Diagnosis and Prognosis: Prediction of Epilepsy using EEG Signals in Combinationwith Machine Learning Classifiers

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ABSTRACT
Epilepsy is a type of neurological disorder which impacts the brain's central nervous system. While the effects vary from person to person, they com- monly include mental instability, moments of loss of awareness, and seizures.There are several classi- cal approaches for analysing EEG signals for seizures identification, all of which are time-consuming. Many seizure detection strategies based on machinelearning techniques have recently been developed to replace traditional methods. A hybrid model for seizure prediction of 54-DWT mother wavelets analysis of EEG signals using GA (genetic algorithm) in combination with other five machine learning (ML) classifiers: Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Artificial Neural Net- work (ANN) Naive Bayes (NB) and Random Forest is used in this paper.Using these 5 ML classifiers, the efficacy of 14 possible combinations for two-class epileptic seizure detection is evaluated. Nonetheless, the ANN classifier beat the other classifiers in most dataset combinations and attained the highestaccuracy.

Keywords
Electroencephalogram (EEG), discrete wavelet transform (DWT), genetic algo- rithm (GA) support vector machine (SVM), artificial neural network (ANN), k-nearest neighbor (k-NN), naive bayes (NB) random forest (RF).

1. INTRODUCTION
One of the necessary yet critical jobs is the affective or cognitive detection of psychological state in realtime. It is useful in a variety of fields, including health care, neuroscience, education, and so on (Lin et al., 2010). Intelligent development in the health sector need efficient methods for human- machine interaction in real-time scenarios. One of the alternatives for interacting with machines is to use peripheral brain activity signals. Elec- troencephalograms, or EEGs, are a type of brain signal. It measures and transmits voltage using electrodes wrapped all around human scalp. The EEG electroencephalogram) was a game changer in the healthcare area. It is used to record and analyse electro-magnetic activity of neurons derived from the human scalp (Berger, 1929). This intelligent healthcare technology enabled us to address critical challenges such as neuropsychological abnormalities (Stam et al., 2005), sleep-wake cycle (Ferrara & De Gennaro, 2011), cerebral maturation (Brovelli, Battaglini, Naranjo, & Budai, 2002), and functional networks in the nervous system (Boersma et al., 2011). In recent years, there has been tremendous growth in the processing and analysis of EEG signals. On a daily basis, the brain is a complex lattice of around 86 billion neurotransmitters that process and control unconscious and conscious decisions (Azevedo et al., 2009).

Several research for detecting biological movements and physiological changes utilising neural signals have been conducted for a variety of reasons, includ- ing medical diagnostic and brain-computer interface (BCI) (Genuth, 2015). One of the most difficult issues of brain-machine interface applications is mapping the neural activity pattern to the temporal mental states. One of the key difficulties in the healthcare arena is the segmentation of the EEG signal because the EEG data signals are nonlinear, complicated, unpredictable, and non-stationary.

Several machine learning algorithms have been used in the classification of EEG signals past the last two decades. These ML (machine learning) based solutions have been used in a variety of applications and for a variety of goals. The model's feasibility is determined by the problem's complexity and application area.

Machine learning algorithms provide a high level of confidence in the segmentation of EEG-based datasets. It can handle and process Exploratory Data Analysis (EDA) both in real-time and offline environments. When it comes to EEG-based health- care classification for applications like depression, alcoholism, dementia, behavior modification, eye state recognition, identity verification, activity recognition, epilepsy, drowsiness detection, multi- class task identification and sleep stage, traditional classification algorithms like SVM, LR, NB, LDA, QDA, KNN, LS-SVM, CNN, Bagging, RF, MLP,

Ensemble Classifiers, DT, ANN, Boosting, and several hybrid classification models have been presented from time to time, with varying degrees of success(Correa, Orosco, & Laciar, 2014; Mumtaz, Vuong, Xia, Malik, & Abd Rashid, 2016; Subasi, 2007a; Acharya et al., 2018; Anuragi & Sisodia, 2019; Yuvaraj, Rajendra Acharya, & Hagiwara, 2018; H. Yu, Lei, Song, Liu, & Wang, 2019).

