Salp Swarm Optimization Based Machine Learning Algorithm on Epileptic Seizure Detection and Classification Model

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Abstract: In recent days, machine learning (ML) becomes a familiar topic and is extensively used for decision making in various real time applications, particularly healthcare. ML approaches in healthcare make use of massive quantity of healthcare data to enhance the medical services to the patients. At the same time, Epilepsy is unavoidably identified as a critical and persistent neurological illness affecting the human brain. Electroencephalogram (EEG) is commonly employed as an important tool to identify distinct neurological illnesses of the human brain, specifically seizures. The ML approaches find useful to examine the EEG signals to determine the presence of seizures. With this motivation, this paper presents an optimal least square support vector machine (OLS-SVM) based automated epileptic seizure detection tool using EEG signal. The proposed OLS-SVM model incorporates different processes such as pre-processing, classification, and parameter tuning. The EEG signals are initially pre-processed to remove the unwanted signals. In addition, the LS-SVM model is employed to classify the EEG signals into the presence of seizures or not. Moreover, the OLS-SVM model is designed by the parameter optimization of the LS-SVM method utilizing salp swarm optimization algorithm (SSA). The use of SSA as parameter optimization tool for LS-SVM model shows the novelty of the work. For examining the enhanced diagnostic performance of the OLS-SVM technique, a wide range of experiments are performed and the outcomes were investigated in distinct measures.

Keywords: Epileptic seizures, Machine learning, Healthcare, Disease diagnosis, LS-SVM model, Parameter tuning

1. Introduction

The emergence of digital technologies in the healthcare field is categorized by the continuous problems in practicality and application. The combination of distinct healthcare schemes has been slower and the adaption of a fully combined healthcare scheme in almost all portions of the world hasn't been established [1]. The inherent nature and complexity of human biology, also the variations among specific persons have reliably exposed the significance of the human elements in treating and diagnosing diseases. But, the advancements in digital technologies are certainly becoming an essential tool for healthcare experts in offering optimal care to the patient. The development of data techniques, comprising data transfer speeds, storage size, and computational power, has empowered the extensive adaption of ML in several healthcare fields are involved.

Globally, the adaption of electronic health records (EHRs) is raising and it could be handled with the help of prediction approaches and data analyses. Prediction analysis, at the same time, aims for predicting the results of a person's [2] by creating a statistical module from the monitored data and utilizing this module to make a prediction for a person is depending upon their exclusive feature. The predictive modelling is a kind of algorithmic modelling [3] that considers the procedure whereby the data are created to be unknown (and maybe unknowable). This modelling approach measures the efficiency using calibration, precision, and recall that compute distinct concepts of the frequency where a techniques prediction is accurate. ML is the procedure of learning an adequate statistical module through monitored data for predicting the results or classify the observation in upcoming data. Especially, supervised ML approaches train the modules by an observation on instances wherever the classes or forecasted value of the result of attentiveness are previously identified (a gold standard). EHR provides access to a huge amount and various parameters which empower high quality prediction and classification [4, 5], whereas ML offers the approaches for handling huge amounts of high dimension data that are common from healthcare settings.

Epilepsy is a general brain disorder that affects peoples in all age groups. It can be chronic neurological disorder where frequent seizure arises because of anomalous neuronal activities within the human brain and influences the sensorium, mood as well as motion of the human body [6]. Commonly the electroencephalogram (EEG) identifies the seizure activity since it reveals electrophysiological condition of brain at certain time [7] and is extensively utilized for diagnosis because of its lower cost. EEG signal is, improved by the pathological and physiological data, are utilized for evaluating and assessing the progress and treatment of epileptic persons. In general, EEG recording is lengthier (hours to days) and has a large number of data gathered in the persons [8]. Henceforth, various automated Computer Aided Diagnostic (CAD) approaches are established by ML methods to assist diagnosis of epileptic seizures [9]. CAD methods are depending upon the extraction of time, linear, and non-linear as well as frequency domain features from EEG signals. Additionally, ML classifications are utilized for detecting and characterizing seizure activity.

