

Diagnosis of Tobacco Addiction using Medical Signal: An EEG-based Time-Frequency Domain Analysis Using Machine Learning

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ABSTRACT

Addiction such as tobacco smoking affects the human brain and thus causes significant changes in the brainwaves. The changes in brain wave due to smoking can be identified by focusing on changes in electroencephalogram pattern, extracting different time-frequency domain features. In this aspect, a laboratory-based study has been presented in this paper, for assessing the brain signal changes due to the tobacco addiction. Four classifier models, namely, Logistic Regression (LR), K- Nearest Neighbor (KNN), Support Vector Machine (SVM) and Random Forest Classifier (RFC) were trained and tested for assessing the performance of the time domain, frequency domain and fusion of time-frequency domain features, with a five-fold cross-validation. Four different performance measures (sensitivity, specificity, accuracy, and area under the receiver operating characteristic curve) were used to measure the overall performance, and the results suggested that the classifiers based on time-frequency domain features perform the best while using combinedly. Using the utilized fusion of the time-frequency domain features, the classification models can identify the smoker group with an accuracy ranged from (86.5-91.3%), where the RFC shows the best accuracy of 91.3%, which is higher than the three other classifiers models.

1. Introduction

This paper is an extension of work originally presented in International Conference on Computer, Communication, Chemical, Materials and Electronic Engineering (IC4ME2) [1]. The presented paper [1] utilized electroencephalogram (EEG) for the diagnosis of tobacco smoking based on only one machine learning model (artificial neural network), where the current article is expanded further to validate the EEG based diagnosis using multiple machine learning models. Also, this paper examines the utility of the time domain and frequency domain, individually and their combination on the EEG based tobacco addiction diagnosis.

In this modern era of life science, research in the field of neuroscience and cognitive engineering is flourishing with technological evolution. Electroencephalogram (EEG) is being

used in this sector to understand sophisticated conditions of the brain as this is sensitive and susceptible to any action, especially for drug addiction, for example, alcohol, morphine, heroin or Cannabis addictions. Different stages of drug addiction can be determined only through EEG analysis, and this is very much necessary in the treatment of drug addiction. Some drug elements, such as nicotine is found in nature (from *Nicotiana tabacum* and *Nicotiana rustica*). They also have good effects on health; for example, nicotine is being used in the treatment of cognitive disorder and depression. Its impact on the body depends on the way of its metabolism and absorption, such as P-450 pathway degrades several body parts. At a level, it strengthens/weaken other taken drugs. A review work has done to analyze the pros and cons of nicotine, where limitation they noted are the analysis of the complex way of changing cognitive function and host inflammatory response [2]. By analyzing the EEG response, the changing pattern can be determined easily. Drug elements like

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tobacco, tar and nicotine affect on mood and behavior, which is controlled by human brain consisting of neurons [3].

2. Literature Review

A significant amount of public awareness against tobacco addiction have been conducted to date, but not all the public announcements were effective. To know the degree of effectiveness of public service announcement against smoking, a pilot study was conducted in Rome by collecting EEG, heart rate and galvanic skin response. Based on approach withdrawal, effort and emotional indexes, it was found that these parameters that show notable differences between effective and ineffective perception [4].

In addition to the public awareness, several studies have been conducted on identifying the physical and mental changes due to the smoking habit and potential treatments. An analysis was performed by [5], who had experimented on 21 male smokers. The authors had analyzed the EEG wave of the participants before and after the horizontal rotation treatment. They found that the treatment is beneficial in improving the EEG Alpha band, which reduces the smoking effect. An increment in alpha rhythm denotes higher relaxation and concentration ability of subjects [5]. Another study was conducted on 19 smoker participants. The functional magnetic resonance imaging (fMRI) and EEG analysis represented the effect of nicotine on the brain while doing oddball tasks, which is a response time task [6]. The study suggested that the integrated EEG-fMRI system is better identifying the brainwave changes due to smoking.

