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ORIGINAL RESEARCH

DepML: An Efficient Machine Learning-Based MDD Detection System in IoMT Framework

Geetanjali Sharma[1,3] · **Amit M. Joshi**[1] · **Emmanuel S. Pilli**[2]

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Abstract

This paper aims to propose an automated and less complex machine learning-based depression detection system DepML utilizing the IoMT framework in smart hospitals. This paper focuses on the method to identify relevant features and effective classifiers that can classify depressed and healthy individuals with high accuracy and less complexity. The model implementation is done in three steps: (1) Several essential features, including statistical, time, linear, fractal dimension, non-linear, and coherence, are derived from multichannel EEG. (2) Most relevant features are chosen using three feature selection methods, including Principle component analysis (PCA), Relief-based algorithm (RBA), and Neighbourhood component analysis (NBA). Then, the performance of these feature selection methods is compared, and the best method is used in implementing the model. (3) Classification of normal and depressed subjects is done using five different classifiers, including radial-basis function (RBF)-support vector machine (SVM), logistic regression (LR), K-nearest neighbour (KNN), decision tree (DT), and naïve Bayes classification (NB). The paper concludes that by combining a non-linear feature set and an RBF-SVM classifier, the best classification accuracy of 98.90% is achieved. This paper also concludes that the classification time gets reduced to approximately half after reducing the feature matrix. The results given in this work are utilized to design a depression detection system in smart healthcare and remote applications using IoMT framework.

Keywords Electroencephalography · Depression · Feature extraction and selection · Machine learning · Artificial intelligence · Internet of Medical Things (IoMT)

Introduction

There are around 120 million people around the world suffering from Major depressive disorder (MDD) which is one of the most common neurological disease [1]. The global health organisation (WHO) ranks this condition as the fourth major cause of cognitive disability [2–4]. Long-term despair, loss of energy, bad mood, sense of worthlessness, lack of attention, and, in the worst-case scenario, suicidal thoughts are among the common symptoms of depression disorder [5]. Specialist psychiatrists should diagnose and treat this mental disease as quickly as possible. The Beck Depression Inventory (BDI) and Depression Rating Scale (DRS) are often used to make a manual diagnosis of MDD, although manual diagnosis is vulnerable to subjectivity and ambiguity. Thus, an automated and dependable depression detection system with good compatibility and high accuracy in a real-time applications is needed. Various studies using biomarkers such as computed tomography (CT), functional magnetic resonance imaging (fMRI), and electroencephalogram (EEG) have been attempted to diagnose the depression disorder in recent years [6–11]. Because of its non-invasive mode of acquisition, ease of application, and cost-effectiveness, EEG has earned a huge interest in the diagnosis of depression. The brain's electrical activity is measured using an EEG, which provides the direct information regarding brain abnormalities [12, 13].

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✉ Geetanjali Sharma
gsharma@msit.in

[1] Department of Electronics and Communication Engineering, Malaviya National Institute of Technology, Jaipur, India

[2] Department of Computer Science and Engineering, Malaviya National Institute of Technology, Jaipur, India

[3] Department of Electronics and Communication Engineering, Maharaja Surajmal Institute of Technology, New Delhi, India

Several deep learning and machine learning based techniques for the brain-computer interface have been developed as technology and its execution in real-time applications advanced in last few years [14–16]. Even with depression detection, several models have been implemented including [17–23]. Although, in this branch of EEG-based data processing, dependability and complexity remain an issue. Since EEG signals are very nonlinear and complicated, there is a significant need to recognize and extract relevant features that might assist in the automated detection of depression. Several deep learning approaches have demonstrated outstanding accuracy in detecting depression in the literature, but their implementation in real-time environment is still a concern due to the extremely complex structure. Machine learning models, on the other hand, are easier to implement and understand [24, 25]. Despite this, their classification accuracy is limited due to inadequate feature and classifier selection [26–30].