In the healthcare area, even a minor decision can make a significant difference in the development of a machine-based solution that will benefit individuals while also addressing the numerous deficiencies of the health service. It will also aid in the development of innovative healthcare infrastructure. A hybrid ML method for epileptic seizure detection using electroencephalogram signals is proposed in this research. This hybrid model was tested against other classical ML models to determine its applicability and validity.

The following is how the paper is structured: Section 2 covers some similar work that has been presented in the literature. Part 3 covers the methodology of proposed work, whereas Section 4 demonstrates model validation and experiments. Sections 5, 6 and 7 shows the evaluation, results and discussion respectively. Section 8 illustrates the conclusion and future work suggestions.

2. RELATED WORK

A list of authors have previously reviewed seizure detection systems and techniques. This is a summary of various seizure detection algorithms based on signal characteristics.

The authors of (Satapathy, Jagadev, & Dehuri, 2017a) used three learning strategies: MLR, SVM and LMTs. LMT classifier outperformed the other with respect to accuracy. (Lima, Coelho, Madeo, & Peres, 2016). Chen et al. (X. Chen, Ji, Ji, & Li, 2018) proposed a cost-sensitive deep active learning technique for detecting epileptic episodes. In the double DNN, these were tested: Recurring neural networks, 1D CNNs, and recurring neural network models with GRU (gated recurrent units). The author of (Raghu & Sriraam, 2018) proposed a novel device called "CADFES in their study.

In order to optimise the number of features, the authors first retrieved 27 characteristics from the data set. The method performance was then as- sessed using SVM, KNN, Random Forest, and the AdaBoost classifier. The EEG signal supplied critical information regarding the electrical activity of the brain. The interpretation of such signals was essential in detecting epilepsy. Due to the human factor, epilepsy diagnosis can be arbitrary and potentially incorrect. To overcome this issue, Machine Learning (ML) approaches were developed to eliminate the human involvement. This technique, on the other hand, was counterintuitive in that it incorporated the use of complex criteria for epilepsy detection. (Akut, 2019) developed a wavelet-based deep learning approach that avoided the need for feature extraction and performed significantly better on fewer datasets than existing state-of-the-art ML algorithms.

The author of (Yao, Cheng, & Zhang, 2019a) com- bined a learning algorithm and a dense structure with a deep learning model, to utilise spatial and temporal discriminating qualities. The thick construction was designed to maximise transmission of information between levels. Yao et al. (Yao, Cheng, & Zhang, 2019b) created a new technique for seizure/non-seizure classification using an emerging deep learning architecture called IndRNN (?, ?). This new technology steadily widened the time scales, allowing temporal and geographical data to be retrieved from the localized time period to the whole record. To analyse the noise from the signal across patients, cross-validation trials were employed. Lekshmy et al. (Lekshmy, Panickar, & Harikumar, 2022) compared ML methods for anticipating epileptic seizures and evaluated their efficacy. The data showed that the accuracy rates of the RF and LSTM algorithms were the greatest.

In the study by author of (Kaleem, Guergachi, & Krishnan, 2018), between the wavelets db6 wavelet was used. Reoccurring convolutional neural net- works have surpassed conventional machine learning techniques for sequence modelling using mean cross- validation performance, as shown by the author (Ahmedt-Aristizabal et al., 2020), enabling us to suggest a customised weight initialization strategy.

The model's intuitively important details, such as where to locate the most specific post-stimulus window characteristics, were further elucidated. The conclusions of prenatal and disease influences in the pre-prodromal stage of psychosis were also sup- ported.In determining the cause of seizures in 10 (paediatric) patients at least thirty seconds before seizure start, (Dedeo & Garg, 2021) devised a method for detecting crucial preictal sites in the spectrum of 30 to 100 Hz. Additional investigation into the prospective future prediction performance revealed that detection techniques must take into account a patient's typical extremes' range of inten- sities also.

The usage of DT-CWT by authors of (Li, Chen, & Zhang, 2017) in the decomposition phase was bene- ficial because it allowed for halfway band division. The researcher of (Satapathy, Jagadev, & Dehuri, 2017b) suggested a study wherein they detected seizures using neural networks and SVM on an EEG dataset. A convolutional neural network-based ictal seizure detection approach was put out by Park et al. (Park et al., 2018). The proposed network was built utilizing 1-dimensional and 2-dimensional convolution layers for multi-channel EEG signals and included the spatio-temporal cor- relation features. The 1-dimensional convolutional layer took into account the temporal dynamics of each network's EEG signal, and the 2-dimensional convolutional layer took into account the spatial correlations between EEG channels.