Though most of the studies has investigated the effect of tobacco smoking on the brain using the EEG, very few studies had done the differentiation of EEG characteristics using machine learning algorithms. In a study [7], the authors have done an experiment on 20 participants having 10 smokers and 10 non-smokers, to observe the changes in the EEG signal due to the smoking effect. The authors had used a Support Vector Machine (SVM) classifier based on Radial Basis Function (RBF) kernel and found that the power spectral density (PSD) features performed better than the Fast Fourier Transform (FFT) features. Another study developed an EEG-based architecture to determine the effect of tobacco in the brainwaves, using 3 participants in a laboratory-based work [1].

The authors extracted time, frequency domain features from the EEG and showed that the frequency domain features, especially the power spectral density (PSD) and the Fast Fourier Transform (FFT) are most sensitive to the smoking condition than the time domain features for the smoker detection. The study showed promising results but utilized only one classifier (ANN) for the classification approach and only one performance measure (mean square error) for the assessment of the system [1]. However, considering the sensitivity and specificity metrics are most important for an EEG based detection system. As higher sensitivity with lower specificity leads to the higher false detection and the opposite trend causes the missing of a lot of positive states (in this case, smokers), a compromise between the two metrics is crucial.

This paper embodies a methodology for the diagnosis of tobacco smoking, based on the time-frequency analysis of the EEG signal. Also, the analysis was conducted to find efficient analyzing

model and feature. BIOPAC® system was used for data collection, and Acknowledge-4.1® package [8] was used for extracting features. Later, python 3.6.9 version was used in Google Colab platform for data analysis. Most importantly, four supervised classification models, namely, Logistic Regression, K- Nearest Neighbor (KNN), Support Vector Machine (SVM) and Random Forest Classifier (RFC) were trained and tested for evaluating the performance of each of the EEG rhythm, with a five-fold cross-validation. Moreover, four different performance measures (sensitivity, specificity, accuracy and area under the receiver operating characteristic curve) were utilized to examine the performance of the diagnosis system. The following part of this paper is organized as follows- a brief methodology, including experimental design and tools, then the result section with the findings. Last, the paper was concluded, followed by a short discussion on the outcomes.

3. Methodology

3.1. Experimental Design

The methodology for building an electroencephalogram based tobacco addiction diagnosis system is shown in Figure 1. After selecting three participants, EEG were obtained by the BIOPAC® system. After that the removal of noise and artifacts were considered.

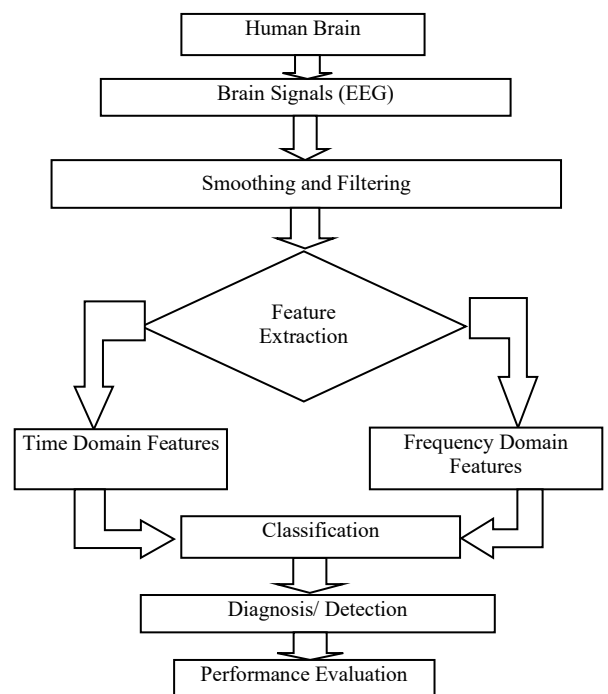


Figure 1: Block diagram for the proposed EEG based smoker / nonsmoker detection system

Afterwards, eight features were extracted for each domain, and the selected features were supplied towards the machine learning tools. Four different classification models, namely K-nearest neighbours (KNN), support vector machines (SVM), logistic regression (LR) and random forest classifier (RFC) models were developed in python 3.6.9 platform. The evaluation of the best classifier and domain was done by comparing their performance.

