Logo, company name

Description automatically generated

**Emotion Recognition using various methods**

**Submitted to DR. Sahar Fawzy**

**In the fulfillment of course: BMD-201**

**BY:**

**Mohaned Atef Abdelaziz : 19106161**

**Mohamed Walid Ahmed : 19104487**

**Marwan Khaled Mostafa : 19104544**

**Marwan Yasser Sayed : 19105432**

**Reham Galal : 19105790**

Contents

[Abstract 3](#_Toc74762470)

[Introduction 4](#_Toc74762471)

[Related Works 6](#_Toc74762472)

[Emotion detection using electroencephalography signals and a zero-time windowing-based epoch estimation and relevant electrode identification 6](#_Toc74762473)

[Extracting the features of emotion from EEG signals and classify using affective computing 8](#_Toc74762474)

[Real-Time EEG-Based Emotion Recognition and 9](#_Toc74762475)

[Its applications 9](#_Toc74762476)

[Real-Time Emotion Recognition System Based on Facial Expressions and EEG Using Machine Learning and Deep Neural Network Methods 10](#_Toc74762477)

[Using Bidirectional LSTM Recurrent Neural Networks to Disentangle Brain Activity from EEG Data 12](#_Toc74762478)

[EEG Signal Time-Frequency Analysis for Human Emotion Detection 13](#_Toc74762479)

[Methods: 14](#_Toc74762480)

[sigmoid logistic regression: 14](#_Toc74762481)

[Naive Bayes: 15](#_Toc74762482)

[random forest: 15](#_Toc74762483)

[Extreme Gradient Boosting: 16](#_Toc74762484)

[K-nearest neighbor: 17](#_Toc74762485)

[Decision Tree 18](#_Toc74762486)

[Support vector classifier 19](#_Toc74762487)

[Bert 20](#_Toc74762488)

[Results 20](#_Toc74762489)

[CNN: 20](#_Toc74762490)

[BERT: 21](#_Toc74762491)

[Logistic Regression: 22](#_Toc74762492)

[XGBoost 23](#_Toc74762493)

[Python built in models used on EEG: 23](#_Toc74762494)

[Conclusion 25](#_Toc74762495)

[Reference list 26](#_Toc74762496)

# Abstract

# Emotions are a silent language that can be expressed physically. It allows us to understand how others feel and how they deal with things. However, humans are not always able to express their emotions. But emotional analysis is now a rising field with numerous applications. Emotions are a neural impulse that pushes an organism to action, causing instinctive reactive behavior that has evolved as a survival mechanism to meet a survival need. This research aims to extract emotions using a variety of methods and to apply them in a variety of applications. We will begin the learning process by detecting if students are confused or not after using cameras and speakers that will allow instructors to see how students engage with their materials in order to maximize the output of the learning process. Machine learning and deep learning models were utilized to extract, assess, and predict emotions using diverse signals. The results showed that EEG has a high accuracy of 94% and face recognition (DCNN) has an accuracy of 82%. The voice had the lowest accuracy, therefore we converted it to text to improve it. It will take some time to create and extract reliable results from audio sources. We conclude that emotion extraction is critical for developing numerous applications in the current and near future that use Deep-Learning, Machine-Learning, and Artificial Intelligence. EEG signals will be the simplest to extract emotion from, followed by facial expressions, however audio signals will require more time to get reliable data from.

# Introduction

Emotional Analysis has been a growing topic for a while with many uses and futuristic features with many forms of display as analysis of audio signals, text, facial recognition, and EEG signals. Humans use facial expression recognition to transmit their emotions and intentions in one of the most powerful, natural, and rapid ways possible. Humans may be unable to express their emotions in some circumstances, such as when they are hospitalized or have certain disabilities; as a result, improved recognition of other human emotions will lead to more effective communication. Human-computer contact has grown ingrained in our lives. Emotion-related declaration is also significant in human connection and communication because of its low cost, reliable recognition, and faster computation time, among other benefits. In other words, it might be a nonverbal communication medium that may be used to create a variety of scenarios that demonstrate superior human interaction through intimate collaboration with human-human communication. Facial expression analysis is a fascinating and difficult subject that has implications in a variety of fields, including human–computer interactions and medical applications. With the emergence of IOT and smart environments in hospitals, smart homes, and smart cities, automatic human emotion identification has gotten a lot of attention recently. With the rise of data, healthcare has entered a new era in which diagnosis may be made straight from raw data such as CT scans or MRIs using data-driven methodologies. Machine learning approaches, particularly deep learning methods, have had substantial success in biomedical and healthcare applications, such as categorizing lung nodules,1 breast lesions2, or brain lesions3 from CT scans, segmenting brain regions with MRI4,5, and emotion categorization using EEG data. There are a variety of techniques to classifying paralinguistic aspects of speech. The detection of emotions from a recorded voice signal is the most well-known application. In the case of speaker dependent categorization, a number of methods have yielded promising results. However, the majority of them fail to recognize emotion in the absence of a speaker. Even in speaker independent classification, some techniques get rather decent results by utilizing very large feature sets. Sentiment analysis is an important activity in a variety of fields, including business, social well-being, politics, security, and software engineering. Several off-the-shelf methods for classifying the sentiment polarity of an input text, that is, it’s positive, negative, or neutral semantic orientation, are currently available for free. None of them, however, support the recognition of distinct emotions like joy, love, or anger. Intelligent personal assistants (IPAs) like Siri, Alexia, Cortana, and others connect with humans using natural language processing, but when coupled with emotions, the level of successful communication and human-level intelligence improves. Hence, our objective is to improve multiple services using this technology. As a starter, improving the teaching-learning process by detecting if these students confused and stress or not during this process, using cameras and speakers and trying to reach the maximum output of the learning-teaching process as the instructor will be able to determine how the students interact with his/her materials. Researchers can utilize another application to detect emotions from input text as well as to train an emotion classifier from scratch using manually annotated data, which can then be used to detect emotions from text. It recognizes emotions in an input corpus that is provided as a comma separated value (CSV) file with one text per line and a unique identifier at the beginning of each line. The text id and predicted label for each item in the input collection are stored in a CSV file.

