Wavelet-Based Approach for Automatic Seizure Detection Using EEG Signals

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Abstract - *People with epilepsy frequently experience seizures, which reduce their quality of life. When electroencephalograph (EEG) recordings of these individuals are categorized precisely between seizure-free and seizure-based segments, it is possible to look into previous seizures and forecast upcoming ones. Modeling an EEG signal can help with the extraction of discriminative characteristics. In this study, a wavelet-based approach is used to break down EEG signals into detailed and approximate coefficients up to the fourth level of decomposition. For the purpose of distinguishing between normal EEG data and signals recorded from epileptic patients, several statistical features have been derived from the wavelet coefficients and fed to various classifiers. The simulation results showed that the suggested model, when applied to the neurology and sleep centre EEG database, New Delhi, attained the maximum classification accuracy of 100 % between healthy and epileptic EEG signals.*

When compared to cutting-edge techniques detailed in the literature, the proposed model exhibits more accuracy.

Key Words: (Cross validation, Electroencephalogram (EEG), Epileptic seizure, Statistical features, Wavelet coefficients, support vector machine.

1. INTRODUCTION

One of the most prevalent neurological conditions, epilepsy affects about 50 million people globally [1]. The most vulnerable groups include older people and children, whose prevalence rates range from 0.7 to 1.0 percent, as well as those individuals with concomitant conditions [2]. Discrimination, misunderstanding, and depression are common experiences for people with epilepsy. Meanwhile, this disorder is dangerous since it can lead to death if a person with epilepsy engages in a dangerous activity [3] [4]. Epilepsy diagnosis and treatment decisions are both customized. Neurologists will identify someone as having epilepsy if they have an epileptic seizure and subsequent seizures within the following 24 hours. Patients may potentially have epilepsy if there is a chance they will experience another seizure after two unprovoked ones during the next 8–10 years [5].

Seizure prevention can be carried out to avert brain damage if a seizure is diagnosed early enough. During an epileptic seizure, the electrical behavior of the brain signal differs from normal brain activity in terms of shape, amplitudes, and frequency [6]. If epilepsy is identified early on and treated with medication and surgery, it is projected that two-thirds of those affected will live seizure-free lives. The researchers have used a variety of neuro-imaging methods to precisely identify seizures [7]. Electroencephalogram (EEG) is one of the foremost tools in neuroscience for assessing brain abnormalities, mostly for seizure detection [8] [9] [10]. The accurate diagnosis of epileptic seizures is carried out by skilled and trained neurologists using continuous monitoring and interpretation of the EEG recordings. This is a time-consuming, expensive, and complex task that could result in an incorrect diagnosis because trained professionals are overworked [8]. As a result, researchers have therefore made numerous attempts to automatically identify epileptic seizures.

Sameer et al. in [11] employed short-time Fourier transform (STFT) to extract delta rhythm, from the time-frequency analysis of EEG signal. Four statistical features namely kurtosis, mean, variance, and skewness have been computed from the delta band of the EEG signal. Using a random forest (RF) classifier, the proposed algorithm achieved a classification accuracy of 97.40 % while discriminating between people suffering from epilepsy and healthy people. In [12], the authors computed epileptic seizure density as a feature that is fed to k-nearest neighbor (kNN) to evaluate the performance of the proposed methodology. Using neurology and sleep EEG dataset, the present study achieved good accuracy of 99 % when classifying between pre-ictal and ictal EEG signals. The authors in [13] demonstrated a hybrid approach based on multi-scale radial basic function and the Fisher vector technique for investigating the high-resolution time-frequency estimation to analyze the dynamic behavior of the non-stationary EEG signals. Sharma et al. in [14] used a novel model based on an orthogonal wavelet filter bank (OWFB) for discrimination of ictal and non-ictal EEG signals using the BONN EEG database and neurology and sleep center EEG database. The suggested method, when used with ten-fold cross-validation, was able to distinguish between pre-ictal and ictal EEG signals with a classification accuracy of 98 % and between inter-ictal and ictal EEG signals with a classification accuracy of 100

%. A stochastic differential equations-based approach for the precise categorization of seizure and healthy EEG signals was reported by Tajmirriahi et al. in [15]. The suggested model achieved the maximum classification accuracy of 99.1 % for the neurology and sleep centre database between healthy and ictal EEG signals using a support vector machine (SVM). Carvalho et al. in [16] explained five adaptive decomposition techniques for the analysis of non-stationary and non-linear EEG signals. It is revealed that among these methods, variational mode decomposition and empirical mode decomposition based approach showed superior results in terms of classification accuracy. Hadiyoso et al. in [17] proposed two features namely relative wavelet energy and wavelet entropy for the accurate detection of an epileptic seizure. The EEG signals are decomposed into five frequency rhythms from which two features have been extracted from each of these frequency bands. Using an SVM classifier, the simulation result showed the highest classification accuracy of 96 % for inter-ictal vs ictal EEG signals. A discrete cosine transform (DCT) based filter bank was suggested by Gupta et al. in [18] to breakdown the EEG signals into five different brain rhythms. For the binary classification of EEG segments, two features—the Hurst exponent and autoregressive moving average—are generated from these rhythms and provided as inputs to the SVM classifier. The efficacy of the present study is assessed in terms of evaluation metrics using two publicly available EEG databases.

