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Analysis of Multiple Emotions from EEG Signal Using Machine Learning Models †

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Abstract: Emotion recognition is a valuable technique to monitor the emotional well-being of human being. It is found that around 60% of people suffer from different psychological conditions like depression, anxiety and other mental issues. Mental health studies explore how different emotional expressions are linked to specific psychological condition. Recognizing these patterns and identifying their emotions is complex in human being since it varies from each individual. Emotion represents the state of mind in response to the particular situation. These emotions that are collected using EEG electrode needs a fine grain emotional analysis to contribute for clinical analysis and personalized health monitoring. Most of the research works are based on valence and arousal (VA) resulting in two, three and four emotional classes based on their combinations. The main objective of this paper is to include dominance along with valence and arousal (VAD) resulting in the classification of 16 classes of emotional states and thereby improve the number of emotions to be identified. This paper also considers 2-class emotion, 4-class emotion and 16-class emotion classification problem and applies different models and discusses the evaluation methodology in order to select the best one. Among the six machine learning models, KNN proved to be the best model with the classification accuracy of 95.8% for 2-class, 91.78% for 4-class and 89.26% for 16-class. Performance metrics like Precision, ROC, Recall, F1-Score and Accuracy are evaluated. Additionally, statistical analysis has been performed using Friedmanchisquare test to validate the results.

Keywords: machine learning; multiclass classification; emotion recognition; VAD; BCI

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1. Introduction

Emotion is the response of a human being when subjected to external stimuli. It affects a person's psychological and behavioral activities in making decisions and processing information. It is an interesting combination of psychology and technology [1] and can be learnt from different disciplines including marketing, philosophy, neuroscience, psychology and artificial intelligence. Brain Computer Interface (BCI) system is used to provide the communication between machine and brain [2]. The emergence of BCI [3] has enabled the neuroscientists to study the emotion of different individuals and process them using this technology.

Affective Computing is an example of BCI that connects computer science, physiology and psychology. It is defined as the computational study of emotions and their manifestations with the systems through brain signals [4]. The recognition of emotion through computational means is communicated to healthcare people like doctors, healthcare educators and medical administrators. The advancement in the technology has contributed for various medical applications like rehabilitation, assisting doctors in mental disease diagnosis like autism etc, assistance for disabled people like prosthetics, and innovation in medical equipments.

Emotions are presented in two different ways namely discrete emotional model and dimensional model. Discrete model was proposed by Ekman with six emotional states namely happiness, anger, fear, sadness, surprise, and disgust. The dimensional model signifies the affective states in the dimensional space and the dimensions are valence, arousal, dominance and liking [5]. Here, the emotions are recognized by rating those dimensions. The 2-Dimensional models are simpler with valence and arousal whereas the 3-Dimensional models are more realistic with valence, arousal and dominance [6].

Human emotions are analyzed by the quick changes in the electrical activity of the brain. These abrupt changes are measured by Electroencephalogram (EEG) which is a measuring device placed on the scalp of the head. Various human cognitive and emotional processes of the brain are studied by the researchers with the help of EEG signals [7]. EEG signals are in the frequency range of 0.5–100 Hz and the lower frequency range is suitable for cognition [8]. It is commonly preferred by researchers because of easy recording and processing them into meaningful information. These physiological signals are processed by different machine learning models.

Machine Learning is a field of computer science that gives the computers the ability to learn without being explicitly programmed [9,10]. It is the subset of Artificial Intelligence that automates the systems and simplifies the working processes using simple programs. It experiences fast growth and major advancements in various fields. It is indispensable in various fields like healthcare, finance, automotive and many other promising fields. It is mainly used when the existing solutions require more tuning for a particular problem. It is also for complex problems when there are no good solutions. It has the ability to adapt to new data and find good solution.

