Electroencephalography classification technique based on statistical denoising and modified k-nearest neighbor algorithm with bipolar sigmoid rectified linear unit's function

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ABSTRACT

Accurate classification of electroencephalography (EEG) data is much needed for early identification of diseases to treat various disorders. In this paper, we propose EEG classification technique based on statistical denoising and modified k-nearest neighbor (k-NN) algorithm with bipolar sigmoid rectified linear units (ReLU) function. The EEG data is subjected to statistical methods to remove the artifacts and then applied to modified k-NN algorithm to categorize the appropriate features giving preference to neighbors closer to one another considering the weighted votes of the k-nearest neighbors before selecting the class label based on the highest weighted vote. A customized activation function that combines these two functions called as hybrid function that uses various portions of each function in particular ranges is used in our work *i.e.,* use of bipolar sigmoid for negative values and the ReLU function for positive values which helps to limit the signal in a particular range. The proposed algorithm's detection accuracy is tested for the confusion matrix of true positive (TP), false positive (FP), false negative (FN)and true negative (TN) and compared to the detection accuracy of other existing algorithms, demonstrating the algorithm's efficiency with a classification accuracy of almost 85 percent and sensitivity of 91% for standard Kaggle dataset.

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1. INTRODUCTION

Electroencephalography is referred to as electroencephalography (EEG). This non-invasive neuroimaging method is used to capture the electrical activity that the brain produces. In order to identify the electrical impulses generated by the brain's neurons, electrodes are applied to the scalp. Brainwaves are the representation of the electrical activity produced by neuronal communication in the brain. These brainwaves are categorized as belonging to beta, gamma, alpha, theta, and delta frequency ranges. Certain mental processes, cognitive states, or activities are linked to each of these frequency bands. In clinical settings, EEG is frequently used to diagnose and track a variety of neurological problems, including epilepsy, sleep disorders, brain traumas, and other abnormalities related to the brain. Additionally, it is employed in research to examine neurological problems, sleep patterns, cognitive functions, and brain function. Neurologists or researchers examine the wave patterns that the EEG signal produces on a computer screen in order to get insight into abnormal brain activity, changes in reaction to stimuli, or brain function. More portable and user-friendly EEG devices have been made possible by advancements in the field. This has allowed researchers to conduct studies in a variety of settings, such as during routine tasks or daily activities, and has deepened our understanding of how brain activity affects behavior and cognition. Brain transmissions are tampered with by unwanted potentials in the EEG signal. Artifacts are these signals, and they should be eliminated before moving on to the processing stage. The artifacts are generated from both physiological and non-physiological of the human body. The precise classification of EEG data is the aim of the field of EEG classification research. A number of strategies and tactics have been put forth to increase the EEG signals' categorization accuracy. One method maps EEG data to a high-dimensional feature space that can be utilized for classification by combining deep convolution networks with long short-term memory networks and attention processes [1]. To improve classification performance, another technique uses labeled and unlabeled data in a semi-supervised learning framework [2].

Furthermore, to extract discriminative features from EEG data, feature extraction methods such dimensionality reduction, statistical analysis, and adaptive segmentation have been used [3]. EEG categorization has been done using machine learning methods such as k-nearest neighbors (k-NN), k-means, artificial neural networks (ANNs), and fuzzy sets [4]. In the fields of machine learning and data analysis, in particular, EEG data can be utilized for categorization tasks. EEG signals are classified by placing them in several groups or classes. This has a number of potential uses: brain-computer interfaces (BCIs) [5]. In BCI systems, where certain commands or actions are linked to specific brain activity patterns, EEG categorization is crucial. Classifying EEG signals linked to distinct motor intents (*e.g.*, using the left or right hand to control a gadget) is one example. Neurological problems: Brain traumas, sleep problems, and epilepsy are just a few of the neurological conditions that can be diagnosed and tracked with the help of EEG signal classification. It is essential that models be able to generalize to new, untested data. Researchers use a variety of approaches, including feature selection, cross-validation, ensembling methods, machine learning algorithms [6] (like support vector machines (SVM) and deep learning (DL)), and signal processing techniques, to overcome these obstacles and improve the robustness and accuracy of EEG classification models.