The structure of this paper is as follows: The database used in this study, the wavelet-based decomposition of the EEG signals, the feature extraction and selection processes have been discussed in Section II, and the classifiers employed are covered in Section III. Section IV presents the simulation results and discussion. The final portion contains the conclusion.

2. PROPOSED METHOD

In this work, the dataset includes segmented EEG recordings of ten epileptic patients from the Neurology and Sleep Centre, Hauz Khas, New Delhi [19]. Amplification equipment from Grass Telefactor called the Comet AS40 was used to record the signals. While obtaining the EEG records, gold-plated scalp EEG electrodes are placed in accordance with the 10-20 electrode placement schemes. A band pass filter with a frequency range of 0.5 to 70 Hz was used to filter all of the recordings after they had been sampled at 200 Hz. Each EEG segment is classified by segmentation into one of three categories: pre-ictal, interictal, or ictal. The entire dataset is divided into 150 segments (50 for each category). Each time series EEG record has a length of 5.12 seconds, or 1024 samples. This dataset consists of fifty MAT files organized into the ictal, inter-ictal, and pre-ictal named folders. In this paper, a pre-ictal folder is named as Set A, an inter-ictal folder as Set B, and an ictal folder as Set C, which are shown in Figure 1. A flow chart of the proposed method is depicted in Figure 2.

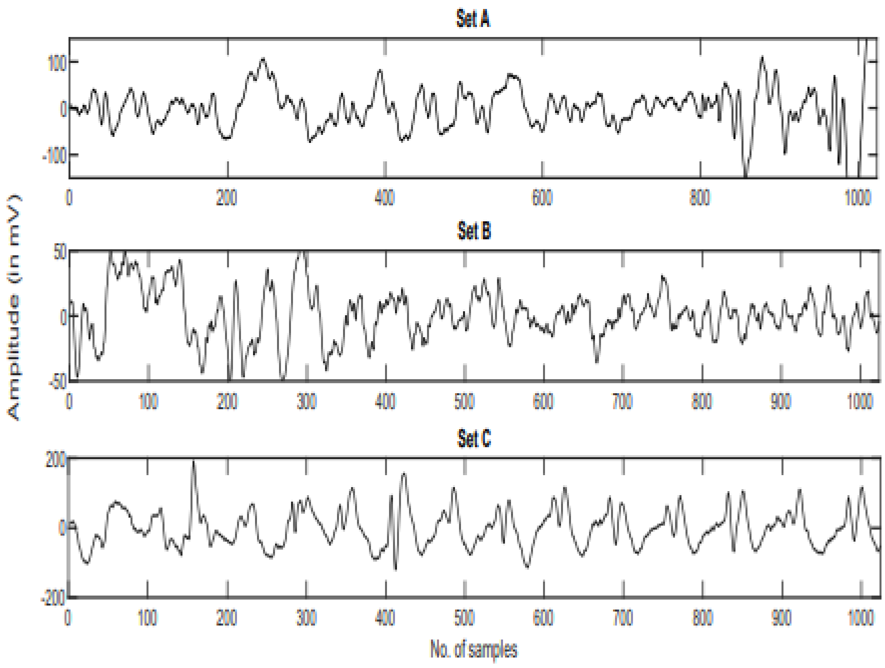

Fig -1: A sample of Set A, Set B, and Set C as preictal, interictal and ictal EEG signals

