# A Comprehensive Data Set for Classification and Analysis of Human Emotion using Physiological Signals

*Abstract*— **In the recent time the importance of emotion recognition has been extended and in this scope of several research works here a multimedia dataset for human emotion analysis is made ready for this paper. The electroencephalogram (EEG) of 40 participants are collected where they are given to watch one minute videos to create emotion in them. The videos with emotional tags have variety range of emotion including happy, sad, disgust, peaceful etc. The experimental stimuli collected are analyzed intensively. Interrelationship between the EEG signal frequencies and the ratings given by the participants are taken to consideration for study. Statistical feature extraction is applied on the dataset obtained and finally it is split to test and train set. Several machine learning algorithms are applied to determine the testing and training accuracy of data.**

*Index Terms*—**Emotion Classification, EEG, Physiological Signal, Emotion Recognition, Statistical Feature Extraction**

## I. Introduction

Emotion is a mental state linked to nervous system effected by various chemical changes which is incorporated with thoughts, feelings, behavioural responses, and a degree of pleasure or displeasure [1][2]. The emotions of ours can impel us to take action and dominate the decisions in lives. Emotion is referred to a list: anger, disgust, fear, joy, sadness and surprise [3]. Emotion detection is a technique used to read the emotions on a human face by using hi-tech image processing software. Humancomputer interaction (HCI) is computer technology, focused on the interfaces between human and computers [4].

There are different approaches of extensive scales of emotion, such like: Plutichik's emotion wheel [5], valence-arousal scale by Russell [6]. In this research this Russel model is applied. According to this process, each emotional state can be plotted into two-dimensional plane where arousal and valence are represented by horizontal and vertical axes respectively. Arousal is split from inactive (e.g. apathetic, weary) to active (e.g. vigilant ,exhilarated), while valence covers from unpleasant (e.g. downhearted, upset) to pleasant (e.g. delighted, exultant) [7].

Valence is positive or negative affectivity, whereas arousal measures how calming or exciting the information is. The common framework for dealing with emotional experience is characterized in a two-dimensional space. Valence ranges from highly negative to highly positive, and arousal ranges from calming/soothing to exciting/agitating. [8] A persons Level of Arousal can be described as a function of alertness, situational awareness, vigilance, level of distraction, stress and direction of attention. In effect, how ready a person is to perform appropriate tasks in a timely and effective manner. [9]

Emotion of human can be studied through his physiological signals, expressions or even by observing his lexical approach or behaviour or even by his gestures [10]. Studies on this field are mainly based on human image processing based through facial expression [11] or even by speech [12]. The main problem lying with facial expression is, it might not detect the right emotion of human. A user might have happy face but he might be sad. To detect it exactly, physiological signals might be the perfect option. The physiological signals to work with will be generated from both central nervous system and peripheral nervous system. Though physiological signals provide good indication of emotion but it has got lesser attention.[7].

Electroencephalogram (EEG) signal is generated from brain scalp using EEG headset [13] which records the electrical activity of brain. It produces four main frequencies including alpha, beta, delta and theta. Delta with highest amplitude and slowest wave is mostly prominent in frontal of adults. It gives signal in case of diffuse wound, metabolic encephalopathy hydrocephalus or deep midline injury. Theta is stated as slow activity demonstrating focal subcortical lesions. Alpha, being higher in amplitude on the dominant side can be seen in the posterior regions of the head on each side. It give signal when relaxing and stops at alert state. Beta can be referred as fast activity. It can observed both at frontal and both sides of symmetrical distribution. It reacts when in alert or anxious state. Thus combination of these signals from brain help to forecast the emotion of human [14].

The rest of the paper is organized as follows: Section II presents the related works in the relevant field, Section III describes the process how signals and videos are selected for the process of dataset creation, Section IV talks about the environment which is created to ensure proper dataset collection, Section V illustrates the total method followed in the process of data analysis, classification and accuracy result, Section VI illustrates the performance of the result obtained through the experiment and finally Section VII and Section VIII conclude the paper talking about the further expansion of the process, pitfalls and success of this research.