Suganyadevi *et al.* [7] propose a classification technique for automated epilepsy identification from EEG data. Prior to feature extraction, the signals produced by the EEG equipment were converted using the discrete wavelet transform (DWT). A method called GBMs fusion was created to detect EEG data using a variety of statistical factors and crossing frequency properties. In addition, a genetic algorithm was used to pick the important features initially. We have tested the ability of the proposed technique to discriminate between ictal and normal EEG patterns using EEG data from the University of Bonn. According to experiments, the proposed fusion of gradient boosting machines (GBMs) may improve the EEG classification ability. With the proposed GBMs fusion, epilepsy may also be 100% accurately identified from EEG data. Additionally, a machine learning technique to the detection of epileptic EEG signals is proposed in this study [8]. In order to conduct a comparison analysis, the benchmark dataset was utilized for this investigation. Three classification models have been used to distinguish between normal EEG and epileptic EEG: random forest (RF), decision tree (DT), and extra tree (ET). Three factors are used to assess the algorithm's performance: sensitivity, specificity, and accuracy. ET performed the best out of all the classifiers; the suggested method's parameters are 99.85, 99.42, and 99.63, respectively. In [9], the Gaussian process classifier (GPC) is used to analyze the results for three distinct types of EEG signals: motor imagery, finger movement EEG data, and steady state visually evoked potential (SSVEP). This paper's primary goal is to investigate whether GPC is useful for classifying EEG data for various tasks. The GPC achieves comparable or greater performances when compared to some well used algorithms. Moreover, both online and offline EEG analysis decision-making can greatly benefit from the probabilistic output that the GPC produces.

Wu *et al.* [10] propose a novel end-to-end structured deep learning model to automatically discriminate between normal and pathological EEG signals. In order to enhance classification performance, we look into the prospect of fusing the fundamental concepts of residual and inception architectures into a hybrid model. We conducted comprehensive experiments on a real-world dataset to evaluate the suggested strategy, and the results demonstrate its effectiveness and feasibility. Our method performs better than other known EEG signal methods when compared to earlier studies on the same data. Therefore, the suggested approach can help medical professionals automatically identify brain activity. Li [11] studied the use of deep learning models on a motor imagery EEG signal dataset with temporal and spatial information categorization job. In order to create training samples for deep learning models and standardize the training samples to enhance the performance of the models, they utilize sliding windows with predetermined window sizes and strides. On the classification and interpretation performance across the relevant dataset, convolutional neural networks and recurrent neural networks (RNNs) are studied and contrasted. When it comes to training efficiency and accuracy, the convolutional neural network outperforms other models. Lazcano-Herrera *et al.* [12] used a variety of machine learning techniques to categorize EEG data. A number of algorithms have been tested for their ability to distinguish between the two categories of movement and inactivity: SVM, k-NN, quadratic discriminant analysis (QDA), linear discriminant analysis (LDA), naive Bayes (NB), and ensemble. The movement class included baseline movement and inactivity data in addition to MI data. The suggested EEG categorization techniques, including NB and QDA, have the highest level of accuracy. Convolutional and RNNs are used for EEG classification applications. This study [13] provides comprehensive details on the deep learning architecture, the EEG preprocessing approach, and the dataset that was employed. Particular advice for hyper parameter adjustment is also covered in this study.

Behera and Mohanty [14] tried to use neural networks for detection and removal of artefacts in order to classify the signals. Although neural network models have only been utilized in the past for classification problems, the innovation in this work is the detection of artefacts. The outcomes of various models, including multilayer perceptron (MLP), radial basis function network (RBFN), and SVM, are contrasted. The results show that the cubic SVM performs better than any other model. Features in the time and frequency domains have been collected to feed the model. Additionally, combining features is another cutting-edge method that improves accuracy over using simply time-domain or frequency-domain information in the cubic SVM model. The results section contains the accuracy, which was found to be 95.1%. The impact of feature extraction for EEG signal training was examined [15] using DWT, impulse response (IIR), SVM, and bagged tree (BT) approaches. The authors also conducted a comparison between all techniques and their effects on dataset training and feature extraction. The precision of several pattern recognition approaches and the sensitivity of eleven mental states, including states involving thought signals and eye behavior, are the main areas of focus for the authors. This paper [16] discusses more contemporary machine learning approaches like ANN and DL in addition to the classic ones like SVM and bagged tree (BT).