3.2. Experimental Equipment

3.2.1. Hardware tool

BIOPAC® MP 36 device was used at Biomedical Engineering lab, KUET for the experimentation purpose. The experimental setup is shown in Figure 2 [8].

3.2.2. Pre-processing and feature extraction software tool

Feature extraction was an important step in this study, which was done using the BIOPAC® student Lab Pro and Acqknowledge 4.1® software Google Colab research platform with the python 3.6.9 for developing the Machine learning-based classification models [9].

3.3. Participants

In total, three subjects participated in this experimental study, who were male, healthy and not suffering from psychological illness. The subjects were instructed to close their eyes while solving some simple arithmetic questions for 20 minutes. An interpreter used to ask the arithmetic question to the participants. In that respect, the brain response (EEG signal) is a result of cognitive event-related potential (ERP) type. A total of ten trials were taken for each subject. The cognitive event was selected because in that case, the participants can easily concentrate and in eye closed condition, there are no eye blinking/ EOG artefacts [9].

Electrodes placement was configured on the right central (C4), and the right occipital (O2) position as the regions are responsible for problem solving and cognitive function, respectively. It is to note that, the authors have selected the cognitive task from their experience from previous pilot studies where the cognitive task gives clear signals with less noise [10, 11].

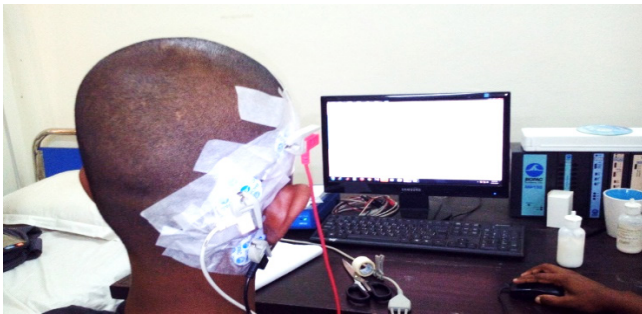


Figure 2: Representational view while conducting the experiment in BME lab, KUET

3.4. Experimental Procedure

3.4.1. Signal Preprocessing

The primarily obtained EEG signals could have contained noise due to muscle movement, eye blinking and hand movement. Along with line frequency was 50 Hz. To pre-process raw EEG was gone through bandpass finite impulse response (FIR) filter with a range of 0.5 to 44 Hz, as it removes the non-linear trends of the signals. Later the signal was further smoothed, taking a moving average over a short period of the signal.

3.4.2. Feature Extraction

Various features were extracted in time and frequency domain, including standard deviation (STDDEV), maximum value (E_{max}),

skew (sk), kurtosis (k), power spectrum density (PSD) mean, PSD max, Fast Fourier Transform (FFT) mean, FFT max (total eight feature) were extracted for each subject using the Acknowledge 4.1® software. For feature extraction was done using a 5-second epoch length.

3.4.3. Feature Scaling

The time and frequency domain features, which were extracted from the EEG signal, have different range in their magnitude. As the machine learning models work with various features putting them in the same matrix, it is essential to put all the features in a same range, which is referred to as feature scaling. Two common types of feature scaling is done in preliminary data: standardization and normalization [12, 13]. MinMaxScaling was done in this study in python 3.6.9 platform, as a part of the normalization process. *MinMaxScaler()* function from *sklearn* library was used for this purpose. Here the data is shrunk within a range between [-1,1].

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

The formula of min-max scaling can be given by equation (1). Here, x_{new} is the normalized value of a feature point x , within a range x_{min} and x_{max} [14].

