients data were taken. The noise from the data was removed between 50Hz and 100Hz using BPS (band pass filter) and minimized the dominance of low power frequency power band and power was normalized across the spectrum. Discriminant analysis called kernel fisher was used to get best feature for testing. But the problem with this method is that it didn't specify the seizure time and it used pre optimized parameters.

In [16], Fourier transforms is employed which has a huge application in detecting EEG since it is a signal processing method using it can be used to extract the features. As the amplitude increases it show the greater the abnormality in the brain hence here is where the Fourier transforms can be used hence author used Fourier transforms to extract some features and complex features by signal processing.

EEG-based epileptic signal classification which relies on stacked generalization model. In this paper [17], 5 types of epileptic classification is conducted with a 20 min scale and various levels of EEG signals are studied and here the stack generalization model is developed over a multiple CNNs with various activation functions are used weighted algorithm and feature fusion was used. But the drawbacks this method faced was every methods suffered from reduction in classification accuracy when applied to states classifications.

A Unified multi-view deep learning framework was developed for automatic EEG seizure detection [18], using clinical scalp multi-channel EEG epilepsy dataset. Here end to end framework is created which can learn multi-view hidden representations by combing inter and intra correlations of EEG channels and a 2D spectrogram is obtained and further the features are extracted using deep learning. As this method is useful in other medical task which has almost same data structures, but here channel awareness is still an unsolved problem.

3 Modelling for proposed Modified XGboost classifier Model:

This section discusses about the mathematical modelling of proposed Modified XGboost classifier Model for the identification of seizure onsets quickly and with high accuracy. In this section, traditional XGboost classifier is modified with the help of focal loss function. Generally XGBoost is composed additive learning method of second order approximation. Furthermore, here, the 1st order derivative is called as "gradient" and 2nd order derivative is called as "hessian" and the loss function is required to fit the model. Further, following section demonstrates the mathematical representation of proposed Modified XGboost classifier Model.

Further, XGboost is a gradient tree boosting approach which is utilized for handling machine learning problems. The key idea behind gradient tree boosting approach is the summation of several tree classifiers.

3.1 Modelling for proposed XGboost Classifier:

Consider for given k number of training samples, number of generated features are f and represented by the following equation,

$$N = \{(i_m, j_m)\} \qquad (1)$$

Where, i_m is expressed by $i_m \in \mathbb{G}^f$, j_m is expressed by $j_m \in \mathbb{R}$ and $|N| = k$. Furthermore, traditional XGboost tree model utilizes L additive functions to estimate the desired result. Then,

$$\hat{j}_m = \Theta(i_m) = \sum_{l=1}^{L} r_l(i_m), \qquad r_l \in R, \qquad (2)$$

Here, R is expressed as $R = \{r(i) = q_{p(i)}\}$ where $p: G^f \to W, q \in \mathbb{R}^W$ represents regression tree space. Then, pattern of every regression tree is denoted by p which can be used for mapping training samples to the respective leaf index. The total number of leaves present in the tree are expressed by W. Each r_l belongs to an individual regression tree pattern p and weights of leaf q. Then, every regression tree provides a constant score on every leaf, unlike the nature of decision trees. Here, score is represented for $m-th$ leaf using weights of leaf q_m. For a given training sample, classification process for leaves is achieved by following decision procedures and summation of scores which is obtained from weights, gives the final estimated output for the respective leaves. Then, the group of functions utilized in this tree model are given by regularized function using following equation,

$$Z(\Theta) = \sum_m z(\hat{j}_m, j_m) + \sum_l \lambda(r_l) \quad (3)$$

Where, complexity function for the regression tree model is defined by,

$$\lambda(r) = \zeta W + (2)^{-1}\Gamma\|q\|^2 \quad (4)$$

Where, z is utilized for the evaluation of change between the estimation $\hat{j}_m$ and the original j_m and expressed as convex loss function which can be differentiated. The smoothness of regularized function on final estimated weights is achieved with the help of complexity function to discard over-fitting. Here, the regularized function selects a regression tree model which has simple estimated functions. Here, regression tree is modelled in such a way that the model can easily parallelize which improves the efficiency of model unlike other tree models.