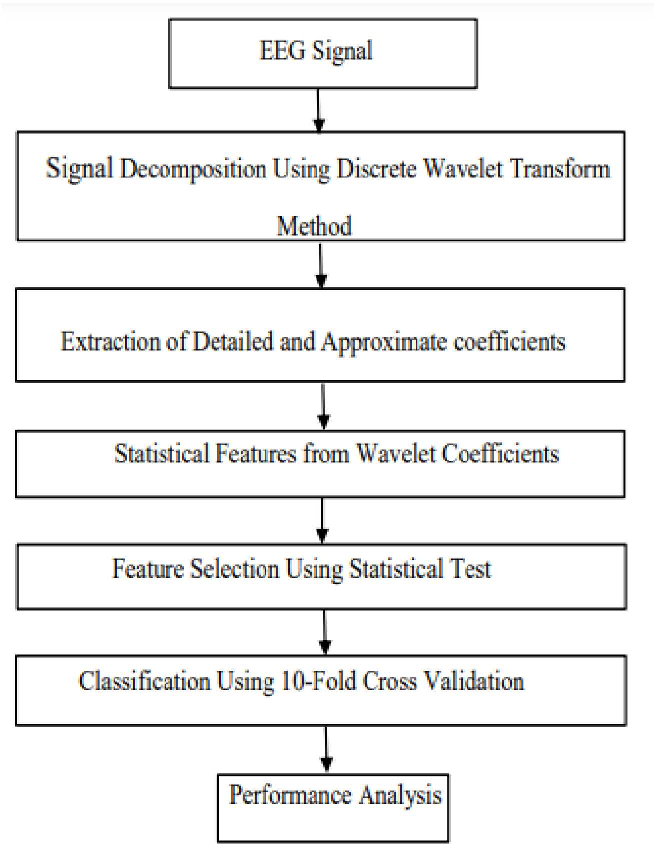

Fig -2: A flow chart of proposed method

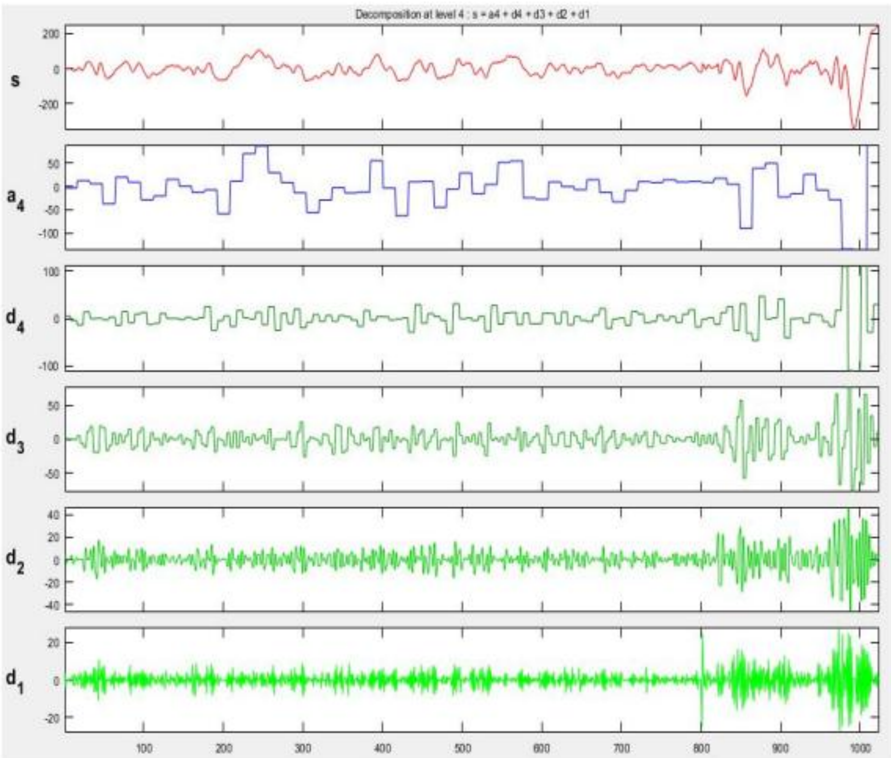

Fig -3: Preictal EEG signal with its detailed and approximate coefficients

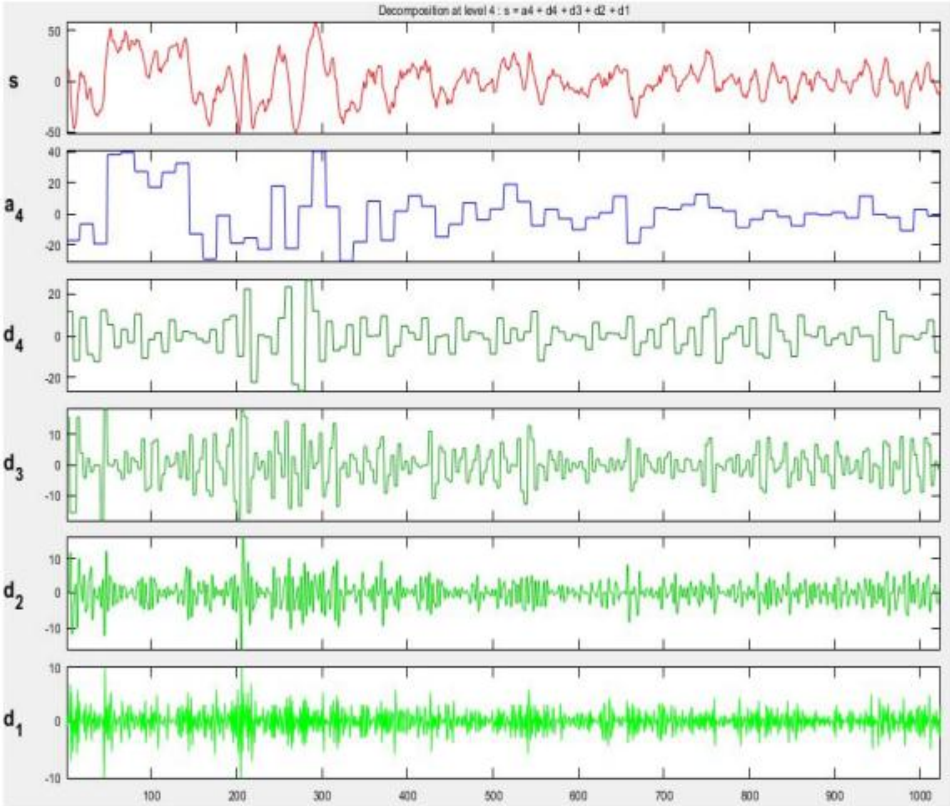

Fig -4: Interictal EEG signal with its detailed and approximate coefficients

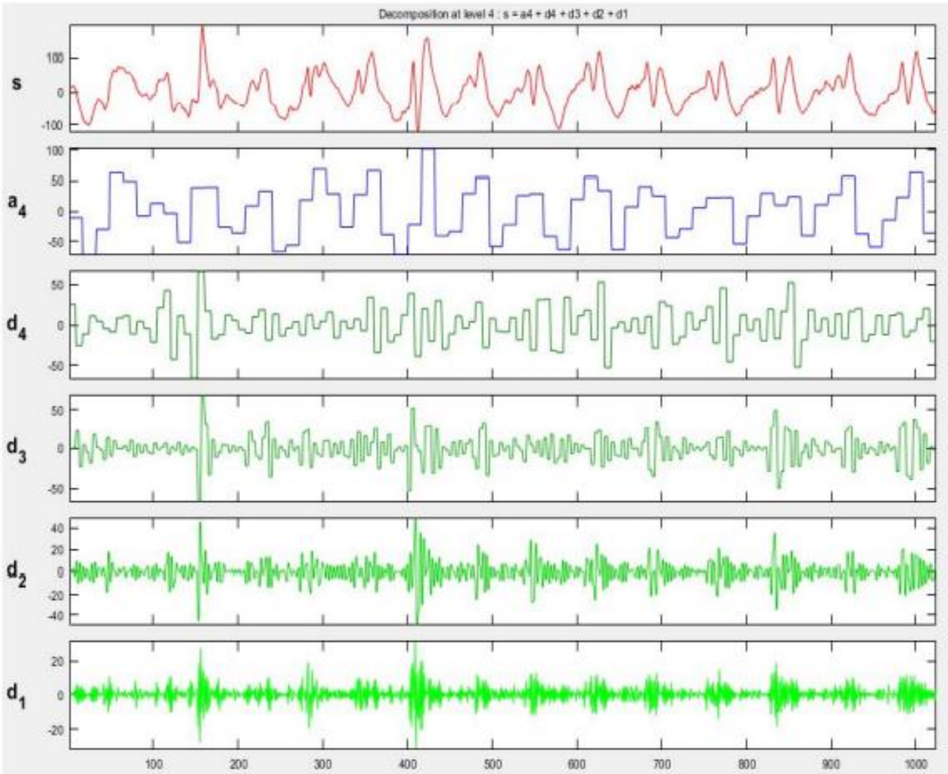

Fig -5: Ictal EEG signal with its detailed and approximate coefficients

2.1 DISCRETE WAVELET TRANSFORM

Wavelet transform is one of the most promising, efficient, and appealing tools for time-frequency representation of non-stationary signals such as ECG, EEG, and others. Wavelet transform is primarily used as a replacement for Fourier transform (FT) and short-time Fourier transform (STFT), as it addresses the shortcomings of both and provides both time and frequency components at any instant, revealing the hidden features of the original signal much more effectively. High frequencies are better resolved in the time domain of the wavelet transform, whereas low frequencies are better resolved in the frequency domain. Wavelet transforms are commonly used on EEG signals for three main purposes: denoising of signal, feature extraction, and signal compression [20] [21]. Wavelet transform has the property to change its finite window length and location depending upon translation and scaling parameters (b, k) which are expressed as:

$$\psi_{b,k}(t) = \frac{1}{\sqrt{k}}\psi(\frac{t-b}{k}), \qquad (1)$$

where the mother wavelet is represented by the function $\psi_{b,k}$, which is scaled by the factor k and translated by the factor of b. When the mother wavelet is multiplied with any signal and integrated overall times, its result is further multiplied with $1/\sqrt{k}$ for the normalization purpose and yield wavelet transform. Continuous wavelet transform is the result of convolution of the signal x (t) and wavelet function ψ (t) and is expressed as:

$$cwt(b,k) = \frac{1}{\sqrt{k}}\int_{-\infty}^{\infty} x(t)\psi(\frac{t-b}{k})dt, \qquad (2)$$