The healthcare system is developing in the field of mobile health as a result of technology advancements, using IoMT to analyze patient data and deliver treatments remotely [31]. As illustrated in Fig. 1, this work has also developed a smart closed loop system for management and detection of depression. The EEG signal is obtained from the patient's brain using a non-invasive wearable device and then pre-processed before being used. Wi-Fi is used to send the pre-processed data to the cloud. Following that, the proposed automatic depression detection system in the cloud is used to extract features, select, and classify EEG data for MDD detection. The healthcare practitioners and caretakers can get a hold of a patient's true status using this system [32]. For securities concerns, encrypted EEG data can also be used for training and classification purpose. This encryption method can help store and securely process the subject's EEG data. The structure of the paper is as follows:

The Literature survey is discussed in Section "Literature Survey". The methodology is discussed in Section "Methodology". Section "Results" covers the results. Finally, Section "Conclusion" concludes the study.

Literature Survey

In recent studies, several EEG-based machine learning models have been presented using variety of feature extraction methods and classifiers. Hosseinifard et al. [22] proposed a machine learning model with an accuracy of 90% using four non-linear features extracted from EEG including Higuchi fractal, detrended fluctuation analysis, Lyapunov exponent and correlation dimension. In this KNN, LR and linear discriminant analysis (LDA) classifiers were used for classification of depressed and healthy subjects. Hosseinifard et al. [22] showed an effectiveness of using non-linear feature set in depression detection. EEG-based synchronisation likelihood (SL) features had been explored in Mumtaz et al. [19] for automatic detection of MDD. In this study [19], three different classifiers were used including LR, SVM and NBA. Mumtaz et al. [19] reported a highest accuracy of 98% using SVM classifier. In [29] the authors investigated power of different frequency bands and EEG alpha inter hemispheric asymmetry as input features for classifying MDD and healthy subjects. This machine learning based models resulted in accuracy of 98.4% using SVM classifier, 97.6% using LR classifier and 96.8% using NB classifier. Kang et al. [33] proposed a model using deep-asymmetry method which converted asymmetry feature set into a matrix image. This matrix image was fed into convolutional neural network as an input for further clarification of depressed and healthy subjects. This method [33] had reported an accuracy of 98.85% using alpha band asymmetry image. In continuation with the above mentioned studies, authors of [18] had explored melamine pattern and discreet wavelet transform (DWT) as feature set for automatic detection of MDD. This paper [18] reported an accuracy of 99.11% using quadratic SVM classifier.