Here, the functions of regression tree model which shown in equation (3) are difficult to optimize with the help of traditional optimization approach. Therefore, regression model is trained in adaptive mode. Then, assume that considering $w-th$ iteration, estimated output is $\hat{j}_m^{(w)}$ for $m-th$ case, parameter r_w is required to optimize regularized function,

$$Z^w = \sum_{m=1}^{k} z\left(j_m, \hat{j}_m^{(w-1)} + r_w(i_m)\right) + \lambda(r_w) \quad (5)$$

Here, the parameter r_w is used to enhance the performance efficiency of regression tree model. Further, second order approximation is performed for the faster optimization of regularized function which is demonstrated in below equation,

$$Z^w \simeq \sum_{m=1}^{k} z\left[\left(\left(j_m, \hat{j}^{(w-1)}\right) + a_m r_w(i_m)\right) + 2^{-1} b_m {r_w}^2(i_m)\right] + \lambda(r_w) \quad (6)$$

Where, gradient statistics of first order and second order approximation considering loss function are denoted by a_m and b_m. Here, a_m is expressed as $a_m = \partial_{\hat{j}^{(w-1)}} z\left(j_m, \hat{j}_m^{(w-1)}\right)$ and b_m is expressed as $b_m = \partial^2_{\hat{j}^{(w-1)}} z\left(j_m, \hat{j}_m^{(w-1)}\right)$. After simplifying equation (7) by eliminating constant terms, we get,

$$\tilde{Z}^w = \sum_{m=1}^{k}\left[\left(a_m r_w(i_m)\right) + 2^{-1} b_m {r_w}^2(i_m)\right] + \lambda(r_w) \quad (7)$$

Then, for leaf case set d, determine M_d as,

$$M_d = \{m | p(i_m = d)\} \quad (8)$$

Then, by simplifying equation (7), we get,

$$\tilde{Z}^w = \sum_{m=1}^{k}\left[\left(a_m r_w(i_m)\right) + 2^{-1} b_m {r_w}^2(i_m)\right] + \zeta W + (2)^{-1}\Gamma \sum_{d=1}^{W} q_d^2 \quad (9)$$

$$\tilde{Z}^w = \sum_{d=1}^{W}\left[\left(\sum_{m\in M_d} a_m\right) q_d + 2^{-1}\left(\sum_{m\in M_d} b_m + \Gamma\right) q_d^2\right] + \zeta W \quad (10)$$

Then, the final optimized weights q_d^* for leaf d can be evaluated considering a fixed pattern $p(i)$ as,

$$q_d^* = -\sum_{m\in M_d} a_m \cdot \left(\sum_{m\in M_d} b_m + \Gamma\right)^{-1} \quad (11)$$

Then, determine their respective final optimized value by following equation,

$$\tilde{Z}^w(p) = -(2^{-1}).\sum_{d=1}^{W} \frac{\left(\sum_{m\in M_d} a_m\right)^2}{\sum_{m\in M_d} b_m + \Gamma} + \zeta W \quad (12)$$

Where, the quality of tree patterns can be determined using scoring function which is demonstrated in above equation (12). This score is used for classification of tree models and evaluated for extensive range of regularized functions. Here, the proposed tree model classify first leaf of the regression tree and then adds other tree leaves. Consider that M_U is case set for left side node and M_V is the case set for right side node after the split. Assume that $M = M_U \cup M_V$ then loss minimization term Z_S after the split is given by following equation,

$$Z_S = (2^{-1}).\left[\frac{\left(\sum_{m\in M_U} a_m\right)^2}{\sum_{m\in M_U} b_m + \Gamma} + \frac{\left(\sum_{m\in M_V} a_m\right)^2}{\sum_{m\in M_V} b_m + \Gamma} - \frac{\left(\sum_{m\in M} a_m\right)^2}{\sum_{m\in M} b_m + \Gamma}\right] - \zeta \quad (13)$$

Here, equation (13) can be utilized for evaluating split candidates in tree model. The proposed tree model is utilized for multi-class classification process as well by combining classification of binary trees.

