Human Emotion Detection with Electroencephalography Signals and Accuracy Analysis Using Feature Fusion Techniques and a Multimodal Approach for Multiclass Classification

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Abstract-Biological brain signals may be used to identify emotions in a variety of ways, with accuracy depended on the methods used for signal processing, feature extraction, feature selection, and classification. The major goal of the current work was to use an adaptive channel selection and classification strategy to improve the effectiveness of emotion detection utilizing brain signals. Using different features picked by feature fusion approaches, the accuracy of existing classification models' emotion detection is assessed. Statistical modeling is used to determine time-domain and frequency-domain properties. Multiclass classification accuracy is examined using Neural Networks (NNs), Lasso regression, k-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest (RF). After performing hyperparameter tuning, a remarkable increase in accuracy is achieved using Lasso regression, while RF performed well for all the feature sets. 78.02% and 76.77% accuracy were achieved for a small and noisy 24 feature dataset by Lasso regression and RF respectively whereas 76.54% accuracy is achieved by Lasso regression with the backward elimination wrapper method.

Keywords-feature fusion; DNN; Lasso regression

I. INTRODUCTION

Emotion detection is a part of artificial intelligence. It is a multidisciplinary area where the major fields involved are medical signal processing, artificial intelligence, machine learning, and brain-computer interfacing. It presents a collection of emotion recognition study scenarios in the following domains: software engineering, website personalization, education, gaming, and medicine. Efforts have been made in recent decades to create new methodologies and techniques for emotion identification. Researchers are increasingly interested in detecting human emotions via biological brain signals [1]. Researchers have been interested in inventing apps that would allow two individuals to communicate without really interacting. Electroencephalography (EEG) headsets are accessible on the market and are inexpensive, allowing the study in this field without having to use complicated brain interfaces. EEG is a reliable and affordable way to measure brain activity. To achieve the criteria of a Brain-Computer Interface (BCI), emotion recognition using EEG data requires a sequence of operations to be performed, e.g. removing artifacts from the EEG data, extracting temporal or spectral information from the time or frequency domain of the EEG signal, and finally developing a multi-class classification strategy [2]. The main problem is that the extracted characteristics are calculated using the entire recorded EEG signal sample, which frequently contains incorrect information. As a result, supplementary procedures like choosing electrodes that show a big shift in brain activity during emotional states to accurately identify emotional states and conspicuous feature selection for a more precise conclusion are becoming increasingly critical. Experiments demonstrate that including these procedures expands the number of possibilities for testing the system's correctness. In the current study, a multimodal technique is employed to assess system accuracy. Techniques such as feature selection and feature fusion are employed [3].

II. RELATED WORK

Earlier research focused on either building feature extraction techniques or evaluating multiple classification models for reliable emotion detection on databases such as DEAP and SEED [1]. It is used to extract characteristics that are constant across all participants from a collection of EEG channels. NNs and SVM models are extensively used for classification and prediction. KNN is the most popular algorithm for testing emotional signals. In the studies mentioned below, work has been done on existing databases. These databases record emotional signals in a controlled environment for a predetermined length of time. It is, however, impossible to record all of the signals in a set time frame. The brain's functioning is complicated and varies from person to person as well as from one emotional state to another. Each

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participant has a varied excitation time interval for each emotion. Hence the real study of emotional signals acquired in the natural world is envisaged, with a primary focus on large applications [3]. In Table I the reviewed related work is summarized.

Work on self-created databases is required in the current context. In applications such as BCI for mentally challenged persons and paralyzed people who can't convey their emotions through words, signals must be collected in the real world rather than in a controlled setting. As a result, research on self-created databases including signals acquired in the natural world is expected. A self-created database is employed in this research investigation. The following part discusses the database construction process. To increase accuracy, the feature fusion approach is applied. For accuracy testing, a multimodal approach for multiclass classification is adopted.