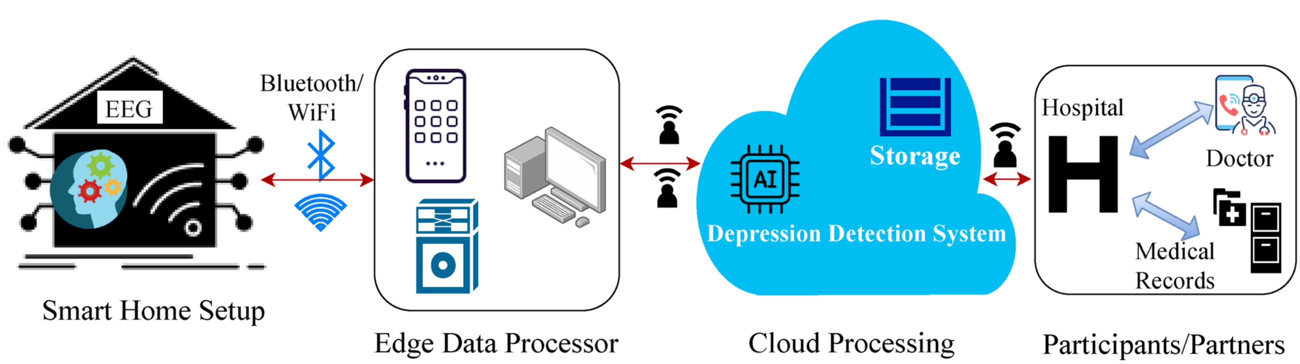

Fig. 1 Closed-loop solution for MDD Detection in IoMT framework

Motivation and Contribution

Several machine learning-based EEG approaches have been presented in the research, differing in approach, classifier, selected features, participants, and sometimes even number of classes [34, 35]. With all of these research using EEG to diagnose depression, there is still scope of technological advancement. For example, high accuracy with minimal complexity, adequate feature and classifier selection, and model feasibility. In our proposed model, different types of linear, non-linear, wavelet and coherence features have been extracted and compared. Three feature selection methods including PCA, NBA and RBA are used to identify efficient and reduced feature matrix. Then, validation is done using classifiers including SVM, KNN, DT, LR and NB. Following the comparative evaluation, the DepML model with 98.90% accuracy is developed, which, to our knowledge, is the finest utilising the machine learning technique.

(a) Novel Contributions

(1) An efficient and reduced feature matrix has been identified which further reduces the complexity of the model.
(2) A highly accurate machine learning based model is proposed.
(3) The model has been implemented in IoMT framework to verify the mental health status in real time applications.

Methodology

The EEG dataset, which is utilised in model implementation and pre-processing, is first presented. In this study, machine learning models with a variety of features and classifiers are used to distinguish healthy and depressed participants, and finally, the performance is evaluated.

Dataset

In this paper, a publicly accessible EEG dataset developed by Mumtaz et al. is utilised to implement an automated and accurate system for depression detection [29]. The dataset includes 64 participants (34 with MDD and 30 without) ranging in age from 12 to 77 years old, with an average age of 20.54 years. All the participants were chosen from the hospital Universiti sains Malaysia (HUSM). There were 24 women and 40 males among the 64 people who took part in the study. Using the diagnostic and statistical manual IV, MDD patients have met the diagnostic requirement of MDD (DSM-IV). The experimental design was authorised by an ethical committee, and all of the participants signed the consent forms. Each subject's EEG was recorded for a total of 10 min, comprising 5 min with their eyes open (EO) and 5 min with their eyes closed (EC). The data was collected at a sample rate of 256 Hz per second, in accordance with the international 10-20 standard. 19 channels were used to collect EEG data, including Fp1, F3, F7, Fz, Fp2, F4, F8, C3, C4, Cz, P3, Pz, P4, O1, O2, T3, T4, T5, and T6. For data filtration, a 0.5–70 Hz filter was employed, as well as a 50 Hz notch filter for the suppression. of power line.

As part of the pre-processing, the EEG data were normalised utilizing z score normalisation for amplitude scaling. Because different types of noise, such as eye blinking and muscle activity, can muddle EEG data, such EEG signals cannot accurately identify brain disorders. Cleaning of such EEG signals is therefore essential for subsequent processing. As part of pre-processing, the ICA technique is employed to remove artefacts. The number of samples used in EEG-based machine learning implementation is important. The data segmentation approach is used to separate EEG data samples into meaningful segments in this study. The 5 min EEG data is partitioned into epochs of 10 s (2560 sample points), each with no overlapping, and given the same labels. Each patient receives 10 min of EEG recording, 5 min with eyes closed (EC), and 5 min with eyes open (EO). As a result, each subject will need a total of $(10 \times 6) = 60$ labelled observations. Figure 2 depicts the architecture for an automated depression detection system based on machine-learning approach.