Equation (14) shows the property of the sigmoid function and it is used for further derivation of loss function,

$$\frac{\partial \hat{j}}{\partial h} = \frac{\partial \delta(h)}{\partial h} = \delta(h)\left(1 - \delta(h)\right) = \hat{j}(1 - \hat{j}) \quad (14)$$

3.2 Modification derived for proposed XGboost Classifier Model:

A Modified XGBoost is proposed which uses Focal losses for classification for binary dataset to reduce mismatching of training and testing samples in classification process which generally affects the prediction accuracy. Since XGBoost is modified version of tree-boosting, its efficiency enhances to a high extent. It is used in various fields of study such as medical record analysis or for cancer diagnosis or for epilepsy while detection of seizures. Thus, Binary Focal Loss is given by following equation,

$$Z_{0_r} = -\sum_{m=1}^{f} \log(\hat{j}_m)\, j_m (1-\hat{j}_m)^{\zeta} + \log(1-\hat{j}_m)(1-j_m)\hat{j}_m^{\zeta} \quad (15)$$

In equation (15), when ζ is set to 0, then above equation is turned into ordinary cross entropy loss. To obtain just the cross entropy loss, the sigmoid activation function can be utilized which is shown in above equation (14) and using its property, first derivative of the focal loss can be obtained by using equation (16) as,

$$\frac{\partial Z_{0_r}}{\partial h_m} = \zeta\Big[\big(j_m + (-1)^{j_m}\hat{j}_m\big)^{\gamma}(\hat{j}_m + j_m - 1)\log\big(1 - j_m - (-1)^{j_m}\hat{j}_m\big)\Big] + (-1)^{j_m}\big(j_m + (-1)^{j_m}\hat{j}_m\big)^{\zeta+1} \quad (16)$$

Then set γ to 0 in equation (16) to determine cross entropy loss. On further simplification of equation (16), we get,

$$\begin{cases} \theta_1 = \hat{j}_m(1-\hat{j}_m) \\ \theta_2 = j_m + (-1)^{j_m}\hat{j}_m \\ \theta_3 = \hat{j}_m + j_m - 1 \\ \theta_4 = 1 - j_m - (-1)^{j_m}\hat{j}_m \\ \theta_5 = j_m + (-1)^{j_m}\hat{j}_m \end{cases} \quad (17)$$

Substituting the short hand notations of equation (17) and in equation (16), we get a simplified equation as,

$$\frac{\partial Z_{0_r}}{\partial h_m} = \zeta\theta_3\theta_2\log(\theta_4) + (-1)^{j_m}\theta_1^{\zeta+1} \quad (18)$$

Then, further derivation w.r.t h_m and combining equation (14) and (18), 2nd order derivative is obtained and given as:

$$\frac{\partial^2 Z_{0_r}}{\partial h_m^2} = \theta_1 \left\{\zeta[\theta_2^{\zeta} + \zeta(-1)^{j_m}\theta_3\theta_2^{\zeta-1})\log(\theta_4) - \frac{(-1)^{j_m}\theta_3\theta_2^{\zeta}}{\theta_4}] + (\zeta+1)\theta_5^{\zeta}\right\} \quad (19)$$

Now when $\gamma = 0$ then the obtained second order derivative is $\theta_1 = \hat{j}_m(1-\hat{j}_m)$ which is similar to 2nd order derivative of ordinary cross – entropy. Therefore, this focus loss function can be utilized in binary classification process to improve accuracy and performance and can be applied for applications like medical record analysis and epilepsy seizure detection.

4 Result and Discussion:

This section discusses about the performance result of proposed Modified XGboost Classifier model for the faster detection of seizures through classification process. The proposed Modified XGboost Classifier model utilizes an additional focal loss function in classification process in order to minimize training and testing inaccuracies which can degrade prediction results for epilepsy. Furthermore, focal loss function enhances classification accuracy performance of proposed classification model. Furthermore, performance of proposed classification model is measured using sample data of several patients from the dataset CHB-MIT SCALP Electroencephalography (EEG). The desired results obtained by using an efficient classification process which can easily differentiate between seizures and non-seizures. The obtained performance results are compared with several state-of-art techniques in terms of average sensitivity and average specificity. Performance results for several patients are demonstrated in terms of classification accuracy, sensitivity and specificity.