Machine Learning systems are classified as Supervised, Unsupervised, Semi supervised and Reinforcement Learning. In supervised earning, the training data has desired solutions called labels before it is given to the algorithm that includes KNN, Linear Regression, Logistic Regression, SVM, Decision Tree and Random forests [10]. In unsupervised learning, the training data is unlabelled and they are not classified. Therefore, the machine uncovers the hidden patterns and creates new labels. The main advantage of this learning is the identification of new unknown patterns. Reinforcement learning has the most advanced learning method since it learns continuously and improves the model by leveraging feedback from past iterations. The term classification in Machine Learning refers to the task of identifying the data points in the dataset and grouping them into different categories. In a multiclass classification, the data is classified into different classes. It is a statistical problem where the predefined class predicts the output based on features of the dataset [11].

Most of the emotion recognition based research has focused on binary classification [12–16]. Few research papers have addressed the 4-class classification [17–19]. It is important to classify emotions to different classes so that many numbers of emotions can be estimated [20]. Dominance is either separately classified [21] or not included in the classification of emotions. Nandhini et al. [22] have used VAD method for emotion recognition for 12 discrete emotions which is 12 class classification using machine learning algorithms. In this paper, there is a discussion about three different types of classification namely 2-class, 4-class, and16-class which is given in Table 1.

The main objective of this research work is given below:

- Develop a suitable VAD model to categorize 16 emotions which is high when compared to the existing state-of the-art techniques.
- Evaluate the performance of the machine learning model for 2-class, 4-class and 16-class and hence identify a suitable machine learning model for multiple class classification of emotion.

Table 1. Emotional classes and its categories.

No. of Class	Categories
2—(V) (A)	Valence(V), Arousal(A)
4—(VA)	High Arousal High Valence (HAHV), High Arousal Low Valence (HALV), Low Arousal High Valence (LAHV), and Low Arousal Low Valence (LALV)
16—(VAD)	Sadness, Shame, Guilt, Envy, Satisfaction, Relief, Hope, Interest, Fear, Disgust, Contempt, Anger, Pride, Elation, Joy, and Surprise

The remaining sections of the paper are organized in the following order. Section 2 discusses about the methodology in preparing the dataset and the explanation of the machine learning models. Section 3 gives the results and discussion of each models and their corresponding performance evaluation. Conclusion is given as the last section in this paper with the summary of the work.

2. Methodology

The interaction between human brain and the computer follows certain steps so that the computer understands the EEG signal. DEAP dataset is used for our proposed work. The EEG signal recorded from the human brain has to be collected from the EEG cap which has 48 numbers of electrodes according to the international 10–20 system. Each participants have rated the video based on valence, arousal, dominance, and liking in the scale of 1–9. The acquired raw EEG signal was recorded for 63 s after the removal of baseline signal of 3 s and stored on a computer device. Figure 1 depicts the block diagram of EEG based emotion recognition for machine learning models. The signal undergoes several processes like down sampling, filtering, augmentation, feature extraction and classification of emotions based on the number of classes. At first, the signal was downsampled to 128 Hz to focus on the frequency of interest and to eliminate higher frequency components in the signal. The dimension of the data is the product of number of video trials, selected number of channels and samples which is 40 × 14 × 8064(63 s * 128 Hz). Windowing technique is used for data augmentation process and thus resulting in 19,520 (40 * 488) data samples for a single subject for 40 trials. Power Spectral Density (PSD) was extracted by considering the five frequency bands of EEG and 14 numbers of channels. The machine learning models that are used for classification are SVM, KNN, LDA, Random Forest, Decision Tree and Naive Bayes.

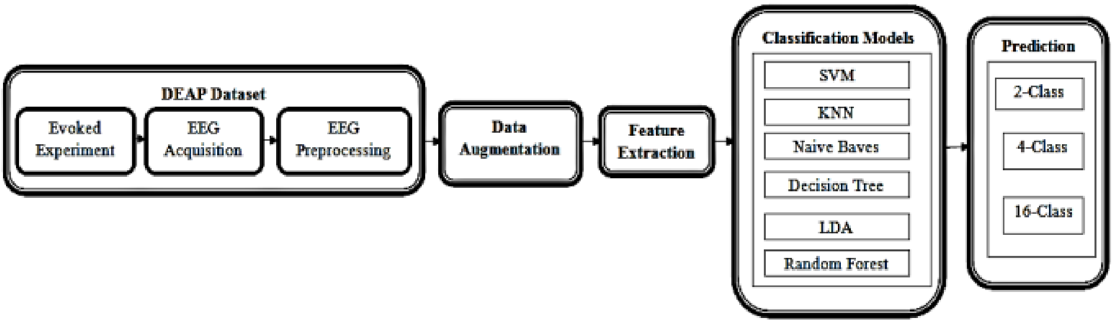


Figure 1. Block Diagram of EEG based emotion recognition for Machine Learning models.