This paper presents an optimal least square support vector machine (OLS-SVM) based automated epileptic seizure detection model using EEG signal. In the proposed OLS-SVM model, the EEG signals are initially pre-processed to eradicate the unwanted signals. Besides, the LS-SVM model is applied for the classification of EEG signal to determine the existence of seizure. Furthermore, the OLS-SVM model is designed by the parameter optimization of the LS-SVM model by the use of salp swarm optimization algorithm (SSA), showing the novelty of the work. For examining the enhanced classification performance of the OLS-SVM model, an extensive set of simulations were carried out and the experimental results highlighted the superior performance of the OLS-SVM model.

2. Literature Review

Amin et al. [10] introduced a new CAD approach on the basis of DWT and arithmetic coding for differentiating the epileptic seizure signal in usual (seizure free) signal. The presented CAD method contains 3 phases. The initial phase decomposes EEG signal to approximation and detail coefficient utilize DWT when removing non-significant coefficients considering threshold conditions; therefore, constraining the amount of significant wavelet coefficient. The next phase transforms significant wavelet coefficient to bit stream with the help of arithmetic coding for computing the compression ratio. During the last phase, the compression feature sets are normalized, at which ML classifier detects seizure activity in seizure free signals. In Li et al. [11], a sequential processing feature extraction way and a new MELM are presented to utilize EEG classification procedures for epileptic seizure detection. Integration of the presented sequential approaches could removal the substantial feature of epileptic seizure signal for the classification. Lastly, a new MELM is presented to utilize classification procedure. Chen et al. [12] propose an architecture on wavelet based non-linear feature and ELM for detecting seizures. The 3 non-linear approaches, viz, recurrence quantification analysis (RQA), approximate entropy (ApEn) and sample entropy (SampEn) have been calculated in original EEG signal and equivalent wavelet decomposed subbands individually. Then the integration of subband features was fed into SVM and ELM classifiers correspondingly.

Savadkoohi et al. [13] explore the features of brain electrical activity from distinct record areas and physiological states for detecting seizures. Polat and Nour [14] executed EEG signals classification of 5 class includes the case of eyes closed, eyes open, healthier, epileptic seizure, tumor region, was executed with the SVM and the standardization approaches contain minimum-maximum, MAD and z-score standardization. For classifying the EEG signals, the SVM classifications contain distinct kernel functions that have been utilized. Deivasigamani et al. [15] proposed an automated detection and analysis of EEG signal to epilepsy disease by soft computing methods as ANFIS and NN. The detection of focal signals are attained using ANFIS classification and the diagnoses of the severe level from focal signal are attained using NN classifier method. Srinath and Gayathri [16] define an automatic classification of EEG signal for detecting Epilepsy disease by a soft computing approach. The projected technique has: (a) ANFIS classification technique, (b) transformation, and (c) wavelet packet decomposition based feature computation.

3. The Proposed OLS-SVM model

In this study, a new OLS-SVM method is presented for epileptic seizure detection and classification process utilizing EEG signal. The overall working procedure of the OLS-SVM technique is demonstrated in Fig. 1. The OLS-SVM model involves different sub processes such as pre-processing, LS-SVM based classification, and SSA based parameter tuning. The comprehensive working of every sub process is offered in the following sections.

3.1. EEG Signal Pre-processing

At the initial stage, the input EEG signals are pre-processed to improve the signal quality. Primarily, minimum-maximum (min-max) approach was employed for normalization of the dataset. At this point, the larger and smaller values from the group of data are assumed. All the data undergoes normalization to this value. The intention is to normalization the mini value to zero and maxi value to one, and distribute other values as to range of [0-1]. Eq. (1) was utilized for defining the model of min.-max normalization.

$$Min - Max.Norm = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Eventually, the class labelling model occurs where the samples from EEG signal datasets are assigned for prospering class labels as 0, 1 for binary class.