Hassan and Subasi (Hassan & Subasi, 2016) em- ployed SVM, GA and PSO to detect seizures. Lah- miri and Samuel citer3125 used the Hurst expo- nent to appropriately classify between the non seizure and seizure. (Kumar, Pachori, & Acharya, 2017). (Kitano et al., 2018) utilized small amount of data to forecast seizures. The data set consisted of 10 minutes of preictal data and 10 minutes of interictal data, and it lasted for 20 minutes. Using 4 sec of window frames for 20-minutes of data, they used discrete wavelet transform to extract zero crossing. On the other hand, Turk and Ozerdem (Türk & Özerdem, 2019) used a CNN structure to learn the characteristics of these EEG data, and the structure's classification performance was compared to that of earlier investigations.

3. PROPOSED METHOD

3.1 Dataset

The data used originate from (Andrzejak et al., 2001) group from the Department of Epileptology, University of Bonn, Germany via that is often produced at random. Each person in a group is represented by a single chromosome, and each chromosome is made up of a vector of components known as genes.

GA resolves by optimizing a single parameter, known as a fitness value. The fitness value indicates the degree of goodness of every (which is a vector of parameter values to be optimised). To create better individuals (a new population from an old one), chromosomal procedures such as crossover, muta http://www.meb.unibonn.de/epileptologie/science/ph tion and selection are used. During the selection ysik/eegdata.html. The total data set contains five sets (A-E), each with 100 single-channel EEG segments. Sets A and B show segments taken from exterior recordings of five healthy volunteers who were awake and had their eyes open (A) or closed (B).

The following sets C, D, and E come from an EEG archive of five separate patients' pre-surgical diagnoses. Sets C and D contained exclusively seizure-free behaviour, but Set E contained seizure activity.

3.2 Data Pre-processing

Using a 12-bit A/D converter, EEG waves were digi- tised at 173.61 Hz. Because the critical information in the EEG lies between the frequency bands of 0 and 40 Hz for epileptic seizure identification, the band-pass filter settings 0.53-40 Hz (12 dB/oct) were used in the original dataset. As in (Subasi, 2007b; Subasi, Kevric, & Abdullah Canbaz, 2019), only A and E dataset of the total data were used in this paper.

3.3 Genetic algorithms

The genetic algorithm (Davis, 1991; Golberg, 1989; Michalewicz, 1999), which is based on the principles of natural genetic systems, is a robust, adaptive, and efficient optimization tool. GA has a wide range of applications in scientific domains such as image processing, pattern recognition and machine learning. GA begins with a population of individuals process, the parent chromosome accountable for reproduction are chosen.

Crossover is a means of sharing information between parent chromosome by combining existing sections of their genetic material. This procedure connects portions of two parent chromosomes to produce kids for the next generation. The mutation procedure is characterized as an arbitrary change in the genetic composition of a chromosome that results in genetic diversity within the population.

3.4 Support vector machines (SVM)

SVM is a binary classification supervised learning model. It has numerous properties, such as being resistant to a broad spectrum of factors and small numbers of samples, and being able to deal with large predictors (Pontil & Verri, 1998; G.-X. Yu, Ostrouchov, Geist, & Samatova, 2003). SVMs are used to solve a variety of issues in text classification (Joachims, 2005), pattern recognition (Pontil & Verri, 1998), and bioinformatics (G.-X. Yu et al., 2003), and have been extended to generic nonlinear problems. The primary goal of classification is to teach a computer the non - linear relationship between characteristics and their related labels. The fundamental goal of SVMs is to divide data into two categories by generating a linear hyperplane. The margin is the length between the class boundaries and this hyper-plane. The SVM's main concept, maximization of the margin, results in improved classifier performance. Nevertheless, data are not linear in nature in almost all real-world applications. In this situation a nonlinear projection from input space to feature space with greater dimensions is developed to render the non-separable classes linearly separable. A nonlinear function defined by the usage of a kernel function should carry out this nonlinear mapping.