Feature Extraction for MDD Detection

From the EEG data, a total of 860 features are derived, allowing the EEG segments to be properly mapped to their appropriate classes. In previous research, all of the extracted features were also investigated thoroughly for human-brain interface systems [36]. The features used in this study are given in Fig. 3. First, a total of 20 statistical features are extracted from EEG signal for automatic detection of depression. Extraction of 20 statistical features from a single channel of EEG forms a 380-dimensional statistical feature matrix. Second, the EEG is decomposed into 4 different frequency bands which are theta, alpha, beta and gamma. Then, for each frequency band and single channel EEG, four different power features are extracted. These power features are power spectral density from each channel, rational asymmetry power and differential asymmetry power from paired channel and cross power from paired channel. This produced 220-dimensional power/linear feature matrix as given in Fig. 3. Third, due to non-linear nature of EEG signal, it is recommended to extract and analyse some non-linear features too along with linear feature set. Therefore, in this paper, five entropy features including sample entropy, spectral entropy, SVD entropy, permutation entropy, and approximate entropy

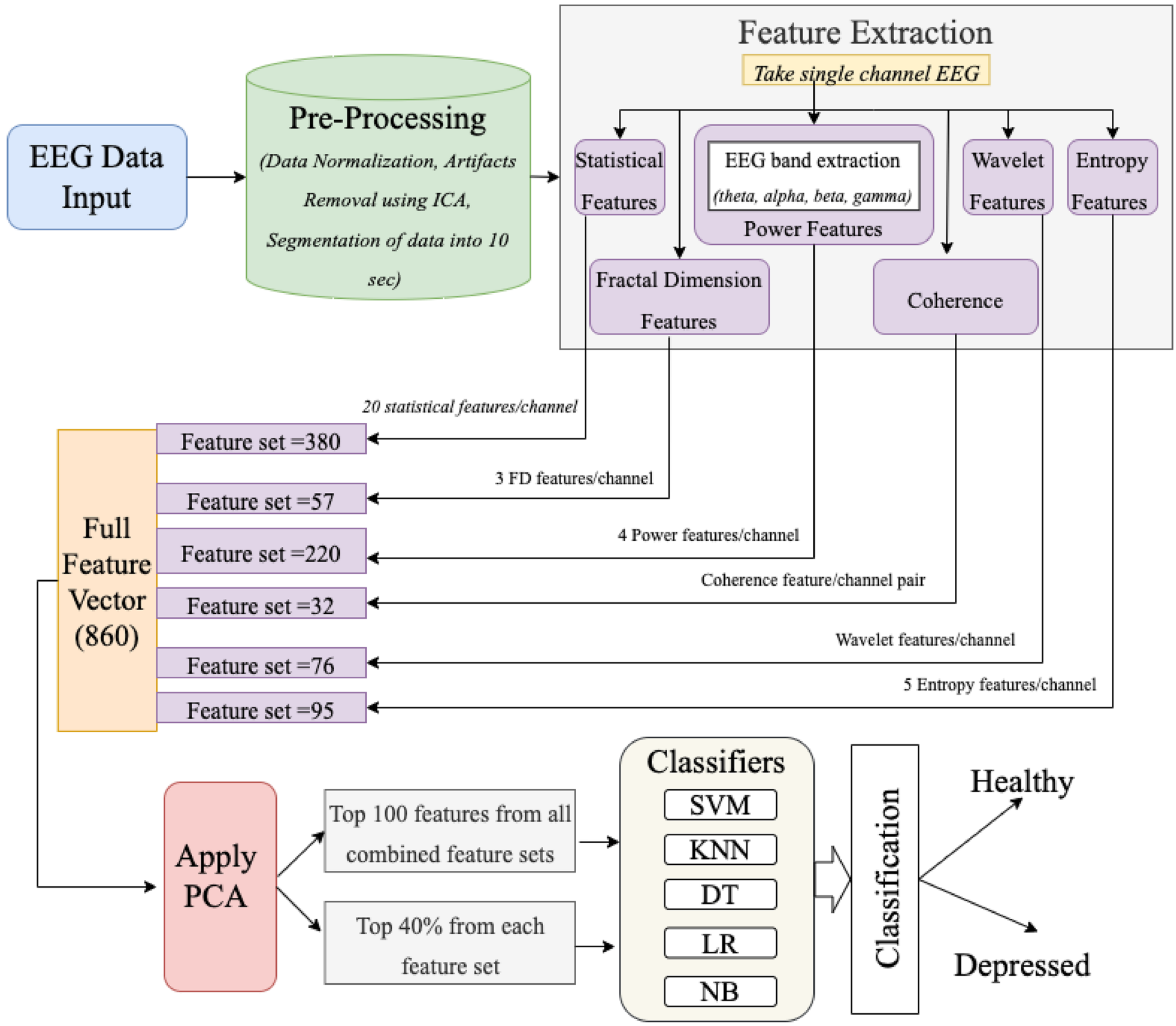

Fig. 2 Architectural design of machine learning based depression detection system

are extracted from each channel for depression detection. This produces 95-dimensional non-linear entropy feature matrix. Forth, along with entropy features, three different fractal dimension features are also extracted from each channel EEG. Fractal dimension (FD) calculates the geometrical complexity of EEG signal and helps in assessing the temporal sequence. This produces 57-dimensional FD feature matrix for depression detection. Fifth, wavelet feature are extracted for each frequency band of single channel EEG, which produces 76-dimensional time feature matrix. Sixth, coherence features are extracted from EEG channel pair which gives the information related to connection and disconnection of neurons responsible for depression. This produces a 32-dimensional coherence feature matrix. In total, a 860-dimensional feature matrix is produced from various typed of features for automatic detection of depression.