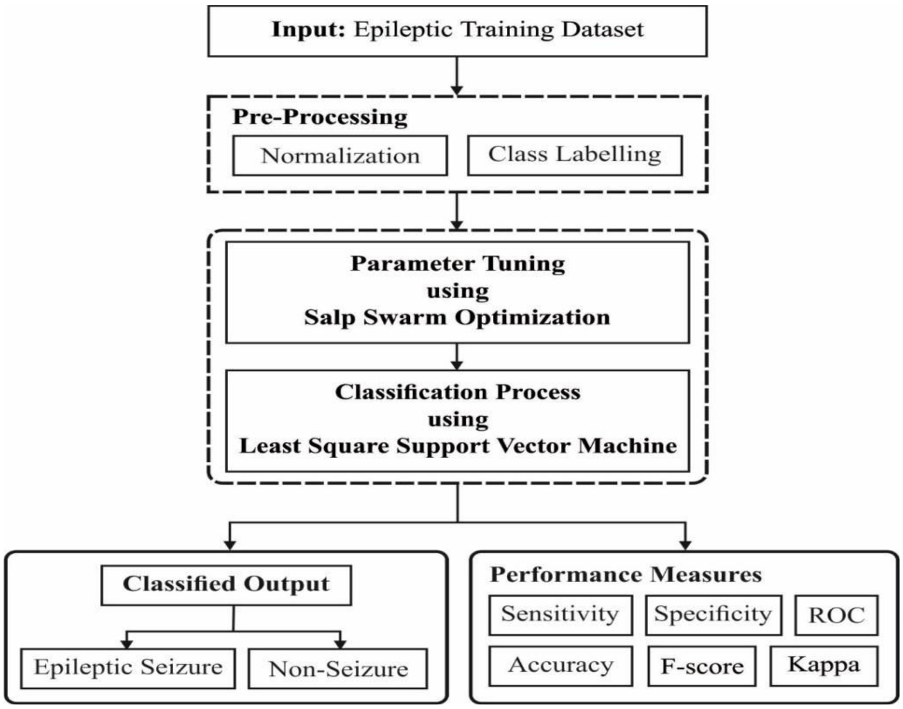

Fig. 1. Overall Process of Proposed Method

3.2. LS-SVM based Classification

During the classification process, the pre-processed EEG signals are fed as to LS-SVM model to determine the existence of the diseases. SVM is determined as a new ML and provides maximal benefit for solving the problems such as over fitting and local optimal. SVM module is efficient and utilized in several applications such as pattern recognition, regression analysis, and so on. LS-SVM is the expanded module of regular SVM that transforms a quadratic programming (QP) problem to linear equation, fast solution speed, and strong real time functions could be achieved. Consider $D = \{(x_u, y_u) | u = 1,2,3, \ldots, N\}$ represents training data, whereas x_u denotes input and y_u indicates outcome. In the event of non-linear regressions, LS-SVM is labelled by:

$$y(x) = \omega^T \varphi(x_u) + b + e_u, \quad (2)$$

whereas ω refers the weight vectors, $\varphi(x_u)$ indicates the non-linear functions, b signifies the deviation, and e_u signifies fitting error, that is error amongst the actual training as well as estimated outputs of the data set u. ω and b is attained in the provided optimization issues [17]:

$$\min J(w,e) = \frac{1}{2}\omega^T\omega + \gamma\frac{1}{2}\sum_{u=1}^{N} e_u^2, \quad (3)$$

Eq. (3) meet the constraints:

$$y_u = \omega^T\varphi(x_u) + b + e_u, u = 1,2,3,\ldots,N, \quad (4)$$

In order to Eq. (3), the main part is for altering the weight and decrease huge weights, and later succeeding part denotes training error. Eq. (3), defines the Lagrange functions L:

$$L(w,b,e,\alpha) = I(w,e) - \sum_{u=1}^{N} \alpha_u \{\omega^T\varphi(x_u) + b + e_u - y_u\}, \quad (5)$$

In Eq. (5), α_u denotes Lagrange multiplier and γ indicates penalty parameter which estimates the effort of LS-SVM methods as $y(x)$ and trained error. Eq. (5) is employed for attaining the partial derivatives of w, b, e and α_u and turn into 0, and attain an optimization state.

$$\begin{cases} \dfrac{\partial L}{\partial w} = 0 \to w = \sum_{u=1}^{N} \alpha_u \varphi(x_u) \\ \dfrac{\partial L}{\partial b} = 0 \to \sum_{u=1}^{N} \alpha_u = 0 \\ \dfrac{\partial L}{\partial e_u} = 0 \to \alpha_u = \Lambda e_u \\ \dfrac{\partial L}{\partial \alpha_u} = 0 \to \omega^T\varphi(x_u) + b + e_u - y_u = 0 \end{cases} \quad (6)$$

The ω is eliminated and the LS-SVM regression module was attained. Fig. 2 illustrates the optimal hyperplane of SVM.