Other kernels proposed in the literature include RBF (radial basis function), gaussian, anova, and poly- nomial. To attain optimal results, many machine learning techniques necessitate careful parameter selection. Similarly, the SVM architecture requires the right kernel values to achieve higher classifi- cation accuracy. For example, the gamma kernel function parameter should be optimised for the RBF (radial basis function) kernel. The empirical trial-and-error method of determining these values is impractical. The goal of this study is to develop a hybrid method for detecting epilepsy using GA along with four machine learning classifiers to determine the best one. (Schölkopf, Burges, Smola, et al., 1999; Schölkopf, Smola, Bach, et al., 2002) provide detailed information on the use of kernels.

3.5 K-Nearest Neighbors (KNN)

K-NN is a nonlinear, nonparametric and straight- forward algorithm for classifying samples (Schölkopf et al., 1999, 2002). It performs admirably on larger training datasets. This algorithm performs data object categorization by calculating the majority of votes of neighbours, and the object will acquire the class that is most prevalent among its k-nearest neighbours. It is mostly dependent on similarity measurements between the training and test data sets, such as Distance function, Manhattan distance, and others. The fresh samples are allocated to the class based on adjacent k data for training in accordance with similarity metrics, therefore the case is classified using the majority of votes of the case neighbours. Between 3 to 10 is the greatest value for K.

3.6 Artificial Neural Network (ANN)

ANNs (Artificial neural networks) include computer programmes inspired by biology that imitate how the human brain organizes data. ANNs learn by finding patterns and correlations in input and learns through experience rather than programming. An ANN is composed of a number of single units, referred to as artificial neurotransmitters or PE (processing elements), that are linked together using coefficients (weights) to form the neural structure and thus are organised in layers. The power of brain calculations is derived from the interconnection of neuron in a network (Mardini et al., 2020). Each PE has a transfer function, weighted inputs, and one output. A neural network's behaviour is defined by the equations of its neuron, the learning rule, and the architecture itself.

Furthermore, ANNs may combine and use both experimental and theoretical data to solve issues. ANN applications can be divided into three cate- gories: classification, prediction, and modelling.

3.7 Naive Bayes (NB) Classifier

A Naive Bayes is a predictive model based on Bayesian theory, with the assumption that each attribute of a given category is independent of all others. Independence is usually a bad assumption. The Bayesian theorem is the foundation of this procedure (Mardini et al., 2020). This classifier analyses the relationship between each feature and the class for each occurrence in order to obtain a likelihood function for these correlations.

Due to the inadequacy of real data to satisfy the criteria of NB, there's many modifications of NB available to serve general data. They achieve varied levels of precision with the distinct uses for each type of NB. Another significant issue with the usage of individual character assumption is the learner's inability to detect any hidden patterns from the information. If the NB is applied without regard for the feature dependency, performance can suffer significantly.

3.8 Random Forest (RF) Classifier

RF is a well-known and effective ensemble supervised classification algorithm. Because of its greater accu- racy and resilience, as well as its capacity to provide insights through feature ranking, RF has been suc- cessfully used to a wide range of ML applications, including those in finance.

Medical imaging and Bioinformatics are two fields of study. RF is made up of a collection of decision trees that are formed using the bagging technique with no pruning, resulting in a "forest" of classifiers selecting for a specific class. To train RF, two parameters must be supplied: the number of trees in the forest (ntree) and the number of randomly picked features/variables used to assess at each tree node (Lestari et al., 2020). The voting cutoff (the frac- tion of the forest's trees required to vote for a spe- cific class) can also be adjusted using RF, which is employed to compute recall, precision, and f-score. The accuracy estimate included into the RF tech- nique and all of its deployments is known as OOB (Out of Bag Error), and it assesses the mean mis-interpretation proportion of samples not utilised for RF training.

4. MODEL VALIDATION AND EXPERIMENT

To classify EEG data for epileptic seizure detection, the suggested method employs 54-DWT mother wavelets, a GA (Genetic algorithm) and five classi- fiers. Fig. 1. depicts the proposed methodology's flow. Before doing feature extraction, the raw EEG data underwent pre-processing. Following that, we trained in 5 algorithms: SVM, KNN, ANN, Naive Bayes and Random Forest classification.