3.5. Classification

For the diagnosis of tobacco smoking, classification is the main and last step, which is done through machine learning. Machine learning is the application of artificial intelligence, which provides a system capable of learning nature from a given data. There are three categories of Machine Learning models and applications, supervised learning, unsupervised learning, and reinforcement learning. Supervised learning is extensively used for the classification and regression problem [15]. Previous studies worked with EEG have used supervised learnings, especially K-Nearest Neighbour [16], Support Vector Machine [17], Random Forest Classifier [18] and Logistic Regression [19]. Based on the previous studies, these four classifiers were chosen for the data classification in this research.

3.5.1. Logistic Regression (LR)

Logistic regression is a supervised learning model, which works based on the linear method, and the predictions are made using a logistic or sigmoid function $\sigma(t)$. The sigmoid function is 'S' patterned curve that takes a real number and maps within a range between 0 and 1. Equation (2) represents the sigmoid function.

$$\sigma(t) = \frac{e^t}{e^t + 1} = \frac{1}{1 + e^{-t}} \quad (2)$$

Considering two types of variables, dependent and independent, Logistic regression predicts the dependant variable based on the independent variable. The 'C parameter' was tuned here in the Logistic regression model to reduce overfitting [20,21].

3.5.2. K-nearest neighbours (KNN)

KNN is a supervised learning algorithm, and a non-parametric method where k nearest training examples in the feature space is taken as input and neighbours vote do the classification generally used for classification and regression. At the very starting point,

KNN read the value of K, type of distance D and test data; then it finds the K nearest neighbours D to the test data and thus sets the maximum label class of K to test data. The same process is gone through an iterative process named looping. In details, its algorithm initializes the value of K from 1 (setting as initial iteration value). After loading data, iteration from initial K =1 (generally) to the total number of training data point while distances specifically Euclidean distance between test data and each row of training data is measured and sorted in ascending order to get topmost k rows from the sorted array and the most frequent class is returned as the predicted class [22]. The value of K was tuned, and the k for best efficiency was chosen in the classifier model in this research to reduce overfitting.

3.5.3. Random Forest Classifier (RFC)

Ensemble learning models, such as Random forests are made of individual decision trees with a logic of group of weak learners to finally make a strong learner while the decision trees operate as divided or conquer. A class is predicted from every decision tree and a final class is predicted by model depending on their vote [22]. Two parameters were tuned in the RFC models in this study, namely, 'n_estimate', which implies the number of trees in the forest and 'max-depth' which signifies the depth of each tree.

3.5.4. Support Vector Machines (SVM)

An SVM is a supervised learning algorithm, which aims to obtain a hyperplane classifying the data point (data points can be at any side of hyperplane) in feature dimensional space while depending on both linear and non-linear regression. Data points distance across to hyperplane are called support vector whose detection can exchange hyper plane's location [22]. The model used a Gaussian kernel for SVM classifier in this research due to the non-linear trend of the dataset. Two parameters- 'C' and 'gamma' was adjusted within a set of values using the grid search algorithm to reduce overfitting.

3.6. Performance Measures

3.6.1. Sensitivity or True Positive Rate (TPR)

True positive rate or Sensitivity is the proportion of the true positives (desired factor), which is correctly identified from the given test set [23]. The definition of sensitivity can be provided by equation (3), where TP = True Positive and FN = False Negative. In this study, sensitivity is the measure of the proportion of successfully identifying a smoker.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (3)$$

3.6.2. Specificity or True Negative Rate (TNR)

True negative rate Specificity is the proportion of true negative (undesired factor) in which was correctly excluded from the given test sets [23]. The definition of specificity can be provided by equation (4), where TN = True Negative and FP = False Positive. In the case of this study, specificity is the measure correctly identifying a non-smoker. In this study, accuracy is the proportion of successful identification, either smoker or non-smoker.