$$y(x) = \sum_{u=1}^{N} \alpha_u K(x, x_u) + b, \quad (7)$$

where $K(x, x_u)$ implies the kernel functions, that is determined as follows:

$$K(x, x_u) = \exp\left(-\frac{||x - x_2||^2}{2\sigma^2}\right), \quad (8)$$

where σ^2 denotes kernel variable. Penalty variable γ and kernel variables σ^2 are limited by the accuracy of LS-SVM method. The generalized ability of a method could be enhanced by decreasing γ,simultaneously training error enhances. Since the kernel variable is minimal, and later the techniques complexity is enhanced, if the kernel variable is high, later it outcomes in lack of learning. Therefore, a substantial γ and σ^2 measured are the major goal for attaining remarkable effectiveness.

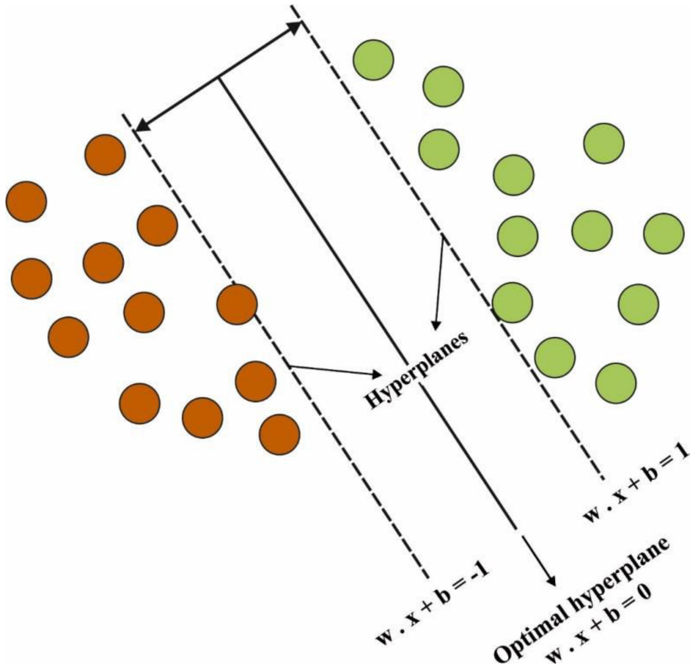

Fig. 2. Optimal Hyperplane of SVM

The procedure included in the LS-SVM module is given below.

1. Execute initiation of variables like CR, iteration count, population size, and scaling factor.
2. Initiation of population, whereas X has σ and C of LS-SVM.
3. Define the individuals fitness value and establish them in descending manner with the group of 3 topmost individuals Xα, Xβ, Xδ as the upside wolves.
4. Upgrading the position of parent population individuals.
5. DE is employed to mutate and cross upgrading procedure thus generates novel children.
6. Upgrades the parent populations, and later upgrades Coe, Acc.
7. Upgrades the parental Pα, Pβ, Pδ, and organize the grey wolf's father population over. When the end condition was attained, the parent Pα and f(Pα) would be given an optimal solution, obtains the output as C and σ.

Create the LSSVM method based on σ and C.

3.3. Parameter Optimization using SSA

Finally, the parameters involved in the LS-SVM model are optimally tuned by the use of SSA and thereby improves the detection performance. In the SSA is a current bio inspired optimized method stimulated using navigation and searching behavior of salp chains, commonly initiate in Deep Ocean. Afterward each iteration, the leader salp alters their location regarding the food source. The leader exploits & explores search space near an optimal solution and the follower salp moves increasingly to the leader. This procedure assists salp in meeting the global optimal fast when avoiding being stuck in local optimal. The front salp of chains are named as leader whereas another salp of chain is named as follower. The leader salps guide the follower salp.