TABLE I. RELATED WORK SUMMARY

Reference	No. of channels	Feature extraction algorithm	Classification models	Accuracy(%)
[4]	10	DWT, Principle component analysis	SVM	91.1
[5]	32	Minimum Redundancy Maximum Eelevance (mRMR)	SVM & RF	60
[6]	5	Time-frequency domain features	DST	81.64
[7]	32	Entropy, time and frequency domain features	ANN	93.75
[8]	3	Probability distribution for wavelet packet coefficients	SVM	70.5
[9]	32	Spectral features	DBN	79.2
[10]	32	Fusing of 6 statistical features	SVM	81.87
[11]	14	Gabor function and wavelet transform	ANN	64.87
[11]	10	WT- wavelet transform	KNN	84: arousal, 86:valence
[12]	Adaptive	Kolmogorov-Smirnov (K-S) test	SVM	80.4: arousal, 71.16: valence
[13]	Adaptive	Feature Fusion- statistical, wavelet energy, wavelet entropy	SVM, KNN, QDA	83.8
[1]	Adaptive	ZTWBES	RNN	89.33

ANN: Artificial Neural Network, DWT: Discrete Wavelet Transform, RF: Random Forest, QDA: Quadratic Discriminant Analysis, ZTWBES: Zero-Time Windowing Based Epoch Estimation

III. THE PROPOSED SYSTEM

The Emotive Epoc 14 channel headset was utilized for data collection. The experiment used a 120-emotion-signal database that was self-created, with 30 signals from each of the four considered classes (Angry, Calm, Happy, and Sad). With proper coverage and electrode configuration, it is possible to rebuild a source model of all-important brain regions and understand how they interact. The sensors are made up of saline-soaked felt pads. In Figure 1 the proposed system is shown. The first step is signal acquisition and database creation.

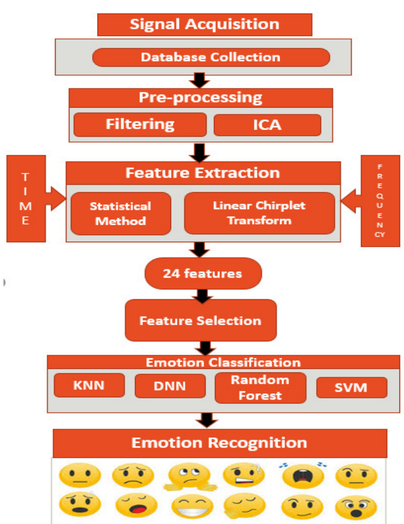

Fig. 1. The proposed system.

A. Database Creation

Healthy individuals were chosen based on their willingness to participate, whereas intellectually disabled subjects were picked with their parent's permission. The Emotive Epoc 14 channel EEG headset is simple to use and comfortable to wear. The training data collection included 22 healthy volunteers (15 females, 7 males) ranging in age from 12 to 70 years old (mean = 35.55, SD = 16.97). Prior to their participation, each subject signed an informed consent form. One of the participants suffers from mild autism. She can communicate and convey basic emotions. A total of 120 emotional signals were recorded. Each emotion class has 30 emotion signals, which were stored in the Emotive cloud and could be used at a later time. Participants were given auditory stimuli to choose from in order to generate a calm feeling. Anger is elicited by the use of a visual stimulus. Self-thoughts are also used to evoke emotion in subjects. Some of our former events are strongly embedded in our minds, and revisiting them might elicit the same sort of powerful feeling. Thoughts have been found to be a very effective sort of stimulus for producing emotions. A single ADC technique and sequential sampling were employed. The rate of sampling was 2048 internal down sampled to 128 fs. The dimension of each recorded file is 41* Number of samples * 60s). The files were edited and only the 14 electrode data were saved in .csv format. The dimension of the database is 120*[128*60]*[14]. The dataset comprised of 120 files and 30 emotion signals of each emotion type (Angry, Calm, Happy, and Sad). $[128*60]_{rows}$ signals were recorded for 1min at 128 fs, $[14]_{col}$ represents the e1.lectrodes. The signals were pre-processed using filtering. ICA is a technique for separating data artifacts (since they are usually independent of each other) [3]. Statistical modeling [5] was used to extract 24 characteristics from the database. The feature set's dimensions are 120*24. Variance, Mean, Standard Deviation Kurtosis, IEEG, Skewness EEG synchronization MAV (Mean Absolute Value), Modified MAV type 1, Modified MAV type 2, Simple Square Integral (SSI), EEG-VEEG Variance Root Mean Square (RMS), absolute standard deviation difference mean2 (DASTD), PXX with autoregression, Waveform Length (WL), Band Power, Max Pow, Max Pow Index, Harmonic Distortion, Hilbert Parameter, Power Spectral Density (PSD) [14] characteristics were considered. Figure 1 depicts the followed multimodal method.