Feature Selection for MDD Detection

Selecting the most significant features to detect the output is an essential and complicated research issue. Few extracted features may be useless or duplicated, that contributes to the dataset's large dimensionality and the model's high computational efficiency. As a result, it is always important to recognize and establish the essential features to more accurately detect the results. It reduces the computational complexity even further. In the literature, several feature selection algorithms for dimensionality reduction have been proposed. This study utilizes three feature selection methods to reduce

Feature Sets	Used Features	Total Features
Statistical	Mean	(19 channels)x(20 statistical moments)=380
	Minimum	
	Maximum	
	Median	
	Standard deviation	
	Absolute Mean	
	range	
	Absolute Standard Deviation	
	Root Mean Square	
	Absolute Median	
	Absolute Variance	
	Skewness	
	Kurtosis	
	Absolute Skewness	
	Absolute Kurtosis	
	Mean Square Deviation	
	Mean of absolute values of first difference	
	Mean of absolute values of second difference	
	Variance	
	Mean Absolute Deviation,	
Linear (Power)	Power from every channel	(19 channels)x(4 bands)=76
	Differential asymmetry power from paired channels	(9 paired channels)x (4 bands)=36
	Rational asymmetry power from paired channels	(9 paired channels)x (4 bands)=36
	Cross power from paired channels	(9 paired channels)x ((4 bands_real)+(4 bands_imaginary))=72
Non- linear (Entropy)	Sample entropy	(19 channels)x(5 entropies)=95
	Spectral entropy	
	SVD entropy	
	Permutation entropy	
	Approximate entropy	
Fractal dimension (FD)	Katz's FD	(19 channels)x(3 FD's)=57
	Higuchi,s FD	
	Petrosian FD	
Time (Wavelet)	Wavelet feature from 4 bands	(19 channels)x(4 bands)=76
Coherence	Coherence from 8 channel pairs	(8 paired channels)x(4 bands)=32