The salp location is determined in the n dimension search space. Whereas n implies the amount of decision parameters from the problems. Consider there is a fee source $\mathbb{F}Sin$ search space as swarm target. According to the position of feed source, leader upgrades thier location by the formula:

$$x_j^1 = \begin{cases} \mathbb{F}S_j + C_1 \times \left[\left(\mathbb{U}b_i - \mathbb{L}b_j\right)C_2 + \mathbb{L}b_j\right], C_3 \geq 0 \\ \mathbb{F}S_j - C_1 \times \left[\left(\mathbb{U}b_i - \mathbb{L}b_j\right)C_2 + \mathbb{L}b_j\right], C_3 < 0 \end{cases} \quad (9)$$

The balance among exploitation & exploration in optimization is preserved using coefficient C_1 given by:

$$C_1 = 2 \times e^{-\left[\frac{4 \times iter_C}{iter- \max}\right]^2} \quad (10)$$

Now, iter_c denotes present iteration amount and iter_max represents maximal amount of iteration permitted, $C_2 and C_3$denotes uniform distribution arbitrary amount in the range zero and one. In SSA, follower updates their position according to Newton's law of movement [18]:

$$x^j = -\alpha t^2 + w_0 t1, i \geq 2 \tag{11}$$

Whereas,

$$\alpha = \frac{w_{final}}{w_0} \tag{12}$$

and

$$w = \frac{x - x_0}{t} \tag{13}$$

Consider, $w_0 = 0$ and the variance among other 2 sequential time steps is one, thus

$$x_j^i = \frac{1}{2} \times \left(x_j^i + x_j^{i-1}\right), i \geq 2 \tag{14}$$

4. Performance Validation

The performance of the OLS-SVM method is validated utilizing a benchmark EEG dataset, which comprises two class labels. The group of 2300 instances fall into class 0 with the EEG signals having seizure activity and a totally of 9200 instances comes in class 1 with the EEG signals not having seizure activity. The details compared with the dataset are depicted in Table 1.

Table 1 Dataset Description

Class Name	Class Label	No. of Instances
EEG signals having seizure activity	0	2300
EEG signals not having seizure activity	1	9200

Fig. 3 illustrates the confusion matrices produced by the LS-SVM and OLS-SVM models. Fig. 3a depicts that the LS-SVM model has classified a number of 1688 instances into class 0 and 8195 instances into class 1. Besides, Fig. 3b demonstrates that the OLS-SVM model has classified a number of 1892 instances into class 0 and 8372 instances into class 1.