B. *Feature Fusion for Feature Selection*

Classification models were utilized to assess the accuracy of emotion recognition, with feature selection and feature fusion strategies discussed. 14 * samples wrtr captured in 1 minute and (128*60) feature set file is used. Feature selection is done by using filter method, wrapper method, and the embedded method. Feature fusion is used on the reduced feature set and tested for RF, KNN, SVM, DNN, and Lasso regression models [15]. For feature selection, filter and wrapper methods were used. As a result, these methods generate a reduced feature set.

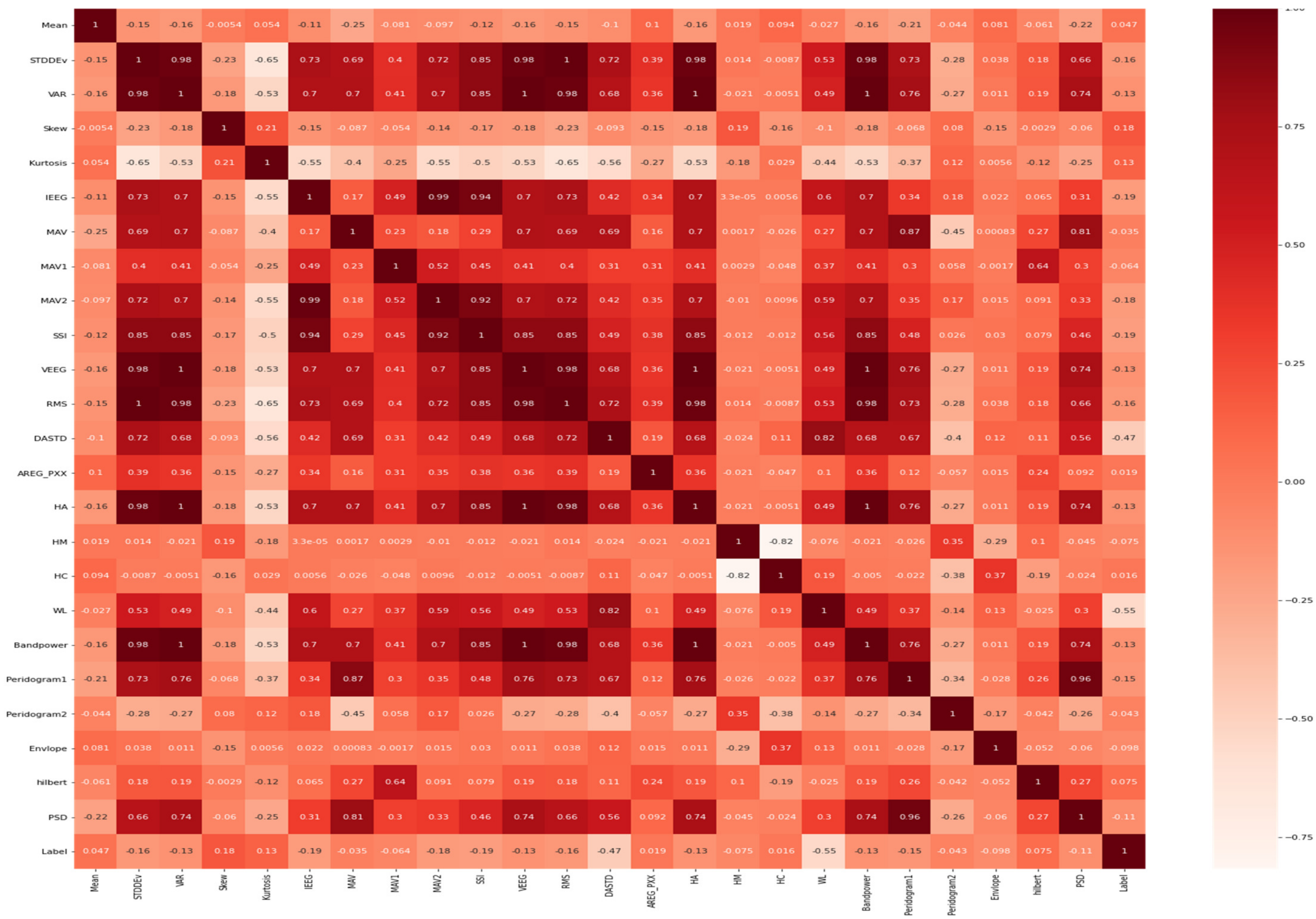

Fig. 2. Correlation matrix.