## II. Literature Review

Currently, researches are conducted on emotion recognition or classification based on physiological signals or speech or face expression image processing.

Koelstra et al. in [7] has formulated a vast DEAP dataset based on electroencephalogram (EEG) and peripheral physiological signals of 32 participants where each of them watched several videos. They worked with classification of arousal, valence, like/dislike ratings of the participants. Mavani et al. [15] in his research has worked on CFEE and RaFD datasets improving the existing CNN model and could reach accuracy of 65.39%.

Another work based on physiological signals like EDA, PPG, zEMG are fused to differentiate 5 major emotion classes using Fina Gaussian Support Vector Machine in [16]. Apart from that to extract features, they applied DBN. They were able to reach at 89.53% accuracy. Tripati et al. [17] have also worked on DEAP dataset classifying emotion using EEG signals using both Deep Neural Network and Convolutional Neural Network proving effectiveness over existing work on this arena. Another research on signal based emotion recognition is done by Alam et al. on [18] using EMG, EDA, ECG sensors analyzed using deep CNN with accuracy of 87.5%. Meanwhile Mohammadi et al. in [19] used support vector machine and K-nearest neighbor classifiers to detect emotion using 10-channel EEG signal. Though researchers have worked with various sensors but their quality and emotion detection capabilities had a great doubt in research work. To check the grade and potentiality of lab based and wearable sensors Ragot et al. in [20] compared their accuracy. However this experiment proved reliability of both types of sensors.

Zhuang et al. in [21] used EMD and EEG signals for feature extraction and emotion recognition decomposing into empirical mode decomposition (EMD). Their multidimensional information is used as features. The researchers have checked their accuracy of classification comparing with several classical techniques, including fractal dimension (FD), sample entropy,differential entropy, and discrete wavelet transform (DWT). Though many research work done on EEG signals but its stability over time was a great question. The frequently used popular feature extraction, feature selection, feature smoothing and pattern classification methods are analyzed and evaluated in [22] using public data-set DEAP and their own developed data-set SEED. The emotion recognition model shows that the neural patterns are relatively stable within and between session. Xia et al. in [23] through their research has enforced activation and valence information for acoustic emotion recognition applying multi-task learning based on DBN. Besides, they have enforced activation and valence in two different ways: category level based classification and continuous level based regression. The fusion of the loss functions from both tasks is used as the objective function in the multi-task learning framework. After iterative optimization, the values from the last hidden layer in the DBN are used as new features and made input into a support vector machine (SVM) classifier for emotion recognition.

Though conventional methods of using EEG signals for emotion recognition skips the use spatial characteristics of EEG signals which contain various salient features, Chao et al. in [24] have used frequency domain, spatial characteristics, and frequency band characteristics of the multichannel EEG signals to build up multiband feature matrix (MFM). Based on input MFM, a capsule network (CapsNet) classifies emotion states. Ullab et al. in [25] has proposed an ensemble learning algorithm for automatically computing the most discriminate subset of EEG channels for internal emotion recognition. This method describes an EEG channel using kernel-based representations computed from the training EEG recordings. This algorithm reduces the amount of data along with improving computational efficiency and classification accuracy at the same time. A complete different arena of emotion detection is represented on [26]. It works with emotion detection from surveillance camera video. The body shape and gesture from video identifies the emotion which is done on basis of publicly available data-set and modeled by Support Vector Machine (SVM) with accuracy of 93.39%. [27] performs continuous emotion prediction on three dimensions: Arousal, Valence, Likability based on audiovisual signals. They have measured the contrast between effectiveness of non-temporal model SVR and temporal model LSTM-RN.

Li et al. in [28] have developed a series of EEG Multidimensional Feature Image(EEG MFI) sequence from spacial characteristics, frequency domain and temporal characteristics mapping them into two-dimensional image. Besides, they have also constructed hybrid deep neural network along with CNN, LSTM, RNN to to work out with EEG MFI sequence to classify human emotion and finally got accuracy over 75.21%.