The label in the DEAP dataset has rating values of each trail for each subject. The rating is based on four dimensions of Valence, Arousal, Dominance and Liking (VADL) and is in the range of 1–9. Most of the researches have used binary classification where the labels are classified into positive and negative emotions. Few researches have used Valence and Arousal (VA) model resulting to four class classification. In this paper, the combination of Valence, Arousal and Dominance (VAD) dimensions is used to categorize into 16 emotions.

3. Result and Discussions

The experimental setup for the investigation is given in Table 2 below.

Table 2. Experimental Setup.

Name/Description	Version
CPU	Intel® Core™ i5
RAM	8 GB
OS	Windows 10
Python	Python 3.11.5
TensorFlow	TensorFlow 2.14.0
Scikit-learn	Scikit-learn 1.3.1
Anaconda	2021.05

3.1. SVM

On experimenting, the dataset with SVM model, it was found that the model has shown good accuracy results for 2-class classification. It is a powerful machine learning tool that is best suited for binary classification. The percentage of accuracy has dropped for 16-class classification to 37.01%. These accuracy rates can be improved when the SVM model is created for each pair of classes. In this model, the value of regularization parameter (C) is 1 and the kernel used for experimentation is linear and RBF. It is important to choose the value of C and suitable kernel for better classification results.

It can be observed from Table 3 that the linear kernel has shown better performance of around 14% higher than RBF kernel for 16-class classification. This is due to the linearization of data with short time interval considerations for FFT. Generally, EEG based emotional dataset has the problem of class imbalance and hence leads to the degradation of the performance [30]. SVM are sensitive to class imbalance and therefore SVM-RBF model has shown poor performance. It needs good tuning to get optimal solution but it requires expertise. Therefore when the number of classes increased, the model failed to separate the data into different classes.

Table 3. Performance evaluation of SVM model.

Model	SVM-Linear			
	Accuracy	**Precision**	**Recall**	**F1-Score**
2- Class	73.81%	72%	64%	65%
4-Class	48.26%	46%	42%	42%
16-Class	37.01%	35%	37%	35%
	SVM-RBF			
2- Class	67.35%	34%	50%	40%
4-Class	38.75%	10%	25%	14%
16-Class	24.4%	2%	7%	3%

3.2. LDA

LDA aimed to maximize the separation between the classes while minimizing the variance within each class. However, as the number of classes is increased, the overlap between classes also increased and made it harder to effectively distinguish between them. It happened since the classes are closely related or inherently ambiguous. Also in multi-class classification, the decision boundaries are highly non-linear, making it difficult to capture the underlying patterns in the data. Therefore, the model's accuracy has dropped from 73.69% to 33.86% when the number of classes increased. The performance metric of LDA is given in the Table 4.

Table 4. Performance evaluation of LDA model.

Model	LDA			
	Accuracy	Precision	Recall	F1-Score
2-Class	73.69%	70%	66%	67%
4-Class	49.97%	49%	43%	44%
16-Class	33.86%	28%	29%	25%

3.3. KNN

In order to select the value of k, different values were tried to find the best out of them. Since there is no definite method, proper care must be taken for the selection of k value. Very low value of k such as 1, 2 may create noise and lead to outlier effect in the model. Selecting large values of k are good and produce stable decision boundaries but create difficulties in computation. This model is easy to implement and highly robust to noise. It has shown good results due to its ability to perform well with large data. It handles 1-D data and multi-class classification well and therefore 89.26% of accuracy has been achieved. Among the different values of k, it was observed that the model attained highest accuracy when k = 3 for all three classes. Table 5 shows the efficiency of KNN using the performance metrics.