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (4)$$

3.6.3. Accuracy

The overall accuracy is the proportion of true results (either true positive or true negative) in an experiment [23,24]. The definition of accuracy can be provided by equation (5), given that TP = True positive, TN= True Negative, FP= False Positive and FN = False Negative. In this study, accuracy is the proportion of the successful identification, either a specific person or not being that person.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

3.6.4. Area under the receiver operating characteristic (ROC) curve (AUC)

ROC is the plot of the sensitivity (true positive rate) against the (1- specificity) or false positive rate, where all the possible combination of TPR and FPR are plotted, showing the trade-off between them [23–25]. As sensitivity and specificity are two major parameters of performance measures, AUC under ROC always provides a compromise between them. Though there are few methods for validation, five-fold cross-validation was done in this study while evaluating the performance measures. The mean value and the standard deviation (SD) were noted, considering the five experimental validations. Thus, the mean sensitivity, specificity and AUC was calculated from the obtained confusion matrix.

4. Results

4.1. Data visualization (Box plot and violine plots)

Data visualization is an important part to observe the data arrangement. Given data points found from the selected features were plotted in box and violin plots to observe the range of each of the features. The following Figure 3 and Figure 4 shows that the time and frequency domain features are having a versatile variation in the range. Range of the difference features varies among themselves either in the time domain or in the frequency domain, and therefore, the feature scaling was performed.

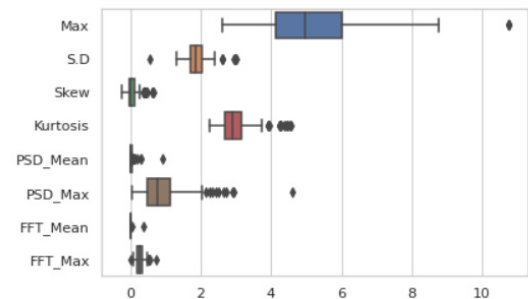


Figure 3: Box Plot of part EEG data showing varying magnitude of different features

4.2. Classification Performance

All the features were scaled and were supplied towards the machine learning models after necessary parameter tuning. Four different performance measures were evaluated, namely, sensitivity or true positive rate (TPR), specificity or True negative rate (TNR), accuracy and area under the receiver operating characteristic (ROC) curve (AUC). The obtained results are listed in the Table 1.

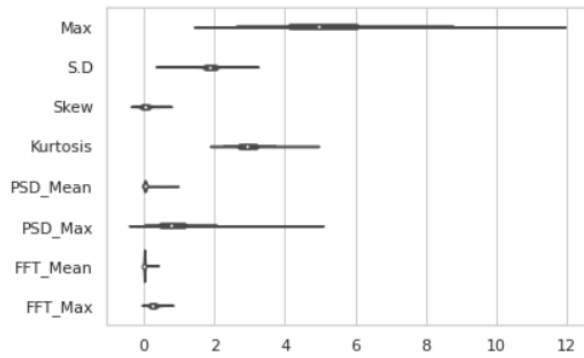


Figure 4: Violine Plot of part EEG data showing varying magnitude of different features

Table 1: Performance measures (mean value) for EEG based smoker detection using four different classifiers, five-fold cross-validation

Domain	Performance Measures	LR	KNN	RFC	SVM
Time Domain	Sensitivity	58.9	56.07	63.6	53.1
	Specificity	55.2	57.54	61.3	55.3
	Accuracy	57.4	55.53	62.4	59
	AUC	53.7	54.04	65	60.1
Frequency Domain	Sensitivity	70.7	77.14	81.2	70.9
	Specificity	70.7	71.35	83.7	76.3
	Accuracy	76.1	73.75	82.9	72.9
	AUC	71.4	77.59	83.2	77.1
Time-Frequency Domain	Sensitivity	89.2	83.75	94.3	85
	Specificity	86.3	91.25	92.1	87.2
	Accuracy	87.2	87.5	91.3	86.5
	AUC	78.3	80.7	92	88.2