1) *Filter Method*

This approach filters unnecessary features and selects only a subset of important features. After choosing the characteristics, the model is produced. Filtering is done with the Pearson correlation matrix. The reduced notable feature set is created using the steps described below.

Step 1: Create a heatmap with Pearson correlations for all 24 features.

Step 2: Examine the relationship between the independent variables and the output variable label.

Step 3: Choose characteristics that have a 0.4 or higher correlation with the output variable. The correlation coefficient ranges from -1 to +1. DASTD and WL characteristics have Pearson correlation coefficients of 0.46 and 0.54 respectively.

2) *Wrapper Method*

It is a repeated procedure. It requires one machine learning method, which is used as an estimation criterion. Based on performance, features might be added or eliminated. This approach is more computationally expensive than the filter method, but it is more accurate. Recursive feature elimination and backward elimination are utilized.

3) *Backward Elimination*

The model is fed with all the potential characteristics. The model is tested every time it is used. Worst-performing features are deleted one by one until the model's overall performance is within a reasonable range. By verifying the pvalue, the features are eliminated. If the calculated pvalue is more than 0.05, the feature is excluded from consideration. For linear regression, an OLS (Ordinary Least Squares) model is utilized. The selected features are: 'Mean', 'VAR', 'Skew', 'MAV', 'VEEG', 'DASTD', 'HA', 'HC', 'Bandpower'].

4) Recursive Feature Elimination

It ranks the features using an accuracy feature ranking approach. The model is created using all 24 characteristics. With 24 features, the Linear Regression model is utilized. It ranks all the variables from most important to the least. True represents a relevant feature and false represents an irrelevant aspect in the output. The model's accuracy is computed repeatedly for each feature. The optimum amount of characteristics with the best accuracy is chosen. It is done by looping through all the features from 1 to 24, and then selecting the one with the best accuracy.

a) Feature Ranking

- Optimum number of features: 10
- Score with 9 features: 0.54
- Index (['STDDEv', 'VAR', 'MAV', 'VEEG', 'RMS', 'DASTD', 'HA', 'Band power', 'Hilbert', 'PSD']

b) Feature Fusion

The output of the feature selection step is a reduced feature set. In this step, 3 reduced feature sets are created and used to test system performance. The system is trained using a reduced feature set and then accuracy is tested for different classification models [4].

C. Multimodal Approach

The classification algorithms used for testing the accuracy of the feature set [7] are: KNN, SVM, RF, Lasso Regression, and multiclass classification using neural networks (DNN) [1].

1) KNN

KNN is a supervised machine learning algorithm, also known as the lazy learner or non-parametric learning method. It uses feature similarity to forecast the values of new data points, which means a new data point will be assigned a value based on how closely it resembles the points in the training set [4]. It is great for nonlinear data since it makes no assumptions about the data, and it is also great for small datasets [16].

2) SVM

The purpose of the SVM is to find a hyperplane that differentiates data points in an N-dimensional space. The number of features determines the hyperplane's size. It works well when there is a clear demarcation between the dimensions and when the number of samples is larger than the number of dimensions [9]. When the data set contains additional noise, such as overlapping target classes, it performs poorly [17].

3) RF

It creates decision trees from several samples, using the majority vote for classification and the average for regression. This method employs a meta-approach and is based on ensemble learning. It aims to improve forecast accuracy by merging predictions from various models. It associates decision tree predictions and chooses the best prediction among them.

4) Lasso Regression

It is based on the concepts of shrinkage and L1 regularization, and it employs a procedure in which data values are reduced toward the central tendency and a penalty proportional to the absolute size of coefficients is applied. This regularization results in sparse models with a few coefficients. Lasso regression helps feature selection by reducing the magnitude of λ to zero if required. The output depends on the value of λ. The followed algorithmic steps are described below:

- Importing data set
- Preprocessing:
- Making a distinction between dependent and target variables.
- Fitting the model
- Model predictions
- Check the initial score of R Square and perform hyper-parameter tuning if necessary. After performing hyper-parameter tuning, a remarkable increase in accuracy is observed. The hyper parameters are: param = {'alpha': [.00001,0.0001,0.001,0.01,0.1], 'fit_intercept': [True,False], 'normalize': [True,False], 'positive': [True,False], 'selection': ['cyclic','random']}. The best found hyperparameters are: {'alpha': 0.01, 'fit_intercept': True, 'normalize': False, 'positive': False, 'selection': 'random'}. After adjusting the alpha parameter and using the best parameters, the accuracy of the model increased remarkably to 78.02, which is the highest among all the models.