Table 5. Performance evaluation of KNN model.

Model	KNN			
	Accuracy	Precision	Recall	F1-Score
2- Class	95.81%	95%	95%	95%
4-Class	91.78%	92%	92%	92%
16-Class	89.26%	89%	90%	89%

3.4. Decision Tree

Decision tree supports both binary and multi-class classification technique. Decision tree with entropy is a key factor that helps to make decisions while splitting the data at each node of the tree. It groups homogenous data and maximizes the information gain by reducing the uncertainty. It was observed that decision tree with entropy has better predictive power for the classification of the tasks due to the ability to quantify the impurity of the dataset. It was estimated that the accuracy of 2-class was 87.56%, 4-class was 77.05% and 16-class was 70.08%. Table 6 shows the performance metric of Decision tree with and without entropy.

Table 6. Performance measure of Decision Tree.

Model	Decision Tree							
	Accuracy		Precision		Recall		F1-Score	
	Without Entropy	With Entropy	Without Entropy	With Entropy	Without Entropy	With Entropy	Without Entropy	With Entropy
2-Class	86.71%	87.56%	85%	86%	85%	86%	85%	86%
4-Class	76.39%	77.05%	75%	76%	76%	77%	76%	77%
16-Class	69.68%	70.08%	67%	68%	68%	68%	67%	68%

3.5. Naive Bayes

Naive Bayes model works mostly on the assumption that the features are independent for the given class label. Complexity in capturing the underlying patterns between the variables has caused the model to fail. Confusion has occurred within the model because the features are correlated with each other. As the number of classes increased, the complexity further increased leading them in poor classification of the model to about 7%. Table 7 shows the performance evaluation of Naive Bayes.

Table 7. Performance measure of Naive Bayes.

Model	Naive Bayes			
	Accuracy	**Precision**	**Recall**	**F1-Score**
2- Class	58.46%	59%	60%	57%
4-Class	38.29%	29%	28%	24%
16-Class	7.55%	18%	26%	7%

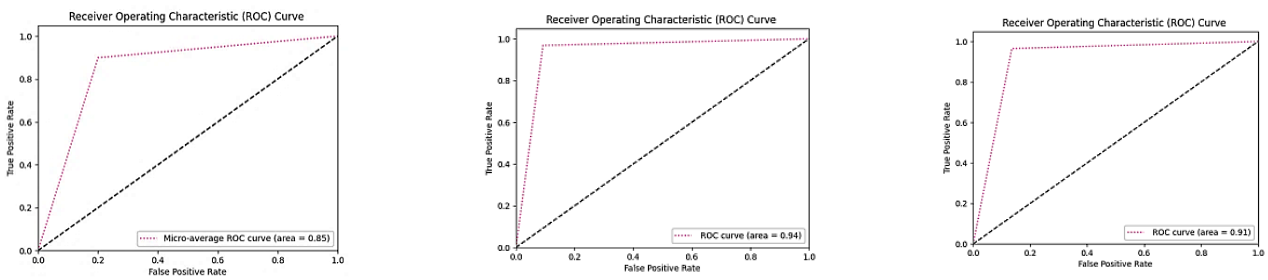
3.6. Random Forest

Random Forest works on multiple numbers of trees instead on relying on single tree. Therefore, it has given an accuracy of greater than 84% for all three types of classification and prevented the problem of overfitting. It has produced high accuracy even when the dataset is large. The selection in the number of decision tree is based on trial and error method. For 2-class classification, number of decision tree (n) chosen to be high was 24 and the maximum accuracy obtained was 93.2%. For 4-class classification, n was 25 and the maximum accuracy obtained was 87.59%. For 16-class classification, n is chosen to be 24 and the maximum accuracy was 84.7%. The other performance metric of the model was calculated and shown in the Table 8.