4.1 Dataset Details:

In this article, epilepsy samples used was from CHB-MIT SCALP Electroencephalography (EEG) database and is a public dataset which is taken from Physionet. Here, total time duration for the EEG recording is 983 hrs. EEG epoch contains offset time intervals, seizure onset ictal activities done manually by the clinical experts. The CHB-MIT EEG database is collected by investigators from the Children's Hospital Boston (CHB) and Massachusetts Institute of Technology (MIT) this database includes 23 pediatric patients with intractable seizures in order to estimate their possibility for surgical intervention. From those 23 patients, 5 patients were male and 17 patients were females and data of 1 patient was unknown. All the males are aged between 3 to 22 years and all the females are aged between 1.5 to 19 years. Most of the patients contain 23 types of EEG signal. However, some of the patients hold 24 or 26 EEG signals. All EEG signals are sampled at the rate of 256 sample/sec and resolution of 16 bit from electrodes. Electrodes are used according to International 10-20 system. In overall 24 cases, signals are partitioned in 1 hour long epochs. It can be seen that several epochs are up to 2-4 hours in duration. Furthermore, all 24 cases are exploring the frequent changes during EEG recordings. Moreover, CHB-MIT dataset is huge dataset which provide several variations of cross-validation methods and patient-specific as well as used by many researchers in several works [27-30].

4.2 Performance Evaluation:

This section discusses about the performance comparison against several state-of-art-seizure detection techniques in terms of average sensitivity and specificity for several patients. There are some essential steps which are necessary for the implementation of proposed classification model using proposed Modified Xgboost Classifier to detect seizures such as addition of channels from one to another epoch and channel selection. Here, only those channel are selected for classification process which are available even after completion of training and testing through cross validation process. However, in cross validation approach, chosen channels can swap with each other. The ultimate aim for swapping of selected channels are to examine the quality of data heterogeneity. Among the available 24 channels, 18 channels shows the stability which are T7-F7, FP1-F3, C3-P3, FP2-F4, F4-C4, P3-01, C4-P4, FP2-F8, T8-P8, FZ-CZ, T7-P7 , CZ-PZ, FP1-F7 ,F3-C3, F8-T8, P8-02, P7-01,P4-02. Further, those stable 18 bipolar raw EEG channels from the dataset are selected to obtain classification output of the proposed classification model.

4.2.1 Performance Metrics:

Furthermore, for classification process, the system performance is evaluated in terms of following parameters sensitivity, specificity and accuracy:

$$sensitivity = \frac{TP}{TP+FN} * 100\% \quad (20)$$

$$Specificity = \frac{TN}{TN+FN} * 100\% \quad (21)$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} * 100\% \quad (22)$$

Where, TP, TN, FP and FN represent true positive, true negative, false positive and false negative, respectively.

4.2.2 Performance Comparison:

Here, the performance results of proposed classification model through modified XGBoost classifier are compared against several state-of-art-seizure detection techniques such as Zabihi et al [21], Yuan et al [22], Tsiouris et al [23], Selvakumari et al [24], Difei Zeng et. al. [25], Dinghan Hu et al [26] and Bhattacharyya et al [2] in terms of Average sensitivity (%) and Average specificity (%). The proposed modified XGBoost classifier model obtain average sensitivity as 99.98%, average specificity as 99.97% and obtained EEG data recordings take 983 hours which is immense compare to other techniques and demonstrated in Table 1. It is evident from the performance results that the proposed modified XGBoost classifier model outperforms all the state-of-art-seizure detection techniques in terms of average sensitivity, average specificity and EEG data. Here, while classification, prediction of seizure or non-seizure comes under 2-class-seizure for subject-specific experiments. Moreover, 2-class-seizure experimental results of proposed classification model are compared against several state-of-art-seizure classification models. The metrics results in this task are nearly 100%. The proposed model achieves improvement in terms of average sensitivity against the best traditional method (Difei Zeng et. al.) as 0.05% and for average specificity as 1% as shown in Table 1. Here, cross validation experiments determine nature of 2-class-seizure as the prediction is seizure or non-seizure.