In the literature, it has been observed that neither STFT nor CWT possesses their practical implementation using analytical equations and integrals, thus there is a need to use them in discrete format. It has been investigated that even after the discretization of CWT, computation becomes possible by using computers, however, this is not an original discrete wavelet transform (DWT) as it simply works on the sampling of wavelet in CWT, which leads to lots of redundant information while reconstructing a signal and ultimately increases computational time. On the other hand, actual DWT is a highly efficient transform that significantly reduces the computation time and can reconstruct signals more efficiently. DWT is frequently employed as a filter bank (comprising low pass and high pass filters) for signal segmentation. Detailed and approximate coefficients have been computed up to the fourth level of decomposition. The detailed coefficients represent high-frequency components of the EEG signal while approximate coefficients represent low-frequency components. In this work, the Haar wavelet is employed as a basic wavelet function.

2.2 FEATURE EXTRACTION

In this paper, ten statistical features, namely mean, median, range, mean absolute deviation, median absolute deviation, standard deviation, L1 norm, L2 norm, maximum, and minimum values have been computed from wavelet coefficients known as detailed and approximate coefficients. These wavelet coefficients are extracted from pre-ictal, inter-ictal, and ictal EEG signals. A brief description of these statistical features is depicted in Table 1.

2.3 FEATURE SELECTION USING WILCOXON RANK-SUM TEST

After computing the statistical features from the wavelet coefficients of each of the three classes of EEG signals, the next step is to acquire a subset of the relevant features using statistical techniques. The Wilcoxon rank-sum test is used in this study to pick significant features using the MATLAB statistical toolbox, with p-value and z-score assigned at a 95 percent significance level. This approach is used to determine how similar the population locations are (medians equal to zero or not).

The null hypothesis argues that two populations have comparable distribution functions, whereas the alternative hypothesis states that they are distinct in terms of medians. Any feature with a p-value less than 0.05 are considered a relevant feature that can be input into the machine learning algorithm to improve classification accuracy. Other traits with p-values greater than 0.05, on the other hand, are unimportant and can be removed.

3 CLASSIFICATION

In this study, three classifiers namely SVM, kNN, and ensemble subspace kNN classifiers have been employed to assess the efficacy of the proposed model. A brief description of these classifiers is as follow:

3.1 SUPPORT VECTOR MACHINE (SVM)

SVM classifier is solely built using statistical learning theory in 1995 by Cortes and Vapnik. It is one of the best-supervised classifiers which is used for binary classification. Also, now-a-days, researchers are using an SVM classifier for pattern classification purposes due to its regularization parameter to avoid over fitting, selection of optimal kernel, and convex optimization [22]. This classifier completely works on the architecture of the kernel function. This kernel function is the most prominent tool, which helps in selecting the most efficient hyperplane to separate training samples of binary classifier without error and also results in distance maximization from both the classes to this separating hyperplane as discussed above [23]. Some of the famous kernel functions of an SVM classifier are the polynomial kernel, linear kernel, and radial basis functions (RBF). In the SVM classifier, the linear discriminant function is q(x) = py+b and the separating hyperplane can be expressed by the equation py+b = 0.

3.2 k-NEAREST NEIGHBOR (kNN)

This classification approach is considered one of the simplest approaches as it follows a non-parametric approach. It can classify a given data point according to viewing its majority of neighborhood points. The kNN algorithm mainly follows a two-step approach. The primary step is to find the number of nearest neighbors, whereas in the second step classification of a data point into a particular class would be done by referring to the primary step. The Euclidean distance technique is used in this study to determine the closest neighbor.

3.3 ENSEMBLE SUBSPACE kNN

By mixing the predictions from various models, ensemble learning is a broad Meta approach to machine learning that aims to improve predictive performance. In this study, random subspace ensembles are used to increase the k-nearest neighbor classifiers' accuracy. Subspace ensembles have the benefits of utilizing less space and handling missing values than ensembles with all predictors.

4. RESULT AND DISCUSSION

In this study, binary problems have been categorized using the three performance measures of sensitivity (Sen), specificity (Spec), and accuracy (Acc) in order to assess the effectiveness of the suggested method.