Fig. 3 Extracted Features

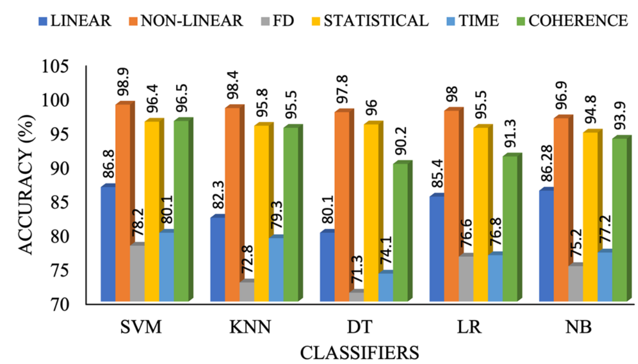

Fig. 4 Classification accuracy comparison without feature selection using all five classifiers based on various feature sets

and recognize the most important features. RBA, PCA, and NCA feature selection methods are used in this study. PCA performs feature selection by making a covariance matrix and utilizing eigenvectors of this matrix. This helps in evaluating the significance of each feature which further helps in recognizing important features for depression detection. RBA is a statistical-based approach that scores the features one by one ranging from + 1 (best) to – 1(worst) for each feature. NCA is a simple and popular feature selection method that assigns positive weights to the features, which helps in selecting the most effective features.

Classification for Depression

This study utilized five distinct classifiers to distinguish the depressed and healthy individuals. First, the radial-basis function (RBF) SVM classifier that generates an optimal hyperplane for separating EEG into two classes is used. Second, the KNN classifier is used, which is considered particularly promising in EEG classification. It takes *k* samples similar to the predicted sample, and the major voters select the label. Third, DT, a classification method based on a divide-and-conquer strategy and a tree-like structure, is used. It has the benefit of having a low computation time and a good level of dependability. Forth, the Logistic Regression classification is used where coefficient estimation is done using the maximum likelihood technique, and it gives a probability value to mark MDD patients. The fifth classifier, NB, assigns and generates conditional probabilities for each and every epoch. This method also works well with EEG datasets.

Results

This study concludes results with the help of three experiments. 1. The influence of several feature sets on the classification of depression is examined. 2. The process that may successfully choose the significant features for depression diagnosis are found after comparing three feature selection methods. 3. Effect of reduction in feature matrix on the implementation of depression detection models is examined, and the best model is proposed. The 10-fold cross-validation approach was used for all of the analyses. Epochs are randomly segmented into ten groups having the equal number of samples in 10-fold cross-validation. After that, nine training groups and one testing group are used. This technique is performed 10 times with a new group each time. As a consequence, the entire dataset is included in the analysis. The ultimate accuracy is the average of all the epochs' accuracies.

Accuracy Comparison Without Feature Selection

Only one feature set is utilized at a time in this experiment to detect depression. Here, six feature sets are used, including non-linear, linear, fractal dimension, statistical, temporal, and coherence features, with detection accuracy utilising all five classifiers presented in Fig. 4.

For all the given classifiers SVM, KNN, DT, LR, and NB, the classification performance using non-linear features is better compared to various other feature. Using an SVM classifier, these non-linear characteristics can distinguish healthy and depressed people with a classification accuracy of 98.90%. Statistical features have also demonstrated high accuracy of 96.1% when using the SVM classifier, which is the highest after utilising a non-linear feature set. It is clear from the Fig. 4 that the proposed model with non-linear features and RBF-SVM classifier provides the highest depression detection accuracy for all available features and classifier combination.

Comparative Analysis of Feature Selection Approaches

Feature selection approaches play an important role in selecting relevant and essential features, reducing the system complexity and feature dimension. Thus, this experiment also presents a comparison of three feature selection methods, including RBA, PCA, and NCA, employing non-linear features and RBF-SVM classifier. After applying all kinds of features to RBA, PCA, and NCA, the top features are identified. The SVM classifier is then used for classification utilizing these top features. The final experiment results are shown in Fig. 5, and it is concluded that the features selected using PCA are substantially better at diagnosing depression than the other two feature selection methods.