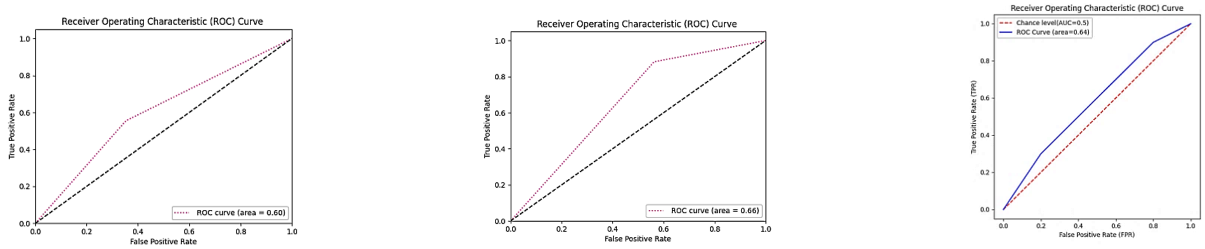
Table 8. Performance measure of Random Forest.

Model	Random Forest			
	Accuracy	**Precision**	**Recall**	**F1-Score**
2- Class	93.20%	93%	91%	92%
4-Class	87.59%	89%	87%	87%
16-Class	84.70%	87%	82%	84%

The Receiver Operating Characteristic (ROC) curve of 2-class classification is shown in Figure 2a–f for all the machine learning models with predicted value in the x-axis and true value in the y-axis. Figure 3a–f portrays the 4-class classification of the experimented machine learning models. In Figure 4a–f, the ROC curve of 16-class classifications of different machine learning models is shown.

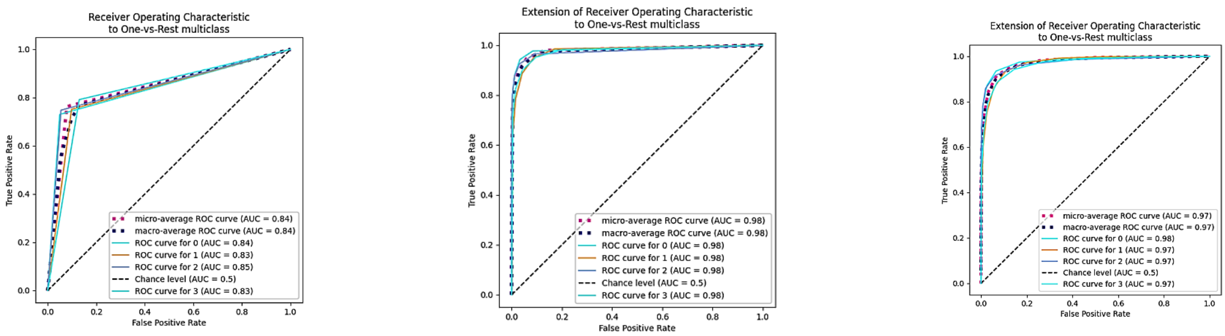


(**a**) (**b**) (**c**)

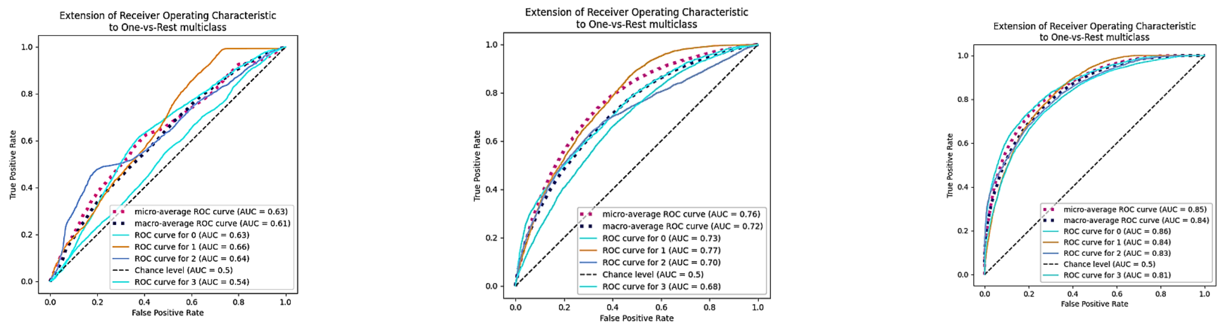


(**d**) (**e**) (**f**)

Figure 2. ROC curve for 2-class classification of Machine Learning models (**a**) Decision Tree (**b**) KNN (**c**) Random Forest (**d**) Naive Bayes (**e**) LDA (**f**) SVM.