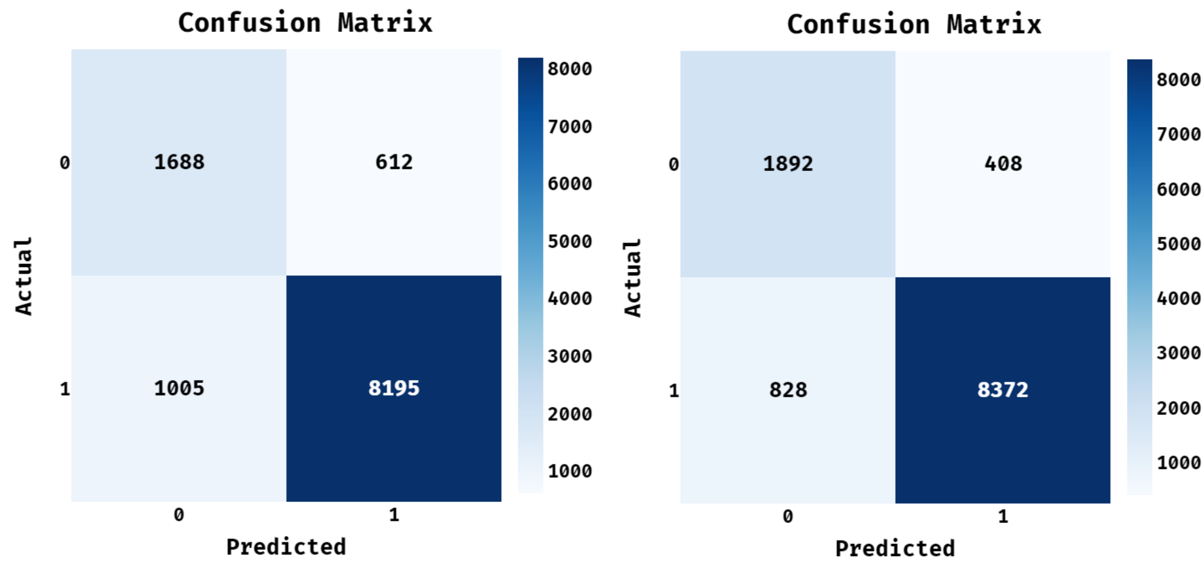

Fig. 3. Confusion Matrix of a) LS-SVM b) OLS-SVM

A brief comparison study of the OLS-SVM model with other ML models takes place in Table 2. Fig. 4 examines the sensitivity, specificity, and accuracy analysis of the OLS-SVM model. The figure stated that the RF model has showcased ineffective outcomes with the least sensitivity of 62.40% and specificity of 63.80%. In line with, the SVM model has gained slightly boosted outcome with a sensitivity of 63.74% and specificity of 62.72%. Followed by, the GBT technique has depicted reasonable efficiency with a sensitivity of 67.64% and specificity of 77.22%. Though the LS-SVM manner has accomplished competitive outcomes with a sensitivity of 73.39% and specificity of 89.10%, the presented OLS-SVM algorithm has resulted in a maximum sensitivity of 82.30% and specificity of 91%.

Table 2 Result analysis of presented OLS-SVM method with state of art techniques

Methods	Sensitivity	Specificity	Accuracy	F-score	Kappa
OLS-SVM	82.30	91.00	89.30	75.40	68.57
LS-SVM	73.39	89.10	85.90	67.60	58.71
SVM	63.74	62.72	63.11	62.60	61.85
GBT Model	67.64	77.22	73.31	75.50	73.25
Rand. Forest	62.40	63.80	62.00	61.60	62.30

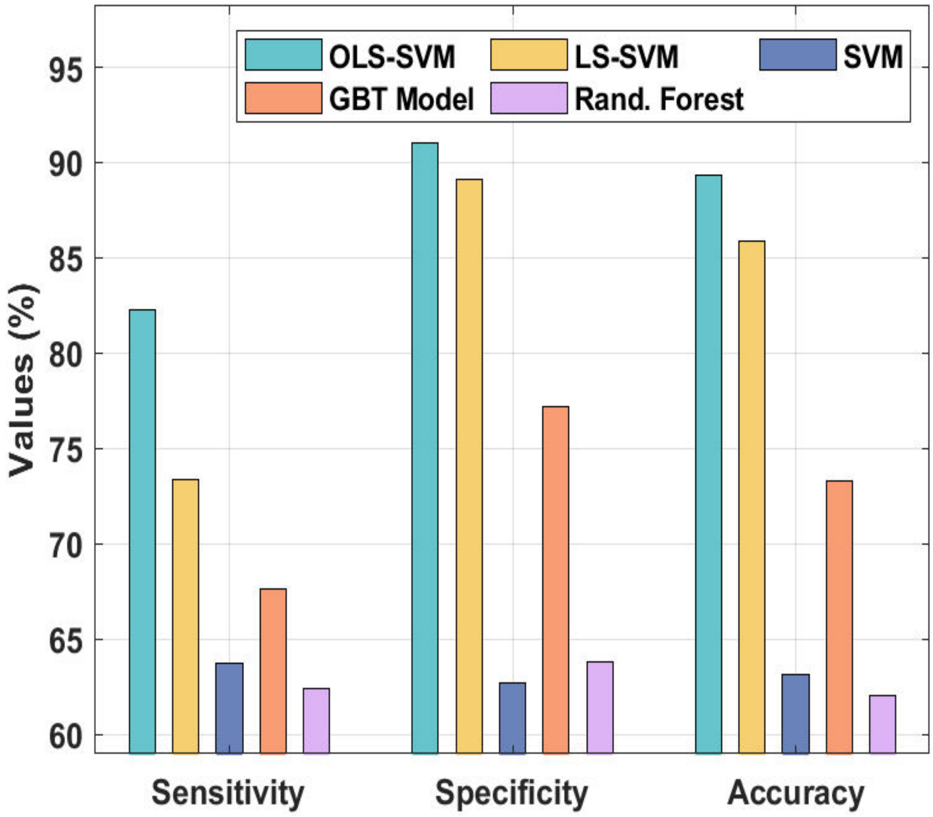

Fig. 4. Sensitivity, Specificity and Accuracy analysis of OLS-SVM model

Fig. 5 inspects the F-measure, and kappa analysis of the OLS-SVM method. The figure exhibited that the RF approach has outperformed ineffective outcomes with the worse F-measure of 61.6%, and kappa of 62.3%. Similarly, the SVM manner has achieved somewhat higher outcome with F-measure of 62.6%, and kappa of 61.85%. Along with that, the GBT technique has demonstrated reasonable outcomes with a F-measure of 75.5%, and kappa of 73.25%. Also, the LS-SVM algorithm has accomplished optimum outcomes with a F-measure of 67.6%, and kappa of 61.85%, the projected OLS-SVM methodology has resulted in a superior F-measure of 75.4%, and kappa of 68.57%.