These metrics are defined as:

$$\begin{aligned} Sen &= \frac{TP}{TP+FN} \times 100\% \\ Spec &= \frac{TN}{TN+FP} \times 100\% \\ Acc &= \frac{TP+TN}{TP+TN+FP+FN} \times 100\%, \end{aligned}$$

Table -1: List of statistical features extracted from wavelet coefficients

Feature index	Feature name	Description
1	Mean	It represents the average value of the given signal.
2	Median	It represents the middle values of the given data points.
3	Range	It represents the difference between maximum and minimum value
4	Mean absolute deviation	It indicates the average distance between each observation and mean value of data.
5	Median absolute deviation	It is a measure of variability in the given signal
6	Standard deviation	It represents the deviation of data points from the mean value

7	L1 Norm	Sum of absolute values of data points
8	L2 Norm	It represents the Euclidean distance of data point from the origin
9	Maximum	Maximum value of the given signal
10	Minimum	Minimum value of the given signal

Table -2: A comparison of EEG signal classification performance of proposed method with the existing techniques

Authors and year	Technique used	Features used	Evaluation Metrics
Gupta et al. [18], 2021	Discrete cosine transform	Hurst exponent	Accuracy=96.5%
Li et al. [13], 2019	Hybrid approach	Sub-bands features	Accuracy=99.3%
Sharma et al. [14], 2018	OWFB	Entropy based features	Accuracy=96.2%
Hadiyoso et al. [24], 2021	Wavelet transform	Relative energy and entropy based features	Accuracy=96%
Sameer et al. [11], 2020	STFT	Kurtosis, mean, variance, skewness	Accuracy=98%
Proposed method	Discrete wavelet transform	Statistical features	Accuracy=100%

Here, the terms TP, TN, FP, and FN stand for the respective terms true positive rate, true negative rate, false-positive rate, and false-negative rate. To distinguish between healthy and epileptic EEG signals is the main goal of the current investigation. The categorization challenge has been included in the current work using the publicly accessible data set. By segmenting the complete bandwidth of EEG signals into wavelet coefficients using discrete wavelet transform, the decomposition of healthy and epileptic EEG signals is obtained. A 10-fold cross-validation method was used in the current study to determine how well the machine learning model performed. Each of the ten equally sized chunks of the complete data sample is chosen as a training set at a specific point in time. The first component is used to test the model during the first iteration, while the remaining sections are used for training. The second component is used for testing in the following iteration, and the remaining sections are used to train the model and so forth. This procedure is repeated until a testing set is used for each of the ten sections.

In this study, pre-ictal, inter-ictal, and ictal EEG signals, recorded from ten subjects containing 1024 samples over duration of 5.12 seconds, are considered to evaluate the results. Discrete wavelet based approach is employed to decompose three classes of EEG signals into various detailed and approximate coefficients as shown in Figures 3, 4, and 5 respectively. A total of ten statistical features have been extracted from detailed and approximate coefficients of preictal, interictal and ictal EEG signals. These features are passed to variety of classifiers such as k-nearest neighbor (kNN), SVM, and ensemble (subspace kNN) for the classification of binary problem. The numerous researches that address the issue of classifying epileptic and normal EEG are compared in Table 2. When distinguishing between inter-ictal and ictal EEG signals, the suggested technique achieved exceptional classification accuracy of 100 percent when compared to other strategies discussed in the literature. The proposed model also showed better epileptic detection of 97.2 % when comparing between pre-ictal and ictal type of EEG signals.

Additionally, Figures 6, 7, and 8 depict the confusion matrix for SVM, kNN, and ensemble subspace kNN types of machine learning models. It is concluded from these figures that the suggested model showed good performance by utilizing any type of supervised machine learning models. By comparing predicted and actual classes, it is a well-known description used to imagine the classifier's effectiveness. It shows the precise number of instances that were correctly and incorrectly categorized.