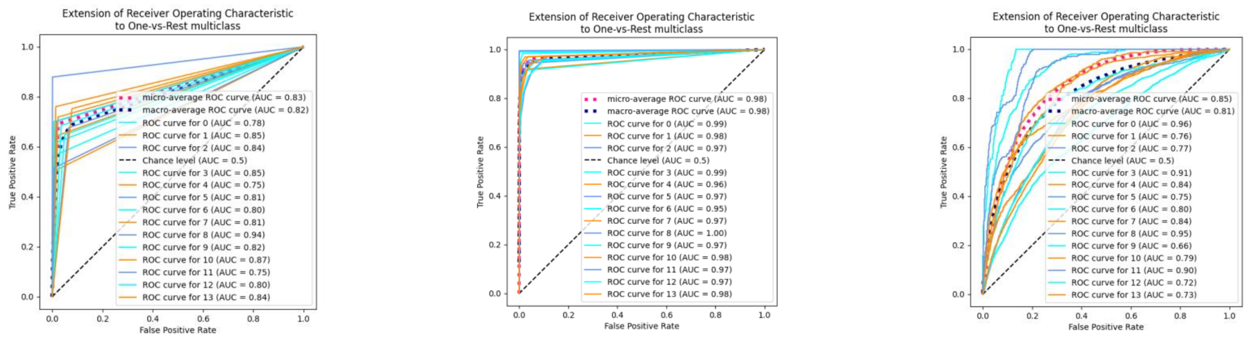


(**a**) (**b**) (**c**)

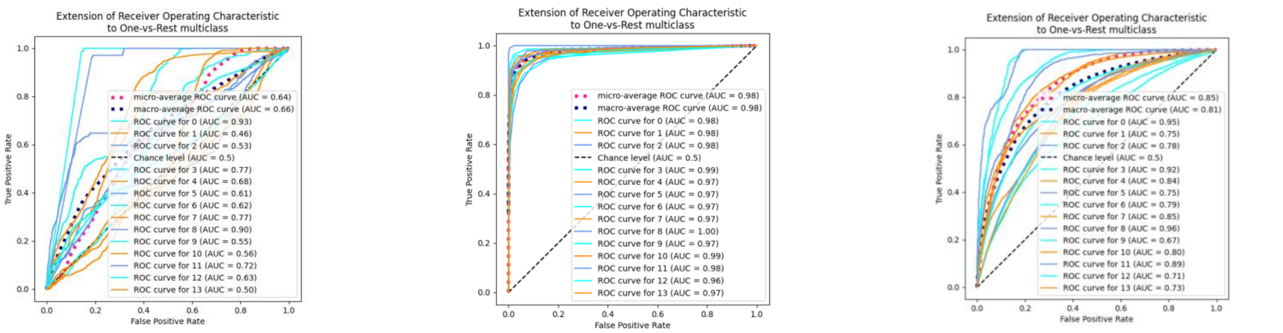


(**d**) (**e**) (**f**)

Figure 3. ROC curve for 4-class classification of Machine Learning models (**a**) Decision Tree (**b**) KNN (**c**) Random Forest (**d**) Naive Bayes (**e**) LDA (**f**) SVM.



(**a**) (**b**) (**c**)



(**d**) (**e**) (**f**)

Figure 4. ROC curve for 16-class classification of Machine Learning models (**a**) Decision Tree (**b**) KNN (**c**) LDA (**d**) Naive Bayes (**e**) Random Forest (**f**) SVM.

The comparison of different machine learning models based on accuracy has been shown in Figure 5. Among these six models, it is observed that KNN has better accuracy for multiclass classification. It has better results for other performance metric which is given in Table 4. It proved to be good for 16-class which is the highest number of emotions than existing state-of-art classification. Random Forest also has proved to be at its best with 84.7% for 16-class classification. Naive Bayes showed worst performance for multiclass classification with 7% of accuracy. Thus, from the complete analysis it is deduced that higher classification of emotional states leads to the degradation of the model's performance. The classification of 16 emotional classes seems to be challenging due to the variation of emotions among each individuals and also the label values that is close to one another.