D. DNN: Multiclass Classification Using Neural Networks

a) Encode the Variable Output

There are 4 alternative numerical values in the output variable. When implementing NNs to represent multi-class classification issues, the output attribute must be reshaped from a vector of values for each class. Each class's value will be represented in the matrix as a Boolean type. This is referred to as "one-hot encoding." It is the process of converting category variables into dummy variables [18].

b) Create the Neural Network Model

Wrapper classes are used to define NNs. A rectifier activation function was used in the hidden layer. The output layer must produce 4 output values, 1 for each class, using one-hot encoding. The highest output value is used to determine the class. Table II summarizes the network structure of this simple one-layer NN. The softmax activation function is employed in the output layer. The output values are between 0 and 1 and may be used to calculate the expected probability. Categorical cross-entropy [10] and Adam gradient descent optimization with a logarithmic loss function [19] were used. Multi-class cross-entropy loss and Leibler Kullback divergence loss are used in multi-class classification problems. The default loss function is cross-entropy. In this, each class is given a distinct integer value, which is the preferred loss function under the maximum likelihood inference paradigm. The loss function should be estimated initially and adjusted if necessary.

TABLE II. NEURAL NETWORK TOPOLOGY

Feature Set	Feature extraction method	Topology of layers in DNN
24 feature set	Actual feature set	24 total inputs → [48 hidden nodes] → 4 outputs
Accurate24_RF_FM.csv	Extracted features after filter method	2 total inputs → [4 hidden nodes] → 4 outputs
Accurate24RF_WM_BEL.csv	Extracted features after wrapper method backword elimination	10 total inputs → [20 hidden nodes] → 4 outputs
Accurate24_RF_RFE.csv	Extracted features after wrapper method recursive feature elimination	10 total inputs → [20 hidden nodes] → 4 outputs

The average difference between the actual and the anticipated probability distributions is calculated via cross-entropy for all classes [20]. A measure of how dissimilar one probability distribution is from another is the Leibler Kullback divergence. It determines the wasted data (in bits) when the anticipated probability distribution is used to approach the desired target probability distribution. In the training phase, the number of epochs passed was 200, and the batch size was 5 [10]. Using the 10-fold cross-technique, the model was evaluated on the dataset, a process that takes around 10s to be concluded, and it provided an object that specifies the assessment of the 10 built models for each of the dataset splits.

IV. DISCUSSION

In this study, features are produced using the feature fusion approach, and multiple classification models are used after parameters are adjusted to attain maximum accuracy. The goal of this research is to get the maximum accuracy possible for the multiclass classification issue with tiny and noisy data sets. For this sort of database, the Lasso regression and RF algorithms appear to perform better.

TABLE III. ACCURACY COMPARISON

Feature selection method	Feature fusion	DNN	Lasso regression	KNN	SVM	RF
24 feature set	'Mean', 'STD', 'VAR', 'SKEW', 'Kurtosis', 'IEEG', 'MAV', 'MAV10, 'MAV20, 'SSI', 'VEEG', 'RMS', 'DASTD', 'AREG_PXX', 'HA', 'HM', 'HC', 'WL', 'BANDPOWER', 'PERODOGRAM1 (MaxPow)', 'PERODOGRAM2 (max Pow index)', 'ENVELOPE (Harmonic Dis)', 'Hilbert', 'PSD' [3]	29.17	78.02	33.33	44	72.66
Filter method	WL , DASTD	31.67	51.19	63	19.4	66.6
	WL	31.67	51.89	63	0	68.44
Wrapper method: Backward elimination	'Mean', 'VAR', 'Skew', 'MAV', 'VEEG', 'DASTD', 'HA', 'HC', 'Bandpower','PSD'	30.83	76.54	36	25	64.58
Wrapper method: RFE	'STDDEv', 'VAR', 'MAV', 'VEEG', 'RMS', 'DASTD', 'HA', 'Bandpower', 'Hilbert', 'PSD'	15.83	63.46	36	19.4	67.47