To overcome problem of learning efficiency and computational complexity of Deep Neural Network(DNN), [29] has worked on Softmax regression-based deep sparse auto encoder network(SRDSAN). Their proposed process has overcome local extrema and gradient diffusion problems and vigorously of neural network. They proved better efficiency and accuracy here. Human facial expression is not the best way to determine human emotion. This is because, a person might be mentally sad but showing false happy emotional expression through his face. Thus working with facial emotion recognition might decrease the accuracy rate of the work. The best way to work with this problem is physiological signals. Brain impulse are used here which is EEG signal and it generates different types of signals for different types of emotions. As a result this process of emotion classification is more trustworthy and accuracy result here is more than other processes. Here the four emotion states funny, sad, disgust and peaceful are considered and dataset is collected. Based on the dataset statistical feature extraction is done and finally based on various machine learning algorithms the accuracy result of testing is checked.

## III. Stimuli Selection

To conduct the experiment of emotion classification, distinct stimuli were exerted. In the course of process, 100 inceptive stimuli were selected, among which half were chosen semi-automatically and rest were in manual process. For each of the stimuli, a one-minute highlight part was determined. Ultimately, by the process of web-based subjective evaluation, 40 final stimuli were fixed. Throughout the next few steps, the complete process is illustrated:

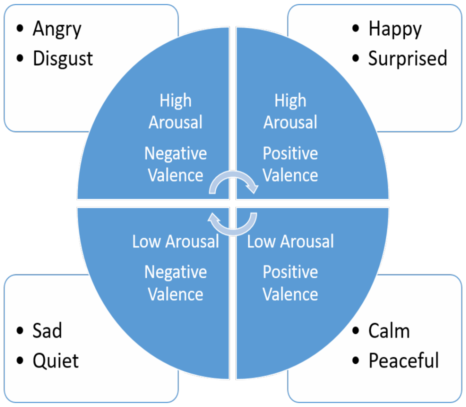


Fig. 1: Arousal Valence Scale of Emotion

### A. Initial stimuli selection

The initial challenge is to draw out the emotional retort of the test participants and also to choose the hyper-efficient stimulus materials. However, it is decided to adopt the process of semi-automation while selecting stimuli so that the problem of biasing can be avoided.

50 out of 100 stimuli were picked from the famous Bangladeshi Bengali music channel ”GaanBangla”. The music videos and songs played on its YouTube channel are tagged with various music categories, as a result easing the experiment to find out with proper emotion based tagged video. According to the set of emotional keywords from [30] and other synonymous words source, a total of 300 keywords are set up. Based on the set keyword, commensurately available tags from GaanBangla were collected. However, among the resultant tags set, the most frequently tagged videos were chosen. The total process yields a set of 1000 songs.

The valence-arousal space to work on emotion classification can be split into 4 regions: low arousal/low valence(LALV), low arousal/high valence(LAHV), high arousal/low valence(HALV) and high arousal/high valence(HAHV) as illustrated in Fig. 1. To confirm the variety of induced emotions, among the 1000 songs 20 were selected manually for each region based on following benchmark:

*1) Does the tag precisely illustrate the emotional index?:* Songs which had no connection with its tag and content or the songs were tagged to any particular emotion just based on song name were dismissed as inadequate

*2) Is a music video obtainable for the particular song?:* Many videos were fetched from YouTube for the songs, but in some cases there was no relevant music video for the song.

*3) Is the song apposite for experimental purpose?:* As the participants for experiment were mainly students and staffs from the university, so based on their general taste, genre of songs and music videos were designated for them.

Apart from the above selected videos, 40 stimulus videos were chosen manually, 10 for each of the four regions of arousal-valence space. This was done to bring out those videos which prompt out the most explicit reactions for each of the four regions in the space. Thus merging the set of manually selected and tag based automatically selected videos, a total of 100 stimulus videos were selected.