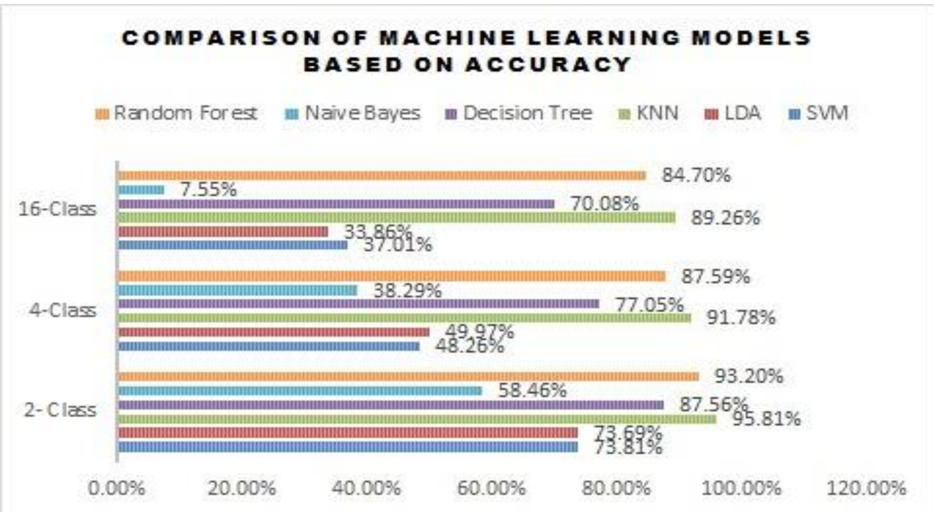


Figure 5. Comparison of different machine learning models in terms of accuracy.

3.7. Statistical Analysis

Friedmanchisquare statistical analysis test was performed for the machine learning models discussed above in this paper and the corresponding statistic values and p-value is given in the Table 9. For 2-class classification, the estimated p-value is 0.0014 so there is a significant difference between the models. For 4-class classification, the obtained p-value is less than 0.05 and therefore, it is found that there is significant difference between the models. Dunn-Bonferroni test was performed to compare the models in pair. While performing Dunn-Bonferroni test, it was evident that there is significant difference between KNN and Naive Bayes model with p-value of 0.00091, 0.00088, 0.001123 for 2-class, 4-class and16-class respectively. In addition, Random Forest is also significantly different from Naïve Bayes with the *p*-value of 0.018, 0.0238, 0.020634 for 2-class, 4-class and16-class respectively. In 16-class classification, KNN model is also significantly different from LDA with the *p*-value of 0.01568.

Table 9. Statistical Analysis for 2-class, 4-class and 16-class.

2-class	
Friedman Test Statistic	19.60431
p-value	0.001482
4-class	
Friedman Test Statistic	19.49275
p-value	0.001555
16-class	
Friedman Test Statistic	20.0
p-value	0.001249

4. Conclusions

The main aim of this analysis is to identify an efficient machine learning model for EEG based emotion recognition using VAD model. DEAP dataset has been used for the experimentation of the models. The data was trained using models like SVM, KNN, LDA, Naive Bayes, Decision Tree and Random Forest. These models were evaluated using training data and have given varying value of accuracy based on the number of classification and the type of machine learning model used. The performance metrics like accuracy, precision, recall and F1-score were used to evaluate and compare the model. Among these models, KNN has achieved the high accuracy for all three types of classification. It has given an accuracy of 87.31% for 16-class, 90.29% for 4-class, and 94.86% for 2-class classification. The Naive Bayes model performed least among other models with an accuracy of 7.55% for 16-class, 38.29% for 4-class, and 58.46% for 2-class. Both Random Forest and KNN models showed good results for multiclass classification using VAD model. These results shows that these machine learning models could be useful for EEG based emotion classification with less computational complexity. In the future, these models with proper tuning could be experimented to provide better results for multiclass classification.

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