Table 1 comparison of the Performance for different methods on CHB_MIT Dataset

Method	EEG Data(h)	Average sensitivity (%)	Average specificity (%)
Zabihi et al	172	91.5	95.16
Yuan et al	958.2	95.65	95.75
Tsiouris et al	980	-	95.00
Selvakumari et al	-	97.50	94.50
Difei Zeng et. al.	-	99.93	98.5
Dinghan Hu et al	-	98.48	98.97
Bhattacharyya et al	178	97.91	99.57
Our work	**983**	**99.98**	**99.97**

Here, Table 2 demonstrates performance results of proposed modified XGboost Classifier model considering performance metrics like Sensitivity (%), Specificity (%) and Classification Accuracy (%).Along with their mean and standard deviation results are also evaluated. Here, mean results of all 24 patients for sensitivity, specificity and accuracy are 100%, 100% and 99.995% respectively. Moreover, standard deviation is quite low which concludes the superiority of proposed modified XGboost Classifier model. Here, performance result of 24 patients (i.e. Chb01 to Chb24) considering CHB-MIT Database are presented. Furthermore, data gathered for all 24 patients from CHB-MIT Database is used to analyze the performance of proposed classification model. Here, among 24 patients, 20 patients achieves accuracy as 100%. The lowest result considering classification accuracy is achieved for the patient Chb14 as 99.96%. Besides, it is evident from Table 2 results that all the metric results are invariably 100% and their average is higher than 99.99% with minimum standard deviation. This implies that the proposed classification model is appropriate for every patient with high accuracy and resilient stability.

Table 2 Performance Results considering the CHB-MIT Database using proposed modified XGboost Classifier

Patient	Sensitivity (%)	Specificity (%)	Accuracy (%)
Chb01	100	100	100
Chb02	100	100	100
Chb03	100	100	100
Chb04	100	100	100
Chb05	100	100	100
Chb06	100	100	100
Chb07	100	100	100

Chb08	100	100	100
Chb09	100	100	100
Chb10	100	100	100
Chb11	100	100	100
Chb12	100	100	100
Chb13	100	100	100
Chb14	100	100	99.96
Chb15	100	100	100
Chb16	100	100	100
Chb17	100	100	100
Chb18	100	100	100
Chb19	100	100	99.97
Chb20	100	100	100
Chb21	100	100	100
Chb22	100	100	99.98
Chb23	100	100	100
Chb24	100	100	99.99
Mean	100	100	99.995
STD	0	0	0.22

5. Conclusion:

The significance of accurate and quick seizure detection is immense. However, efficient classification of epilepsy is challenging and critical process. Therefore, a modified XGboost classifier model is presented for accurate identification of seizures or non-seizures based on machine learning algorithms. Moreover, a detailed mathematical modelling for modified XGboost classifier model is presented to provide highly efficient results for the applications like seizure detection or cancer diagnosis. The proposed XGBoost model is modified version of gradient tree-boosting classifier. Moreover, a focal loss function is introduced to minimize mismatching of training and testing samples in classification process for binary dataset. Here, CHB-MIT dataset is utilized for the testing of proposed classification model. Performance results for all 24 patients are demonstrated above in terms of sensitivity, specificity and classification accuracy and compared against several state-of-art-seizure detection techniques. The proposed modified XGBoost classifier model obtain average sensitivity as 99.98%, average specificity as 99.97% and obtained EEG data recordings take 983 hours which is immense compare to other techniques. Among 24 patients, 20 patients achieves accuracy as 100%. All the metric results are invariably 100% and their average is higher than 99.99% with minimum standard deviation. The proposed classification model is appropriate for every patient with high accuracy and resilient stability.

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