Classification Accuracy Comparison with Feature Selection

In this experiment, PCA is used for selecting top 40% features from every type of feature set. The findings for the classification of healthy and depressed participants using all classifiers are shown in Table 1. It is clearly seen from Table 1 that the non-linear features are giving better results in terms of accuracy of 98.7% in comparison to other types of features. When just the top 40% of features are used for classification, the computational complexity is reduced as well. It can also be concluded that after removing 60% of the features, the model's performance does not change dramatically because the important critical information is still contained inside the top 40% of features. This reduction in feature dimension will also aid in implementing the depression detection system in real-time.

Classification Time Comparison Without and With Feature Selection Approach

The classification time comparison for all the feature sets using five different classifiers is given in Table 2. It can

Table 1 Classification accuracy comparison without and with feature selection (FS) method

Classifiers	SVM	KNN	DT	LR	NB
Linear					
Without FS	0.868	0.823	0.801	0.854	0.862
With FS	0.885	0.814	0.765	0.812	0.851
Non-linear					
Without FS	0.989	0.984	0.978	0.98	0.969
With FS	0.987	0.981	0.971	0.978	0.96
FD					
Without FS	0.782	0.728	0.713	0.766	0.752
With FS	0.78	0.73	0.706	0.756	0.742
Statistical					
Without FS	0.964	0.958	0.96	0.955	0.948
With FS	0.965	0.956	0.95	0.951	0.942
Time					
Without FS	0.801	0.793	0.741	0.768	0.772
With FS	0.793	0.79	0.73	0.752	0.75
Coherence					
Without FS	0.965	0.955	0.902	0.913	0.939
With FS	0.964	0.956	0.891	0.884	0.920

Table 2 Classification time comparison without and with feature selection (FS) method (in seconds)

Classifiers	SVM	KNN	DT	LR	NB
Linear					
Without FS	515.34	620.91	231.12	430.22	489.33
With FS	243.88	377.57	102.01	256.34	279.90
Non-linear					
Without FS	491.23	575.14	210.40	398.09	451.13
With FS	259.90	323.38	122.91	176.97	210.00
FD					
Without FS	459.20	543.85	18 3.33	372.34	429.90
With FS	214.19	271.67	99.21	241.30	203.88
Statistical					
Without FS	505.10	589.07	229.04	418.43	470.76
With FS	290.54	259.87	115.54	202.23	253.45
Time					
Without FS	477.19	571.67	197.90	389.28	435.69
With FS	246.56	223.34	99.10	171.29	231.29
Coherence					
Without FS	433.79	481.69	159.36	393.88	380.80
With FS	209.46	239.63	80.54	179.09	149.73

Table 3 Comparison of models developed in literature for depression detection using EEG of same dataset

References	Method used	Accuracy	Recall	Tnr
(2017) [29]	Power+Alpha asymmetry features+SVM	0.984	0.975	1
	Power+Alpha asymmetry features+NB	0.976	0.966	0.985
	Power+Alpha asymmetry features+LR	0.983	0.966	1
(2017) [37]	Wavelet+STFT+EMD+LR	0.905	0.916	0.887
(2019) [21]	Power+Symmetry features+SVM	0.883	–	–
(2020) [33]	Linear+Non-linear features+MLPNN	0.933	–	–
(2020) [38]	Asymmetry image+2D-CNN	0.988	0.991	0.985
(2021) [18]	Melamine pattern+wavelet features+Quadratic SVM	0.991	0.984	0.998
2022, [39]	Wavelet coherence+CNN	0.981	0.980	0.982
DepML	Non-linear features+RBF-SVM	0.989	0.992	0.997