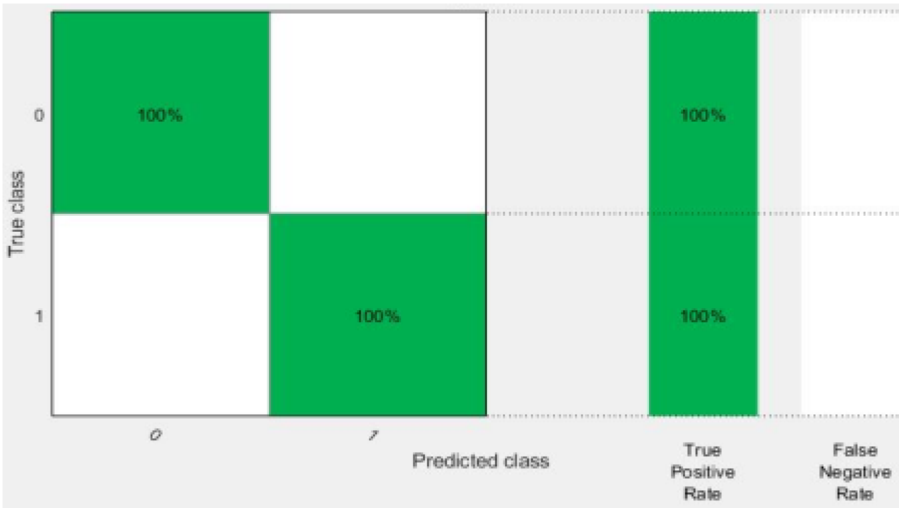

Fig -6: Confusion matrix of SVM classifier

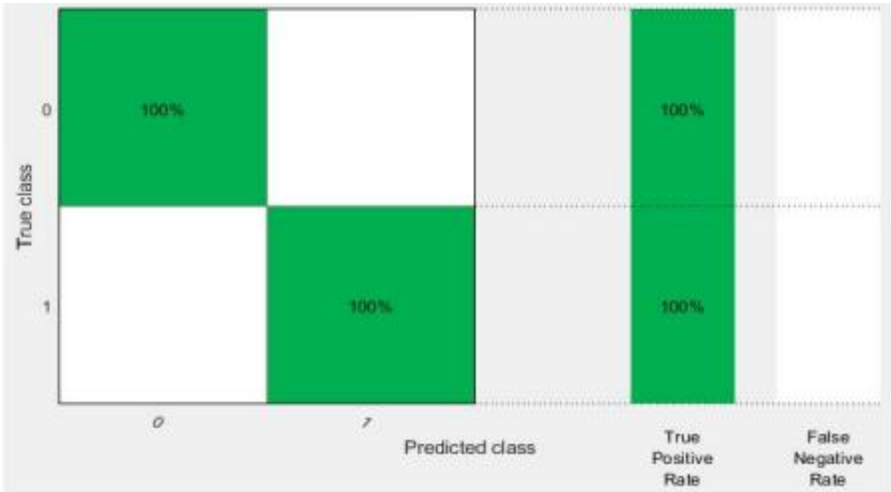

Fig -7: Confusion matrix of kNN classifier

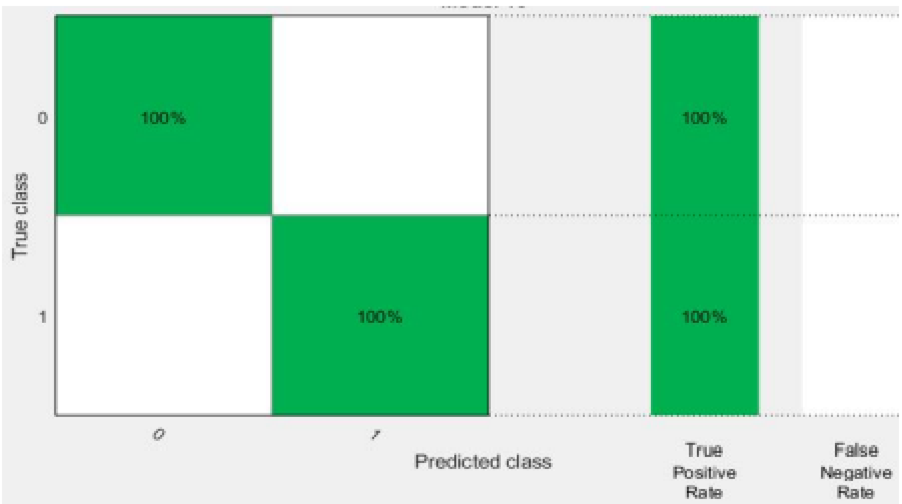

Fig -8: Confusion matrix of ensemble subspace kNN classifier

5. CONCLUSIONS

This study presents an effective method for classifying EEG signals as either normal or those recorded during epileptic seizure activity. Using discrete wavelet transform, ten statistical features have been computed from the wavelet coefficients. The significance of the extracted features is performed by applying Wilcoxon rank sum test. Any feature having p-value less than 0.005 is discarded at 95 % significant level. These features are then supplied to variety of classifiers such as kNN, SVM, and ensemble to assess the success rate of the proposed method. The proposed study, which outperformed the previous approaches, used 10-fold cross-validation to achieve a classification accuracy of 100 % when differentiating between inter-ictal and ictal EEG data. This technique may be used in the future to diagnose a variety of brain illnesses.

REFERENCES

[1] World Health Organization. (2019). Epilepsy. [Online]. Available: https://www.who.int/en/news-room/fact sheets/detail/epilepsy, accessed on 28-Aug-2019.

[2] Kuroda, N. Epilepsy and COVID-19: Associations and important considerations. Epilepsy and Behavior, 108: 107122, 2020.

[3] Moshé, S.L., Perucca, E., Ryvlin, P., Tomson, T. Epilepsy: New advances. The Lancet, 385(9971): 884- 898, 2015.