In summary, SVM, neural networks, hidden Markov models, k-NN, DTs, and, more recently, DL techniques like convolution neural networks (CNNs) and RNNs are examples of machine learning algorithms that are frequently used in EEG analysis. It is possible to diagnose neurological disorders, comprehend brain function, and create novel applications in neurology, brain-computer interface technologies, and healthcare by combining machine learning algorithms with EEG data. The main contributions of this paper are:

a. The use of statistical based approach for denoising and to reduce the effect of artifacts in the EEG signal by likelihood ratio test (LRT).
b. The use of weighted voting in k-NN: This method uses weights based on distances to assign a class label, favoring neighbors who are closer together.
c. The use of modified prediction function in k-NN which chooses the class label based on the highest weighted vote after taking into account the weighted votes of the k-NNs.
d. To Optimize the training using “Bipolar sigmoid rectified linear units (ReLU) function” that combines traits from different activation functions

2. METHOD

Figure 1 illustrates the proposed method for classifying EEG signals using based on statistical denoising and modified k-NN algorithm with bipolar sigmoid ReLU function. The raw training EEG data is preprocessed to smoothen the artifacts in order to obtain noise-free EEG data. The likelihood test ratio is applied in the block that computes interference and separates the EEG data into discrete portions with nearly consistent noise characteristics. Further, the filtered EEG data is subjected to modified k-NN block to extract the features and these features are applied to bipolar sigmoid ReLU function that combines traits from different activation functions to limit the range of sample values and compared with test database to obtain the accuracy.

2.1. Database

The dataset [17] comprises of 5 different folders, each folder is having 100 files, each file represents a single subject/person. Each file has 23.6 s duration, captured by the international 10–20 electrode placement scheme. There are 4,097 data points in the corresponding time series. Each data point is the value of the EEG recording at a different time point.

2.2. Denoising

Dynamic interference [18] can result from noise, distortions, electromagnetic interference, and other undesired signals interfering with a signal's transmission or reception. Utilizing signal processing techniques and comprehending the interference's properties are usually necessary for calculating or minimizing dynamic interference. Several methods for controlling or estimating dynamic interference include: Signal filtering is the process of removing noise or undesirable frequencies from a signal by using filters. Depending on the type of interference, this may include the use of low-pass, high-pass, band-pass, or notch filters. Using methods that can adjust to changing interference situations is known as adaptive signal processing. Adaptive filters, for example, have the ability to continuously modify their parameters in order to minimize interference in a changing environment. Estimating interference or noise characteristics and coming up with mitigation or removal strategies are known as noise estimation and removal. This could entail spectral or statistical analysis to locate and remove undesired elements. The artifacts in EEG signals are identified by means of a dynamic interference calculation technique. This technique uses a unique strategy developed from the modified robust subspace detection method to examine interferences in the learned subspace. The previously computed unknown interferences can subsequently be used to identify the real interferences. Examine the EEG signal, which may be mathematically represented as follows and is made up of EEG data and some unknown noise:

$$z = x_s + x_u + \partial \tag{1}$$

here x_s is the EEG data before noise, x_u is interference in terms of artifacts, and ∂ is the noise interference level.

As shown in (1) specifies the region that holds the complete EEG signal. To offer exact interference, a subspace computation technique is used. Let S be the subspace for data estimation. In order to determine the entire subspace, as shown in (1) is therefore changed as follows: a K vector and an M-subspace, or wide dimensional signal, are used.

$$x = S\theta + U\phi + \eta \tag{2}$$

where θ is the unexpected noise gain, U is amplitude of noise, and ϕ is noise phase.

As shown in (2)'s likelihood ratio test [19] produces the following as the equation for log yields:

$$\lambda(x) = \left(\frac{1}{\omega_1}\left\|x - s\overline{\theta}\right\|_2\right)^2 + \left(\frac{1}{\omega_0}\left\|x - N\overline{\phi}\right\|_2\right)^2 \tag{3}$$

Applying the likelihood ratio test to (2) using (3) results in the division of the entire data signal of EEG into incredibly small segments with nearly constant noise characteristics. Effective signal denoising will be made possible by this, as it will be simpler to track the relevant noises that are present for limited periods of time.