The preprocessing stage's major goal is to boost and improve system performance by separating noise from EEG signals (Zakeri, Assecondi, Bagshaw, & Arvanitis, 2014). To remove the noises, we apply the Bandpass filter and smoothing approach (Hamad, Houssein, Hassanien, & Fahmy, 2018a). The goal of the feature extraction phase is to extract statistical features from EEG signals (D. Chen, Wan, Xiang, &

Bao, 2017). Our technique relies heavily on 54-DWT mother wavelets. This wavelet is then decomposed further to extract the required features.

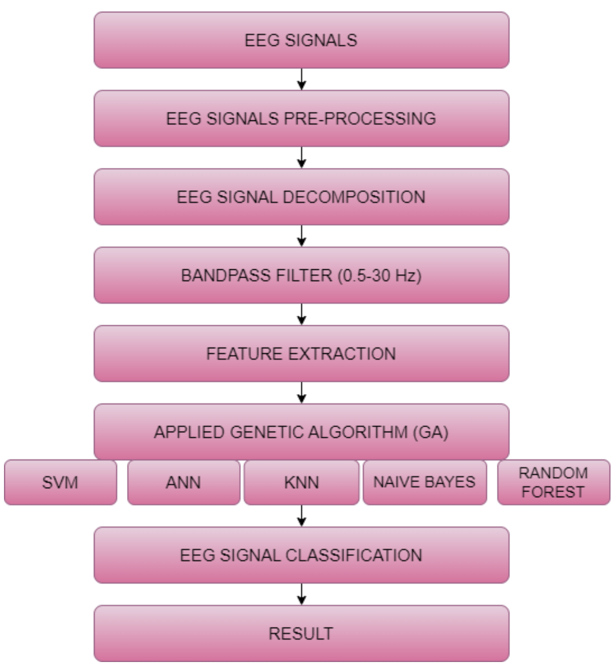

Figure 1: Flowchart of proposed methodology

The statistical parameters are then applied to the detailed coefficients. The coefficients of the low pass filter g[n] are then transmitted to the low and high pass filters in the following level, with the fre- quency resolution increasing and the time resolution decreasing with each step. The process is repeated until each DWT wavelet has a significant level of de- composition.

After the wavelet coefficients are formed, the feature matrix is used to represent the signal. The approx- imation and detailed coefficients were used to shape the feature's matrix.

These equations define the frequency band range of 0.05 -86 Hz.

Accuracy	$ACC = (TP + FN)/(TP + TN + FP + FN)$
Sensitivity (True Positive Rate)	$TPR = TP/(TP + FN)$
Specificity (True Negative Rate)	$TNR = TN/(TN + FP)$

Figure 2: Classifier Performance

In this study, we use the following features namely:

i. Mean Absolute Value
ii. Average Power
iii. Standard Deviation
iv. Variance
v. Mean
vi. Skewness
vii. Shannon Entropy
viii. Max: measure the maximum wavelet coefficientsin each sub-band.
ix. Min: measure the minimum wavelet coefficientsin each sub-band.
x. Normalized SD
xi. Energy

The first five features, as well as feature eight and nine, are conventional statistical features. Shannon entropy is a measure of the system's disorder. Nor- malized SD attempts to describe typical devastation using a 0-1 scale. Every gene has a score or cost that indicates its energy, that is calculated in feature eleven.

The feature selection and reduction stage aims to reduce feature dimensions and choose the most appropriate features. We used the genetic algo- rithm in this work (GA). GA is a problem-solving technique that focuses on optimization problems (Hamad, Houssein, Hassanien, & Fahmy, 2018b). It is based on natural selection and heredity in natural evolution. The best-adapted individuals profit from the evolutionary principle of survival.

Genetic Algorithm (GA) is used to minimize the statistical characteristics, which are subsequently applied to the classifiers (Kołodziej, Majkowski, & Rak, 2011; Nasiri, Sabzekar, Yazdi, Naghibzadeh, & Naghibzadeh, 2009). Classifiers are used for identifying the unknown samples based on known samples. ANN, SVM, KNN, Naive Bayes and Random Forest are among the five classifiers we used.

5. EVALUATION

Band pass signals were used for 0.5-30Hz only, in the pre-processing phase because this range contains brain frequency signals, . For non-seizures signals, the power spectral density peak was observed around the delta frequency range. Yet, in the case of seizure signals, the PSD peaks shift to theta frequency.