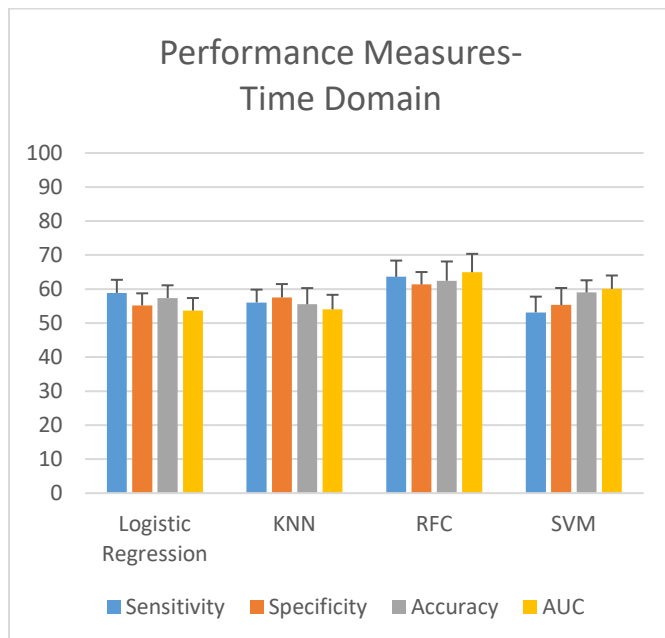


Figure 5: Performance measurement of time domain

4.2.1. Scenario-1: Classification using Time Domain Features

The following Figure 5 shows the plots of the performance measures (mean \pm SD) obtained from the classification of smokers and non-smokers using the time domain features from four different classifiers, LR, KNN, SVM and RFC, respectively. The plots show that the gap between sensitivity and specificity is highest in LR (3.68%) and lowest in the case of KNN (1.44%). Overall, RFC gives an accuracy of 62.4%, which performs the best.

4.2.2. Scenario-2: Classification using Frequency Domain Features Domain

The following Figure 6 shows the plots of the performance measures (mean \pm SD) obtained from the classification of subjects addicted to smoking using the frequency domain features from four different classifiers, LR, KNN, SVM and RFC, respectively. The plots show that the gap between sensitivity and specificity is higher in KNN (5.8%) and SVM (5.4%) and lowest in the case of LR (0.05%). Overall, RFC gives an accuracy of 82.9%, which performs the best.



Figure 6: Performance measurement of frequency domain

4.2.3. Scenario-3: Classification using the Time-Frequency Domain Features Domain Features

The following Figure 7 shows the plots of the performance measures (mean \pm SD) obtained from the classification of subjects addicted to smoking using the time domain features from four different classifiers, LR, KNN, SVM and RFC, respectively. The plots show that the gap between sensitivity and specificity is the highest in the case of SVM (7.5%) and lowest in the case of RFC (2.2%) and ANN (2.2%). Overall, RFC gives an accuracy of 91.3%, which performs the best.