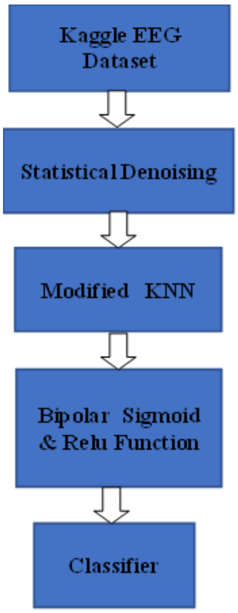

Figure 1. Proposed methodology

2.3. Modified k-NN algorithm

2.3.1. Existing k-NN

In machine learning, the k-NN algorithm [20] is a straightforward and efficient method for both classification and regression problems. It is a kind of non-parametric, instance-based learning in which the model forecasts a given data point by considering its closest neighbors. The existing k-NN selects the standard set of features using defined radius where there is a probability of selecting non prominent features.

2.3.2. Modified k-NN

While k-NN is very easy to implement, it can be computationally expensive for large datasets. To get optimal performance, it is crucial to select the appropriate 'K' and properly preprocess the input. A data point's class label is assigned by the standard k-NN technique based on the feature space's k nearest neighbors' majority class. The following properties are included in this improved k-NN algorithm: i) weighted voting: This method uses weights based on distances to assign a class label, favoring neighbors who are closer together and ii) effective prediction: the prediction function chooses the class label based on the highest weighted vote after taking into account the weighted votes of the k-NNs. To experiment with the algorithm, adjust the distance calculation approach based on the particular problem domain or develop unique distance measures. Depending on the specifications of your assignment, change the value of k and the selected distance measure. For both the training and test data sets, the data's features must be retrieved and classified. Next, the categories where most of the K data matched were removed, as were the k-NN data from the test set. Lastly, the data that needs to be classified is arranged using this category. Using the k-NN classification technique, several samples in S1, S2, S3, and so on are categorized. Here, the training samples are selected as parts of N, and their selection is contingent upon our needs. We now need to use K distance to locate samples that are close by. This helps to increase training speed and further restricts the number of features used. The discriminant function is $g_i(x) = k_i, i$ =1, 2, ..., S, and $g_i\ (x) = Max(K_i)$ determines the classification category for sample X.

The modified k-NN classification algorithm's $g_i(x)$ implementation procedures are as follows: First, the training and test samples are created using the dataset. We can presume that A is the test sample and X is the training sample. Within sample S, the training sample data set can be categorized into = $a1$, $a2$, ..., aN. Assign the initial k value to X's closest neighbor in the second step. Measure the separation between each training sample point and the test sample point in the third phase.

$$d(j) = \sum_{i=1}^{N} (\mathrm{x\ i} - \mathrm{w\ p})2 \tag{4}$$

The distance was sorted in ascending order, and the appropriate k value was selected in the fourth stage.

Select the k samples that are most similar to the selected sample using thresholding in fifth stage. The counting of K known samples with the highest probability within the category is the sixth step. Sort the test sample points into the relevant group by applying the statistics from step six. Finally, Sort the test sample points into the relevant group by applying the statistics from step six.

2.4. Bipolar sigmoid ReLU function

It seems that the phrase "bipolar sigmoid ReLU function" [21] combines traits from different activation functions. A sigmoid function, which is bipolar, converts any input value into a value between 0 and 1. In contrast, a bipolar sigmoid maps values between -1 and 1. The expression for the regular sigmoid function is (5).

$$f(x) = \frac{1}{1+e^{-x}} \tag{5}$$

While a bipolar sigmoid function may be defined as (6).

$$f(x) = \frac{2}{1+e^{-x}} - 1 \tag{6}$$

This function transforms the input into the range [-1, 1].

When a positive input is received, the ReLU activation function returns the input value; otherwise, it returns 0. It is able to be stated as (7)

$$f(x) = max(0, x) \tag{7}$$

A customized activation function that combines these two functions called as hybrid function that uses various portions of each function in particular ranges is used in our work. For example, you could use a bipolar sigmoid for negative values and the ReLU function for positive values. This helps to limit the signal in a particular range.

3. RESULTS AND DISCUSSION

The entire flow was simulated using the MATLAB software [22] and the Kaggle EEG database from the study [17] were used to validate the proposed methodology in terms of accuracy and sensitivity. The results obtained were used to measure the performance various performance parameters.