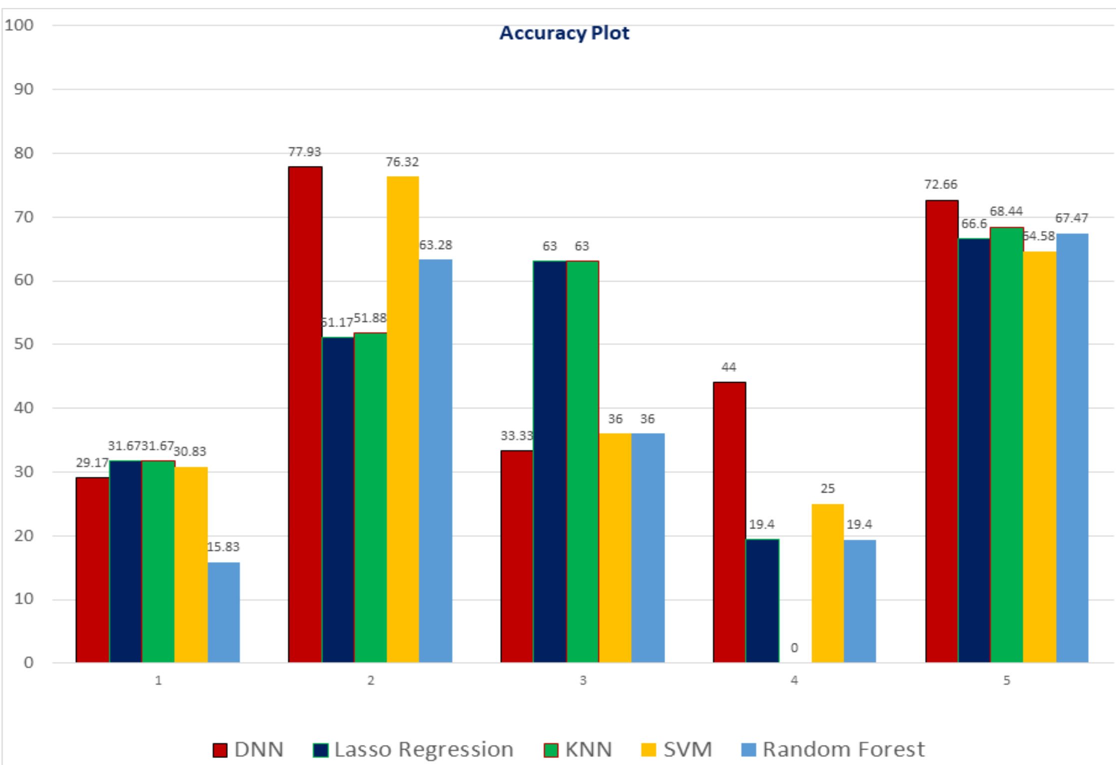

Fig. 3. The accuracy plot.

In Table III, the comparison of the accuracy using feature fusion and the multimodal approaches for multiclass classification is presented. In this research study, 24 features are extracted from the database. Three feature sets are constructed using the feature fusion approach, which are then utilized to assess the classification accuracy using KNN, SVM, NNs, RF, and Lasso regression classification models. Four feature sets were used to evaluate the performance of the KNN method. For the 24 feature set, the greatest accuracy produced by KNN was 33.33% for most of the K values and 36% for the feature set generated using the wrapper technique, which is extremely low due to the high dimensional database. It is calculated in a significant way for the feature set produced using the feature selection filter approach. For this small and noisy database, SVM and DNN –models did not perform well. RF performed better because it is less prone to overfitting, it is typically resistant to outliers, and can deal with them on its own. After changing the hyperparameters to match the model, Lasso regression works well for the 24 feature set and the feature set produced using the wrapper technique. It is quite difficult to acquire high accuracy for a self-created database of signals gathered in natural settings.

V. CONCLUSION

After changing the hyperparameters for the 24 feature set, Lasso regression was found to have the greatest accuracy of 78.02%. The best hyperparameters were adjusted as mentioned above, with the trial and error method. Backward elimination of the wrapper approach achieved 76.64% accuracy. For all the feature sets, the RF algorithm worked admirably. When compared to other classification models, the DNN algorithm's accuracy is quite low, and the database's limited size might be the cause. Also the SVM model did not perform well, because the limits of target classes overlap. The experimental findings show that on small and noisy datasets, Lasso regression and RF employing feature selection and feature fusion techniques perform better.

INSTITUTIONAL REVIEW BOARD STATEMENT

This research study was conducted according to the guidelines of the Declaration of Helsinki. This research study is not at all being conducted for diagnosis or treatment of any disease. This research study is purely used for research applications and personal use.

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