Figure 7: Performance measurement of the time-frequency domain

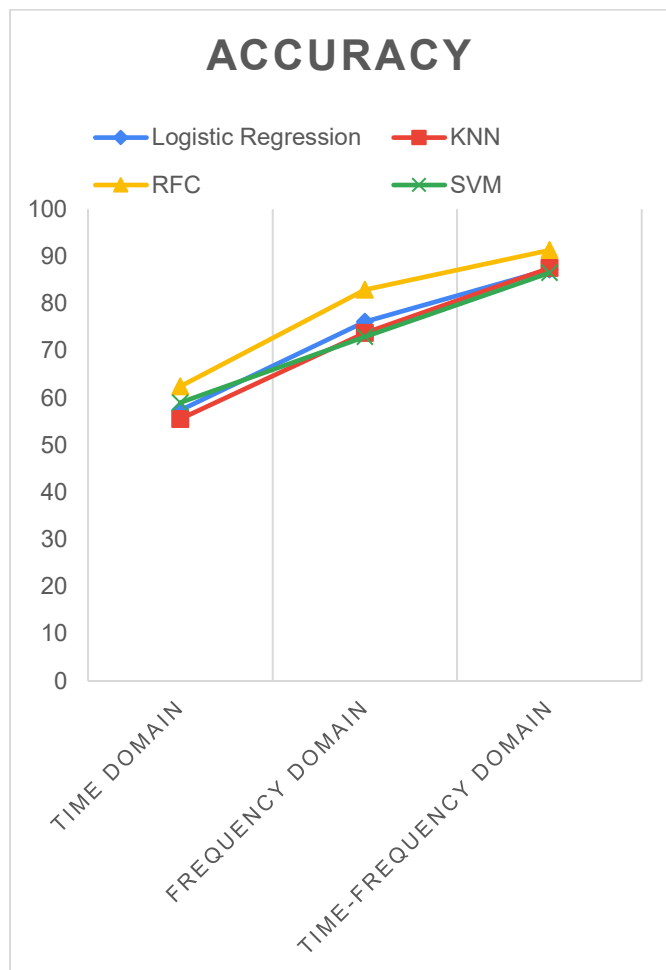


Figure 8: Comparison of accuracy metrics for four different classifiers

4.3. Choosing the best Scenario

The overall accuracy was considered as the reference metrics while finding out the best scenario, as it is difficult to compare different classifiers using several measures. The plots of the accuracy for four different classifiers corresponding to different domain are shown in the Figure 8 below. From the given figure, it is evident that the accuracy for random forest classifier is better than any other domains for all the four classifiers.

The accuracy plots also reveal the relative comparison among the time domain features, frequency domain features and the effect of the fusion of both time and frequency domain. It is evident that the frequency domain features perform better than the time domain features for all of the classifiers. Again, the time-frequency fusion outperforms the previous scenarios when the time or frequency domain feature were used individually. So, in the rest of the paper, the combined-time frequency domain features will be considered for further analysis.

4.4. Choosing the best classifier

The plots for the area under the ROC curve for the classifiers built using the time-frequency domain of EEG features are shown in the Figure 9 below. The figure illustrates that the RFC classifiers show the best compromise between sensitivity and specificity, with covering the highest area under the ROC curve (AUC= 0.92%).

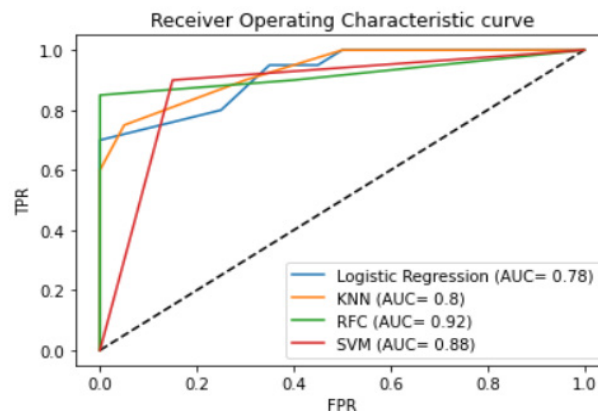


Figure 9: Comparison of AUC for four different classifiers for time-frequency domain