3.1. ROC graph

The Figure 2 displays the receiver operating characteristic (ROC) curve that was obtained. The graphs of the noiseless data currently available in the EEG database for a random person and the noisy EEG data smoothed by our suggested method are almost identical and overlap, proving the accuracy of the denoising. The similarity of the ROC curve suggests that the EEG data appears nearly identical to the original data prior to noise interference. Further, the false positive rate graph is plotted as shown in Figure 3 to show that the proposed method is prone to less mismatch compared to existing method.

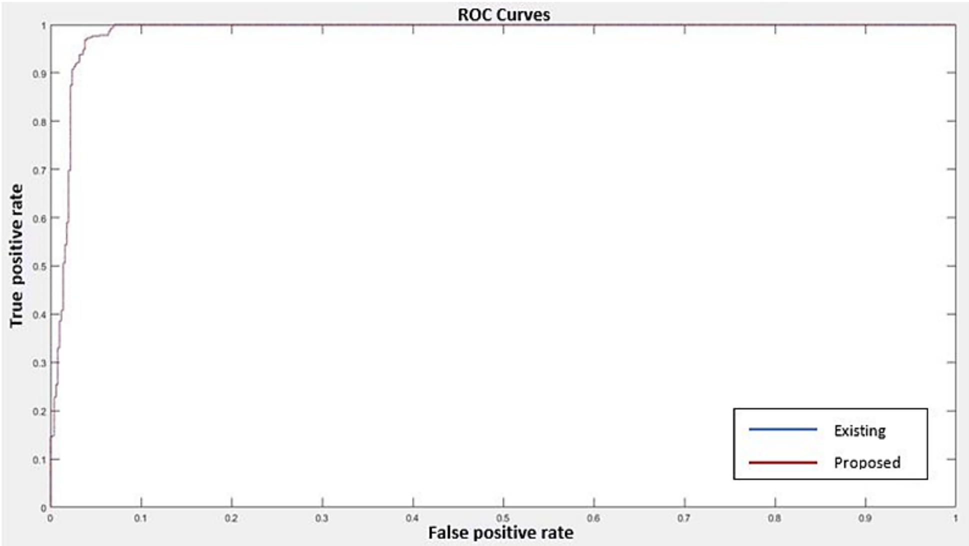

Figure 2. Comparison in terms of ROC Graph

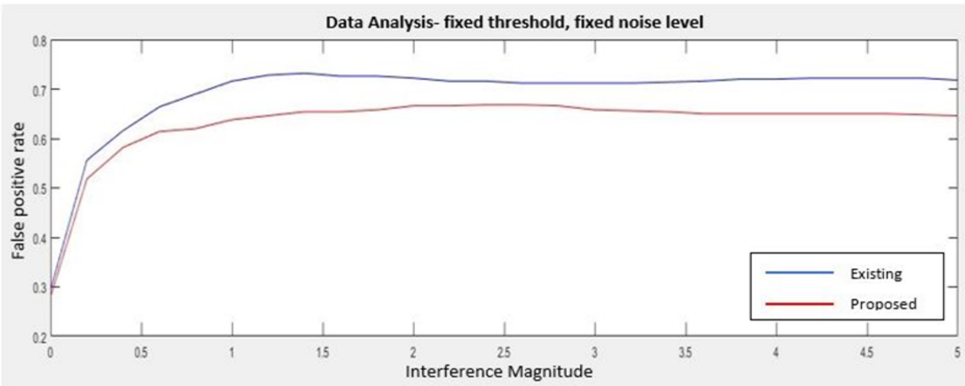

Figure 3. False positive rates graph

3.2. Peak signal-to-noise ratio calculation

The average peak signal-to-noise ratio (PSNR) calculations are done for random samples taken from Kaggle epileptic dataset with 10% of Gaussian noise and impulse noise, as shown in Table 1. It is observed that the results of PSNR are high indicating the quality of filtering. The Gaussian and impulse filter both have almost same average PSNR values.

Table 1. PSNR Values

Samples	PSNR Value (dB) (Gaussian noise)	PSNR Value (dB) (Impulse noise)
Sample 1	72.15	72.85
Sample 2	71.25	71.65
Sample 3	71.14	71.75
Sample 4	71.21	71.34

3.3. Comparison of PSNR values

The accuracy of the two techniques is compared in Table 2, and the proposed methodology is shown to be superior in PSNR vale as we use likelihood detector test to limit the effect of artifacts present in the EEG signal. Table 3 shows confusion matrix obtained for testing epileptic subjects. The confusion matrix exactly provides the detailed information regarding true positive (TP), false positive (FP), false negative (FN) and true negative (TN).