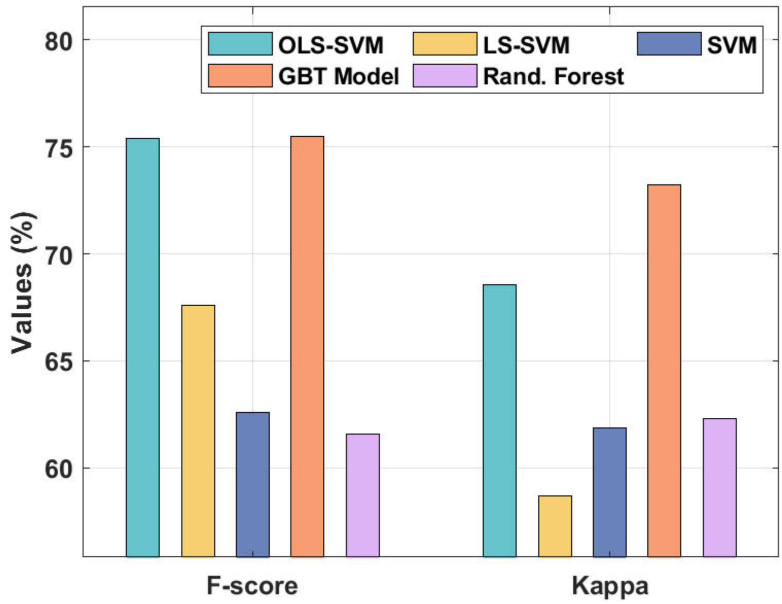

Fig. 5. Result analysis of OLS-SVM model interms of F-score, and kappa

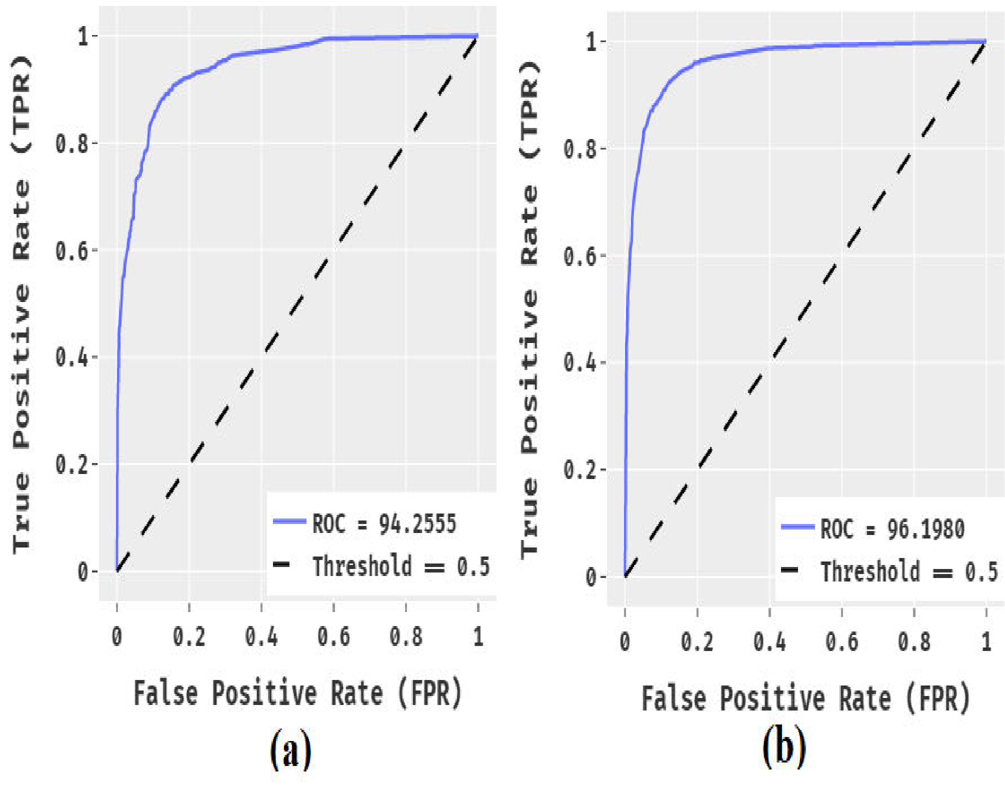

Fig. 6. ROC of a) LS-SVM b) OLS-SVM

Fig. 6 showcases the ROC analysis of the LS-SVM and OLS-SVM models. These figures pointed out that the LS-SVM model has obtained a ROC of 94.2555 whereas the OLS-SVM model has resulted in an increased ROC of 96.1980.

To further validate the improved performance of the OLS-SVM technique, a comparative analysis with recent state of art methods [14] take place in Table 3 and Fig. 7. The experimental outcomes pointed out that the KNN, MLP, and linear SVM approaches have accomplished reduced performance with accuracy of 76%, 78%, and 77.10% correspondingly. Followed by, the Cubic SVM and M-Gaussian-SVM models have demonstrated moderate outcomes with the accuracy of 82.30% and 81.70% respectively. Moreover, the LS-SVM model has gained competitive performance with an accuracy of 85.90%. However, the proposed OLS-SVM model has outperformed the recent method and resulted in a maximum accuracy of 89.30%.

Table 3 Comparative analysis of Recent Methods with Proposed OLS-SVM on Applied Dataset

Methods	**Accuracy**
OLS-SVM	89.30
LS-SVM	85.90
Linear SVM	77.10