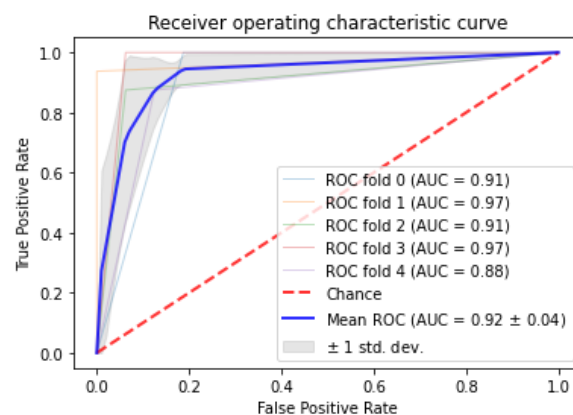


Figure 10: ROC Plots for time-frequency domain-based RFC model with 5-fold CV

Area under the AUC curve plots for 5 different experiments in 5-fold cross-validation with time frequency domain features using RFC classifier is shown in Figure 10. The AUC ranged from (0.78-0.92) for all the models with the time-frequency domain features, with a mean of 0.92 and 0.04 standard deviation. This signifies that the time-frequency domain shows an excellent performance than the other domains of EEG signal in tobacco smoking diagnosis.

5. Discussion

Four different classifiers were used in this study for assessing the performance of the EEG domains for the diagnosis of tobacco smoking. The results revealed that the time-frequency domain performs the best among the other domains. It also revealed that the maximum performance was obtained using the RFC Classifier, with a sensitivity, specificity and accuracy of 94.3%, 92.1% and 91.3%, respectively. Moreover, RFC based model time-frequency domain-based dataset shows promising AUC (0.92), which is a good compromise between sensitivity and specificity.

The finding of this study is consistent with some of the previous studies [1,7]. The study [7] achieved an accuracy ranged from 97.33-97.50%, while using the frequency domain features, such as, PSD and FFT features of EEG signal, which also supports the finding of the current study. Though the study of [7] used only RBF kernel based SVM, the current study validated the other classifiers which support the findings. In another study [1], where authors found the time-frequency domain as the best performing domain, though they have used only one classifier (ANN), and one performance metrics (Accuracy). Contrarily, the time domain performed the worst (RFC accuracy= 62.4%) in their study, while using a holdout approach for validation. The current study used a five-fold cross-validation and validated the outcome of the previous research with multiple classifiers.

Based on the results and analysis in the study, the following research implications and recommendations can be provided. First, using the frequency domain features is always recommended to diagnose tobacco smoking using the EEG signals. However, using time-frequency fusion is highly recommended as this combination provides a higher classification performance. Second, the given outcomes could be correlated with the drug-related impairment in the human brain, which could provide further insight into the correlation between the two addiction.

There are some feasibility issues with the study. First, using EEG sensors to detect the smoking habit could be a cumbersome procedure. However, the research could add value to observe the effect of different cigarettes depending upon their nicotine levels and their impact on the human brain. Second, the use of EEG as ground truth in tobacco-related experiments. If the setup is available in the lab, the EEG measurement could be used as ground truth when observing the effect of Tobaccos smoking on other factors. Third, the impact of drug addiction is more severe in the human brain than smoking. This experiment can add value to the relative comparison of the drug and tobacco addiction. However, the scope of the paper is not out of limitations. Inter-individual difference among participants is another factor, which is needed to be considered. As the paper represented a novel methodology of EEG based diagnosis of tobacco smoking, more research is required to find out the feasibility in real-world conditions as well.

6. Conclusion

To develop an EEG based diagnosis of tobacco addiction, an analysis was done in this study to find out the feasibility of the time and frequency domain features using this proposed model. Here, ultimate results were obtained after applying several steps- feature scaling, tuning of classifiers, and finally with five-fold cross-validation of the developed models. The research investigation found that the combination of the time-frequency domain features with RFC classifier showed the best accuracy while the time domain features showed the lowest accuracy. This analysis shows that time-frequency domain shows the best Accuracy with SVM (86.5 %), LR (87.2%), KNN (87.5%) and RFC (91.3%), Time-domain shows the lowest accuracy with all classifiers while the frequency domain shows higher accuracy than time domain, but still, this is less than the combined time-frequency domain performance. Among all the classifiers, RFC showed the best Accuracy and SVM showed the lowest accuracy. However, the experiment could be done on more number of participants to validate the model based on leave one participant out approach. Also, efficiency will increase with the addition of more EEG channels which could be considered for future implications.

Conflict of Interest

The authors declare no conflict of interest.

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