Table 2. Comparison of proposed and existing method in terms of PSNR

Author	Technique	PSNR (db)
[23]	Adaptive filters	46.6
Proposed	Mathematical Model	71

Table 3. Confusion matrix

		Actual Values			
		Positive		Negative	
Predicted Values	Positive (P)	(TP)	30	(FP)	4
	Negative (N)	(FN)	3	(TN)	9

The accuracy of proposed technique with existing techniques is shown in Table 4, and the proposed methodology is shown to be better. It is observed that we are getting better results compared to existing works and also with our own work [24] where we improved the k-NN modification by considering:

a. The use of statistical based approach for denoising and to reduce the effect of artifacts in the EEG signal by likelihood ratio test.
b. The use of weighted voting in k-NN: This method uses weights based on distances to assign a class label, favoring neighbors who are closer together.

Table 4. Comparison in terms of accuracy

Serial No.	Disease type	Accuracy (%)
[25]	Maximum marginal approach (Kaggle dataset)	86
[26]	Modified Kohonen neural network II (Self built dataset)	86
[24]	Modified k-NN K Means +SVM (BCI dataset)	80.81
Proposed	Statistical denoising + Modified k-NN + bipolar sigmoid ReLU (Kaggle dataset)	84.78

The sensitivity factor of proposed technique with existing techniques is shown in Table 5. It is observed that we are getting better results compared to existing works [27]–[29] where we improved the k-NN modification by considering:

a. The use of modified prediction function in k-NN which chooses the class label based on the highest weighted vote after taking into account the weighted votes of the k-NNs; and
b. To Optimize the training using “bipolar sigmoid ReLU function” that combines traits from different activation functions

By comparing our proposed method with existing reference works it is clearer that the removal of artifacts by likelihood ratio test and modified k-NN to extract the selective unique features improved the accuracy of proper diagnosis. Further the sigmoid ReLU function limited the number of training features to improve the speed of training.

Table 5. Comparison in terms of sensitivity

Sl. No.	Disease Type	Sensitivity (%)
[27]	Wavelet + CNN (MIT, MSSN)	87.8
[28]	Short time Fourier transform CNN (MIT, 13 patients)	81.2
[28]	Short time Fourier transform CNN (Kaggle, 7 patients)	75
[29]	MODWT with 1D-CNN (CHB-MIT, 23 Patients)	82
[29]	MODWT with 1D-CNN (Kaggle)	85
Proposed	Statistical denoising + Modified k-NN + bipolar sigmoid ReLU (Kaggle dataset)	90.9

4. CONCLUSION

The Statistical denoising, modified k-NN algorithm and bipolar sigmoid ReLU function are combined in this paper to create an effective approach for classifying EEG signals for correct disease identification. After applying statistical techniques to denoise the EEG data, a modified k-NN algorithm is used to classify the relevant features where neighbors who are closer to one another are given preference, and the weighted votes of the k-nearest neighbors are taken into consideration. Finally, the class label with the highest weighted vote is chosen and to optimize the training “bipolar sigmoid ReLU function” that combines traits from different activation functions is used. The efficiency of the suggested algorithm is demonstrated with a classification accuracy and sensitivity test, where the detection accuracy of true positive (TP), false positive (FP), false negative (FN), and true negative (TN) is tested and compared to the detection accuracy of other existing algorithms.

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AUTHOR CONTRIBUTIONS STATEMENT

Thejaswini Bekkalale Mahalingegowda developed the idea and performed the methodology computations. Glan Devadhas George performed the formal analysis, investigated and verified the analytical methods. Satheesha Tumakur Yoga and Kaliyamoorthy Ezhilarasan encouraged to investigate and supervised the findings of this work. All authors discussed the results and contributed to the final manuscript.

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Glan Devadhas George					✓		✓			✓	✓	✓	✓	
Satheesha Tumakur Yoga				✓	✓	✓				✓	✓			
Kaliyamoorthy Ezhilarasan				✓	✓					✓	✓			

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to declare. All co-authors have seen and agree with the contents of the manuscript.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article [and/or] its supplementary materials.

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