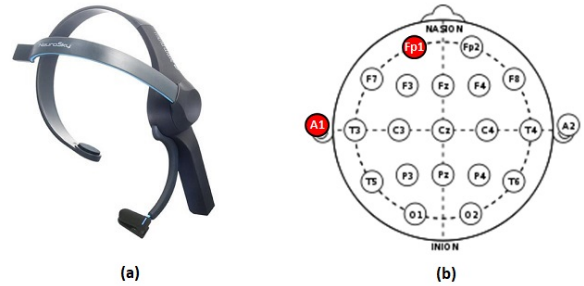


Fig. 2: EEG-headset (left) and its electrodes positions (right)

### B. Distinguishing one minute climax

Based on linear regression method proposed in [31],arousal and valence in each movies was determined. Loudness and energy of the audio signals, motion component, visual excitement and shot duration were considered for arousal calculation. The regressors were trained using dataset of [31] for better valence and arousal estimation. Using the concept of Relevance Vector Machine(RVM) from RVM toolbox from [32] which is capable of refusing the vague features throughout the training process. The emotional climax score of i-th segment $e_i$ was calculated using the equation where $a_i$ and $v_i$ are arousal and valence respectively:

$$e_i = \sqrt{a_i^2 + v_i^2}$$

Thus one minute highlight was chosen.

### C. Online instinctive notation

Test participants rated the music videos they have watched on scale of 9 for valence, arousal and dominance. After rating all the videos, the videos with maximum rating are selected. A normalized arousal and valence value is obtained by $(\mu_x/\sigma_x)$ for each video x. However, videos with ratings at extreme corner of each quadrant is mentioned precisely.

## IV. Experimental Setup

### A. Materials and Setup

The total process of experimentation was setup in a controlled environment of lab where the physiological signals including the EEG was accumulated. In order to portray the stimuli and recording of the user, Neurobehavioral system [33] is used. The deployment of EEG headset electrode is displayed in Figure 2 [34].

### B. Experimental Protocol

Among the test participants, the gender distribution of male and female was done equally and it was ensured that all of them were physically and mentally well. The participants were made to watch the video in proper environment ensuring to express proper emotional feedback.

## V. Methodology

The data collection was conducted from 40 participants and taken for next stage of data cleaning where the task is to find out the missing values and assign them based on mean. We have here worked with following states of following frequencies: Beta(12-30Hz), Alpha(7.5-12), Gamma(31Hz-above), Theta(3.5-7.5), Delta(0.5-3.5). The data scaling technique is applied to fix the problem of outliers using unit scaling technique. Next, statistical feature extraction is applied on the dataset for further test and trial of data. Mean, median, skewness, kurtosis, standard deviation and root mean square value is calculated for all eight features from each data namely: delta, theta, alphaLow, alphaHigh, betaLow, betaHigh, gammaLow and gammaHigh. Skewness shows the process of measurement of the asymmetry of the probability distribution of a random variable which is real values around its mean. Besides, kurtosis is a indicator of the structure of a probability distribution of real values random variable. The root mean square value is the square root of the squared mean, that is the arithmetic mean of the squares of a set of feature values. Standard deviation is a measurement that is used to show the amount of variation or dispersion of a set of feature data values. Here in this case of research these are determined for the features identified above. The mentioned features are selected among many other features of dataset because these eight features have direct impact on the emotion classification and thus these are used. That is features of main dataset like timestamp, poor signal, attention, meditation, eeg raw values, eeg raw value volts and blink strengths are not considered for final test and train since they have no direct role in classification of emotion. Thus in total (8*6=48) features are collected from each dataset. Similar process is followed for all other datasets(4*40=160) of 4 individual emotions and all of them were combined. The combined datasets are labelled for test and train as shown in correlation map of data in Fig. 3. Now the combined dataset is split into train and test set randomly. Several machine learning algorithms like Bagging Classifier, Passive Aggressive Classifier, Decision Tree Classifier, Extra Trees Classifier, Gradient Boosting Classifier, Random Forest Classifier, Perceptron, K Neighbors Classifier, SGD Classifier, Ridge Classifier CV, Gaussian NB, Logistic Regression CV, Linear SVC, Ada Boost Classifier, Bernouli NB, Gaussian Process Classifier, SVC, NuSVC are applied on the train and test dataset. Thus data training is done and test data is checked against the train data to find out accuracy.