Cubic SVM	82.30
M-Gaussian-SVM	81.70
KNN	76.00
MLP	78.00

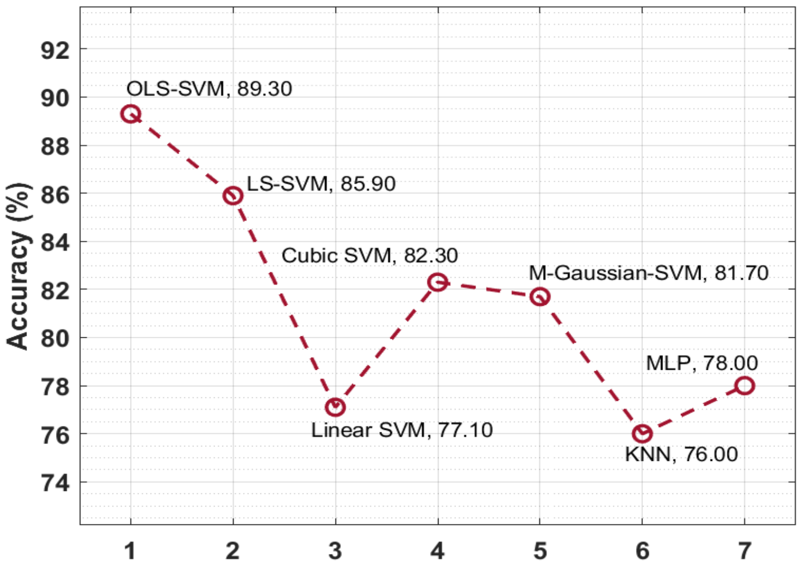

Fig. 7. F-score analysis of OLS-SVM model with exiting techniques

5. Conclusion

This paper has developed a novel OLS-SVM model for epileptic seizure detection and classification model using EEG signal. The proposed OLS-SVM model involves pre-processing, LS-SVM based classification, and SSA based parameter tuning. In order to effectively tune the values involved in the LS-SVM model, the SSA is used in such a way that the classification performance gets improved to a maximum level. For examining the enhanced classification performance of the OLS-SVM method, an extensive set of simulations were carried out and the experimental results highlighted the superior performance of the OLS-SVM method. The presented OLS-SVM technique can be utilized by physicians to aid the seizure diagnostic process. As a part of future work, the diagnostic performance of the presented OLS-SVM method is boosted by the use of feature reduction and feature selection techniques. Moreover, the OLS-SVM model can be realized in an Internet of Things (IoT) environment to assist physicians and patients from remote areas.

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