In this thesis, various assessment criteria were used to evaluate the efficacy of our suggested model. Accuracy, Sensitivity, and Specificity are the evalua- tion measures. The performance measurements are measured with the holdout test model and k-fold cross-validation (Moshrefi, Mahjani, & Jafarian, 2014), and the results are compared. First, the following elements are defined:

- True positive (TP): an outcome in which themodel forecasts the positive class properly.
- True negative (TN): an outcome in which the model predicts a negative class properly.
- False-positive (FP): an outcome in which the model forecasts the positive class inaccurately.
- False Negative (FN): an outcome in which themodel forecasts the negative class wrongly.

Next we assess accuracy, specificity and sensitivity,as defined in Fig. 2.

Table 1: Evaluation Metrics of SVM, ANN, KNN, Naive Bayes and Random Forestfor Different Cases

DATASETS	PARAMETERS	SVM(%)	ANN(%)	KNN(%)	NB(%)	RF(%)
A-E (Case-1)	Accuracy	93.9	93.9	93.9	93.9	80.3
	Sensitivity	93.9	93.9	93.9	93.9	40.1
	Specificity	93.9	93.9	93.9	93.9	82.8
B-E (Case-2)	Accuracy	93.9	93.9	93.9	93.9	80.6
	Sensitivity	93.9	93.9	93.9	93.9	37.2
	Specificity	93.9	93.9	93.9	93.9	81
C-E (Case-3)	Accuracy	90.1	90.1	90.6	90.1	78.5
	Sensitivity	93.9	93.9	93.9	90.5	40.1
	Specificity	82.9	86.9	86.7	88.5	80.5
D-E (Case-4)	Accuracy	92.3	92.3	93.9	92.4	81
	Sensitivity	93.9	93.9	93.9	90.7	39.8
	Specificity	90.7	88.7	93.9	93.9	80.6
AB-E (Case-5)	Accuracy	93.9	93.9	93.9	92.9	78.9
	Sensitivity	93.9	93.9	93.9	93.9	38.9
	Specificity	93.9	93.9	93.9	92.2	80.6
AC-E (Case-6)	Accuracy	88.3	90.6	89.4	88.3	81
	Sensitivity	90.3	93.9	91.3	89.6	40.3
	Specificity	82.9	86.8	87.4	84.2	82.6
AD-E (Case-7)	Accuracy	93.9	92.8	92.9	92.9	79.4
	Sensitivity	93.9	93.9	93.9	92.3	41
	Specificity	92.2	93.2	87.2	93.9	83.2
BC-E (Case-8)	Accuracy	90.4	90.6	89.4	88.3	79.2
	Sensitivity	93.2	93.9	90.3	86.3	40.8
	Specificity	84.2	83.8	86.4	80.1	80.3
BD-E (Case-9)	Accuracy	93.9	92.8	92.9	92.8	79.7
	Sensitivity	93.9	93.9	93.9	86.2	39.7
	Specificity	93.2	93.2	87.2	86.4	84.8
CD-E (Case-10)	Accuracy	89.4	89.4	90.5	89.4	80
	Sensitivity	93.2	92.2	91.2	92.2	38.9
	Specificity	82.2	85.2	83.6	82.1	82.7
ABC-E (Case-11)	Accuracy	88.8	93.5	90.8	89.5	77.9
	Sensitivity	90.7	90.8	91.7	93.8	39.2
	Specificity	90.2	93.9	88.8	90.4	83.2
ACD-E (Case-12)	Accuracy	88.1	93.5	90.8	88.5	77.9
	Sensitivity	89.7	90.8	91.7	93.8	38.2
	Specificity	90.1	89.2	88.8	90.4	82.2
BCD-E (Case-13)	Accuracy	93.3	92.3	93.5	88.5	78.6
	Sensitivity	93.9	93.8	93.8	92.8	35
	Specificity	92.5	93.9	86.4	83.3	84.1
ABCD-E (Case-14)	Accuracy	93.1	92.6	92.6	93.3	77.8

Sensitivity	92.5	92.3	91.3	93.2	37.8
Specificity	93.9	93.9	89.9	93.9	84.9

Table 2: Average percentage (for the different cases) of Accuracy, Sensitivity, and Specificity using differentML classifiers

	CLASSIFIERS				
PARAMETERS	SVM(%)	ANN(%)	KNN(%)	Naive Bayes(%)	Random Forest(%)
Accuracy	91.6	92.4	92	91	74.4
Sensitivity	92.9	93.2	92.7	91.6	39
Specificity	89.7	90.7	91.4	89.8	76

6. RESULTS

The findings shown here indicate the accuracy, sen-sitivity and specificity of 14 dataset combinations; these results represent the evaluation metrics pro- duced by the genetic algorithm. The datasets were randomly divided into training and testing datasets, with 70% for training and 30% for testing.