## VI. Performance Study

The dataset prepared for the classification using EEG signals results in producing 12 features, among which 8 are selected for final classification since they have direct contribution in the process. Thus a comprehensive heavy dataset is made of 40 participants who are given to watch one minute long video of four emotions and data is collected at one second interval. As mentioned earlier that several machine learning algorithms are applied to check the testing result for the combined data set after feature extraction. The accuracy result for training data and testing data is shown in Fig. 4 for different algorithms. From the graphical representation of testing result in Fig. 5, we can observe that accuracy is obtained highest using Random Forest Classifier at 83.33%. However for few machine learning algorithms we have found very poor accuracy level which indicates that those algorithms did not fit the training and testing properly. Apart from Random Forest Classifier the other algorithms Bagging Classifier, Passive Aggressive Classifier, Decision Tree Classifier, Extra Tree Classifier are able to reach accuracy of around 73% but no as high as Random Forest Classifier. The classification process is completely capable to identify four main emotions: funny, sad, disgust and peaceful. But it is facing problem to discriminate neutral emotion state from all other emotions states.

## VII. Discussion

The classification based on the statistical feature extraction and finally machine learning process help to classify the emotions. The test for checking the accuracy of trained data was collected from few participants. The final result from different algorithms talks about their efficiency in classification and emotion identification. The accuracy of the model thus reached to 83.33%. As mentioned earlier the proposed model is facing difficulty while detecting the neutral state of emotion. Though it is considered the neutral state is the middle in the Arousal-Valence scale. The overall classification accuracy found here(83.33%) is better in comparison to radio frequency based emotion analyzer [35] with 72% accuracy and the other SVM classifier used in [36] with 82.9% accuracy.

## VIII. Conclusion

In this paper, we have presented a multimodal data set for emotion classification using EEG physiological signals. The data set was collected with signals of 40 participants where each of them were given one minute videos of different emotional states like funny, sad, peaceful, disgust etc. Different machine learning algorithms help to classify the emotions based on the features collected from statistical features extraction. The result found from this data set is far better than other random classification methods. In future its is planned to add other classifier techniques with our proposed model to implement the stability for emotion recognition.

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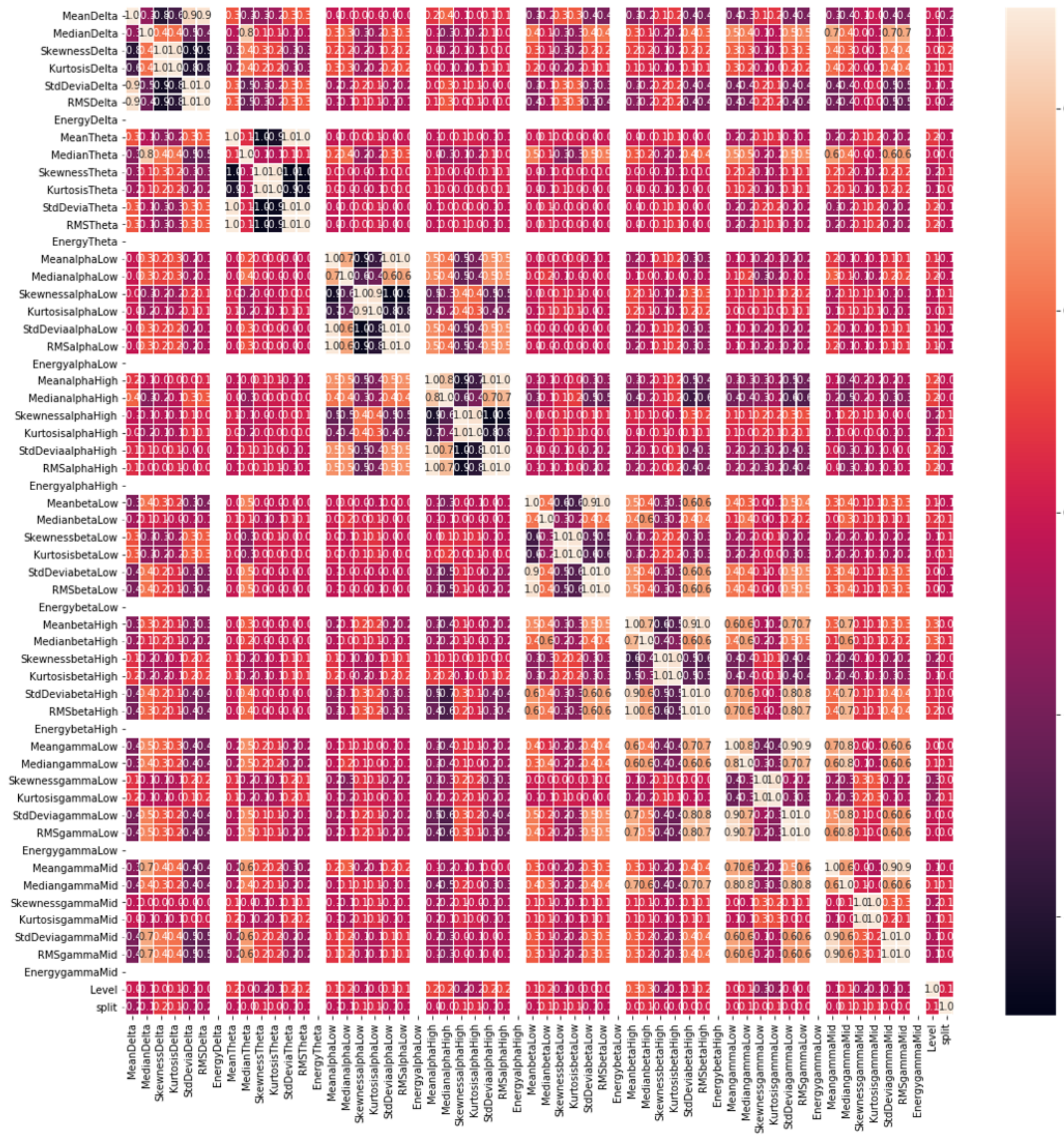