[4] Wijayanto, I., Rizal, A., Humairani, A. Seizure detection based on EEG signals using Katz fractal and SVM classifiers. In 2019 5th International Conference on Science in Information Technology (ICSITech), Yogyakarta, Indonesia, pp. 78-82, 2019.

[5] Falco-Walter, J.J., Scheffer, I.E., Fisher, R.S. The new definition and classification of seizures and epilepsy. Epilepsy Research, 139: 73-79, 2018.

[6] Tripathi, D., Agrawal, N. Epileptic seizure detection using empirical mode decomposition based fuzzy entropy and support vector machine. In: Hwang S., Tan S., Bien F. (eds) Proceedings of the Sixth International Conference on Green and Human Information Technology. ICGHIT 2018. Lecture Notes in Electrical Engineering, vol. 502. Springer, Singapore, 2019.

[7] Anyanwu C, Motamedi G.K. Diagnosis and surgical treatment of drug-resistant epilepsy. J Brain Sci 8(4):1–20, 2018.

[8] Adeli H, Zhou Z, Dadmehrc N. Analysis of EEG records in an epileptic patient using wavelet transform. J Neurosci Methods 123(1):69–87, 2003.

[9] Liu A, Hahn JS, Heldt GP, Coen R.W. Detection of neonatal seizures through computerized EEG analysis. Electroencephalogram Clin Neurophysiol 82(1):30–37, 1992.

[10] Boashash B, Mesbah M, Colditz P.B. Time frequency detec tion of EEG abnormalities, Time-Frequency Signal Analysis and Processing: A Comprehensive Reference, pp 663–670, 2003.

[11] Sameer, M. and Gupta, B. Detection of Epileptic Seizures based on alpha band statistical features. Wireless Personal Communications, pp.1-16, 2020.

[12] Darjani, N. and Omranpour, H. Phase space elliptic density feature for epileptic EEG signals classification using metaheuristic optimization method. Knowledge-Based Systems, 205, p.106276, 2020.

[13] Li, Y., Cui, W.G., Huang, H., Guo, Y.Z., Li, K. and Tan, T. Epileptic seizure detection in EEG signals using sparse multiscale radial basis function networks and the Fisher vector approach. Knowledge-Based Systems, 164, pp.96-106, 2019.

[14] Sharma, M., Bhurane, A.A. and Acharya, U.R. MMSFL-OWFB: A novel class of orthogonal wavelet filters for epileptic seizure detection. Knowledge-Based Systems, 160, pp.265-277, 2018.

[15] Tajmirriahi, M. and Amini, Z. Modeling of seizure and seizure-free EEG signals based on stochastic differential equations. Chaos, Solitons and Fractals, 150, p.111104, 2021.

[16] Carvalho, V.R., Moraes, M.F., Braga, A.P. and Mendes, E.M. Evaluating five different adaptive decomposition methods for EEG signal seizure detection and classification. Biomedical Signal Processing and Control, 62, p.102073, 2020.

[17] Hadiyoso, S., Irawati, I.D. and Rizal, A. Epileptic electroencephalogram classification using relative wavelet sub-band energy and wavelet entropy. International Journal of Engineering, 34(1), pp.75-81, 2021.

[18] Gupta, A., Singh, P. and Karlekar, M. A novel signal modeling approach for classification of seizure and seizure-free EEG signals. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 26(5), pp.925-935, 2018.

[19] Swami, P., Panigrahi, B. K., Nara, S., Bhatia, M., Gandhi, T. K. EEG epilepsy datasets. http://dx.doi.org/10.13140/RG.2.2.14280.32006, 2016.

[20] Alyasseri, Z. A. A., Khader, A. T., Al-Betar, M. A., and Abualigah, L. M. ECG signal denoising using β-hill climbing algorithm and wavelet transform, In 8th International Conference on Information Technology, pages 1-7, 2017.

[21] Kumar, H., Pai, S. P., Vijay, G., and Rao, R. Wavelet transform for bearing condition monitoring and fault diagnosis: A review, International Journal of COMADEM, 17(1):9-23, 2014.

[22] Subasi, A. and Gursoy, .I. EEG signal classification using PCA, ICA, LDA and support vector machines, Expert Syst. Appl., vol. 37, no. 12, pp. 8659–8666, 2010.

[23] Christianini, N., and Shawe-Taylor, J. C. An introduction to support vector machines and other kernel-based learning methods. Cambridge: Cambridge University Press, 2000.

[24] S. Hadiyoso, I. D. Irawati, and A. Rizal, Epileptic encephalogram classification using relative wavelet sub-band energy and wavelet entropy, International journal of engineering, vol. 34, no. 1, pp. 75-81, 2021.