14 classification combinations (training-testing) are used in this paper which is depicted in the form of table in Table I along with different ML classifiers' accuracy, sensitivity and specificity with respect to these 14 cases. We utilized the dataset E in all com- binations because it is the only one that is regarded as a seizure activity. In this study, we compared clas- sifiers for identifying the epileptic signal.

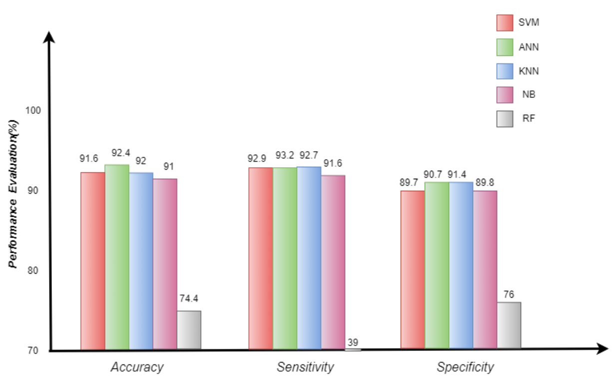

Figure 3: Graphical representation of evaluation performance of classifiers

7. DISCUSSION

Table I shows the performance of five classifiers for the selected features from the genetic algorithm according to the accuracy, sensitivity and specificity acquired from SVM, ANN, KNN, Naive Bayes and Random Forest classifier.

The average value for accuracy, sensitivity and specificity of all the 14 cases were taken. This was repeated for all the four ML classifiers and was listed in the Table II. The observed result showed that accuracy, sensitivity and specificity of ANN classifier was the highest with 92.4% accuracy, 93.2% sensitivity and 90.7% specificity.

After ANN classifier, KNN classifier proved to be the second best classifier in terms of performance metrics with 92% accuracy, 92.7% sensitivity and 91.4% specificity. Following KNN classifier next suit- able classsifier is SVM classifier witn 91.6% accuracy, 92.9% sensitivity and 89.7% specificity and then Naive Bayes with 91% accuracy, 91.6% sensitivity and 89.8% specificity. The least evaluation metric was of Random Forest classifier with 74.4% accuracy, 39% sensitivity and 76% specificity. This is depicted graphically in Fig. 3.

8. CONCLUSION AND FUTURE WORK

Machine learning performs well in classifying non- seizure and seizure EEG data. In this paper, we offer a novel way of diagnosing EEG signals by combining Multi-DWT and Genetic algorithms with four classifiers: SVM, ANN, KNN, Naive Bayes and Random Forest. The experimental results demonstrated that DWT characteristics combined with several machine learning techniques produced noticeable outcomes, and the ANN classifier outperformed all tested clas- sifiers. The new automated technique has a high sen- sitivity for detecting epilepsy. The diagnosis of an epilepsy seizure goes through several stages.

The first phase is the preprocessing of the EEG sig- nals, which is considered the primary step in improv- ing system performance. This step is intended to eliminate the noises. The second phase is feature ex- traction, in which we use numerous DWT to obtain various features, and then the genetic algorithm re- duces these features to picks out the best features from a large number of features. The effectiveness of the proposed approach is demonstrated by repeating the procedure for 14 different dataset combinations. The suggested system was evaluated using several pa- rameters such as Accuracy, Sensitivity, and Speci- ficity. When the ANN was compared to the other classifiers, it outperformed them in terms of the eval- uation metrics in the majority of the 14 dataset com- binations.

For future work, we propose evaluating the use of hybrid ML models by integrating relevant Machine learning techniques and analyzing their outcomes. Additional research can be conducted on cutting-edge deep learning networks in order to overcome the con- straints of classical learning models, which are sensi- tive to the selecting features and extraction phases.

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