Fig. 3: Correlation Map of Data


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| MLA Name | MLA Train Accuracy | MLA Test Accuracy |
|---|---|---|
| RandomForestClassifier | 0.9667 | 0.8333 |
| DecisionTreeClassifier | 1 | 0.7333 |
| PassiveAggressiveClassifier | 0.6778 | 0.7333 |
| BaggingClassifier | 0.9667 | 0.7333 |
| ExtraTreesClassifier | 1 | 0.7 |
| GradientBoostingClassifier | 1 | 0.6667 |
| GaussianNB | 0.8111 | 0.6667 |
| Perceptron | 0.7556 | 0.6333 |
| KNeighborsClassifier | 0.7333 | 0.6 |
| LogisticRegressionCV | 0.8667 | 0.5333 |
| RidgeClassifierCV | 0.9111 | 0.5333 |
| BernoulliNB | 0.6333 | 0.5 |
| GaussianProcessClassifier | 1 | 0.4667 |
| SGDClassifier | 0.6667 | 0.4 |
| AdaBoostClassifier | 0.6222 | 0.3667 |
| LinearSVC | 0.6111 | 0.3333 |
| SVC | 1 | 0.0667 |
| NuSVC | 1 | 0.0667 |

Fig. 4: Accuracy result for training and testing data for different machine learning algorithms

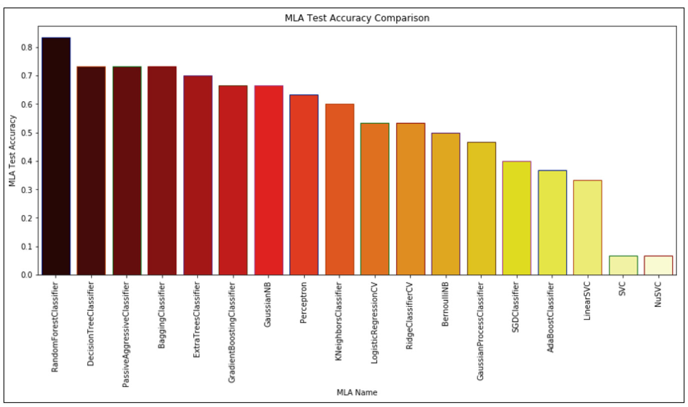


Fig. 5: Graphical Accuracy result for testing data for different machine learning algorithms


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