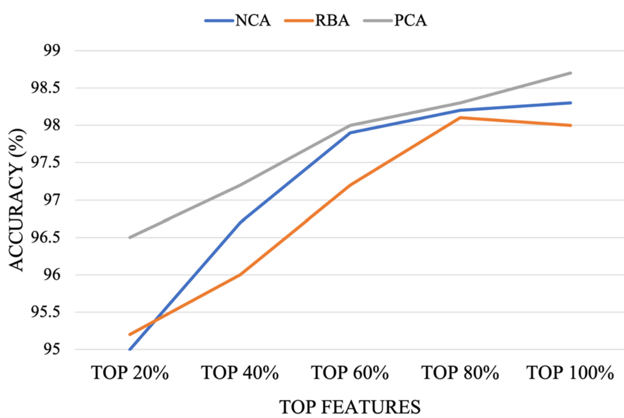

Fig. 5 Comparison of feature selection approaches utilizing non-linear feature set and RBF-SVM classifier

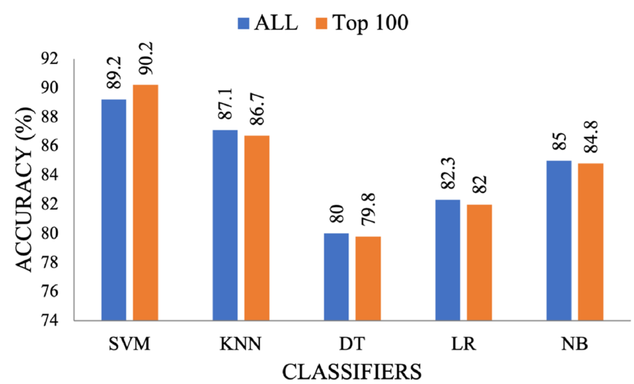

Fig. 6 Accuracy comparison of depression detection model using all and Top 100 features

be concluded from Table 2 that after reducing the feature matrix by 60%, classification time also gets reduced. It can be seen in Table 2 that the classification time of the system using non-linear features and SRBF-SVM classifier is 491.23 s, and after selecting top 40% feature, it gets reduced to 259.90 s. This makes the model faster, which will further help in implementing the depression detection system in real-time applications.

Accuracy Comparison Using all Extracted Features and Ranked 100 Features

Figure 6 depicts the classification accuracy comparison involving all 860 combined features as well as the top-ranked 100 features from all available features. It is evident from Fig. 6 that the accuracy derived from all features and top 100 ranked features have no statistically significant difference. Among all other classifiers, the accuracy of using the SVM classifier with all features combined is somewhat less than the accuracy offered by simply using top-ranked 100 features. There is not much considerable performance declination. This concludes that the computation complexity of the proposed system is reduced while maintaining high accuracy by reducing feature dimensions.

Performance Comparison of Depression Detection Methods Proposed in the Previous Studies

Table 3 compares the performance in terms of accuracy, recall, and TNR of models presented in literature created for depression detection utilizing the same dataset. The proposed DepML offers the highest classification accuracy in classifying healthy and depressed individuals, as shown in Table 3. The proposed model is based on handcrafted feature extraction, using PCA to identify significant features. The RBF-SVM classifier is used to classify the data. Aydemir et al. [18] offered an accuracy of 99.11% employing wavelet and melamine characteristics, which again increases the total computational complexity of the model, as seen in Table 3. Furthermore, the classification accuracy presented in this paper by DepML is 98.9% with a substantially lower computational complexity utilizing solely non-linear features, which may be used in remote-based applications.

Conclusion

An experimental analysis is carried out using six types of feature sets and five classifiers to categorize healthy and depressed individuals. PCA is chosen as the best feature selection approach after comparing three other methods. The highest classification accuracy of 98.90% is achieved using a set of non-linear features and RBF-SVM classifier. After applying PCA, top 40% features are identified among all available features, which concludes to an accuracy of 98.7%, comparable to accuracy without feature selection. The feature dimension matrix was decreased by 60% using this approach, which further lowered its time to detect the classes. This reduction in the feature matrix also decreases the computation complexity of the system. Thus, it can be stated that the proposed MDD detection model DepML, utilizing non-linear features and RBF-SVM classifier provides the best results in terms of classification accuracy. This proposed highest accuracy model is further integrated with the IoMT framework for remote and smart health applications.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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