# Related Works

In this section, many recent papers will be discussed that investigated the emotion extraction and recognition topics through different methods. EEG signals, speech recognition and text recognition were all sources to extract the needed data. The data being collected could be used in various real-world applications including the medical ones and the day-to-day applications.

## Emotion detection using electroencephalography signals and a zero-time windowing-based epoch estimation and relevant electrode identification

A study done by Gannouni et al. (2021) investigated the possibility to improve emotion recognition using brain signals. They employed a novel and adaptive channel selection strategy that recognizes that the brain activity has a distinct behavior that varies from person to person and emotional state to emotional state. To properly detect the epochs in each emotional state, they applied the zero-time windowing method to extract immediate spatial data using the numerator group-delay function. It was discovered that the mentioned strategy performs well when using standard classification techniques. The mentioned method used high-resolution EEG signals to identify the epoch, then looked at variations in brain activity in the selected electrodes. These relevant electrodes were used as feature extraction sources.  Each individual is equipped with electrodes that correspond to one of the four EEG rhythms: alpha, beta, delta, and gamma. The parameters needed to distinguish and classify nine emotions were calculated using these sources. EEG signals were converted from time domain to frequency domain using a function called group-delay. The group-delay function allows for the extraction of high-resolution spectra while also highlighting the spectrum's formant features. To track and extract spectral properties from brief portions of EEG data, they used the ZTW technique. The ZTW method is multiplying a short length of each trial at each electrode with a window function that looks like a zero-frequency resonator's frequency response. The dimensions were mapped to nine different emotions associated with DEAP recordings: delighted, pleasant, relaxed, calm, aroused, neutral, distressed, miserable, and sad. The model was implemented using MATLAB and some tools like EEGLAB, prtools, Data description MATLAB toolbox, machine learning toolbox, and deep learning toolbox. During the same emotional state, the brain activity switched from one frequency band to another. The results demonstrate that using ZTW to choose effective EEG epochs boosted the performance of the final classification stage by + 3.38 percent and + 7.86 percent, respectively. In comparison to previous studies on the emotion recognition problem, the proposed technique is quite competitive. The outcomes of the proposed method were also improved using deep learning algorithms.

## Extracting the features of emotion from EEG signals and classify using affective computing

Another research done by Chinmayi et al (2017) studied extracting emotions from EEG signals. The EEG data with audio-visual stimulus was examined to extract

the characteristics of five emotions, happy, sad, fear, neutral and disgust. A method called independent component analysis (ICA) is used to extract features from EEG data, and the KNN algorithm is used to classify them. The cluster centroids are found Using k-Mean Clustering. One of the characteristics is the spectrum energy of emotional brain processes. Male volunteers between the ages of 20 and 30 were used to acquire the EEG data. Every emotion has its own set of high-intensity spectral energy sites. Happy (26.58, 99.97), neutral (69.18, 12.89), sad (66.45, 29.52), fear (74.22, 9.65), and disgust (63.05, 38.68) are the principal centroids of emotions. the frontal cortex was active When there is happy emotion. The neutral feeling relaxed all of the brain's regions, slowing down all of the brain's processes. Almost every part of the brain is affected by emotion neutral. The sad emotion had reaction centers in the right occipital and left frontal temporal related to the limbic system and demonstrates a range of activity regions. The emotion fear signals were located at left hypothalamus,

frontal cortex, right amygdala and left pre-frontal temporal regions. In the disgust emotion, it was found that the response centers and the prominent centroid lie in the right occipital region proving the results of the valence emotions. For KNN classification, the overall percentage of error is less than 20. The majority of scientists believe that each emotion center is distinct and isolated, however the data reveals that there is a brain-wide distribution of centers. Although the methodology is similar to the constructionist approach, the results reveal that they are not universal. In order to conduct a comparative study, data from female subjects will be obtained in the future.

## Real-Time EEG-Based Emotion Recognition and

## Its applications

A paper by Liu et al. (2011) discussed extracting inner emotions from EEG signals. This was achieved by using real-time fractal dimension-based algorithm and using Arousal-Valence emotion model. After implementing and testing the algorithm the model was able to recognize six emotions such as fear, frustrated, sad, happy, pleasant, and satisfied. Later on, two well-known algorithms were used to calculate the fractional dimension value, the box-counting and Higuchi. The data was collected in the two experiments using Emotive headset which were studied to uncover spatio-temporal emotion patterns of High and low arousal levels, as well as positive and negative valence levels. It was discovered that when watching a good movie scene, the left frontal lobe displays comparatively higher EEG activity, and when watching an unpleasant movie scene, the right frontal lobe shows considerably higher EEG activity. Many fields can benefit from real-time EEG-based emotion monitoring. Three applications were developed as part of this project: an emotional avatar that could display a graphical image of a face and the extracted emotion, EEG-based music therapy to Determine the patient's current emotional state and modify music therapy in real time based on patient brain response., and an EEG-based music player which detects the user's present emotional state, and the appropriate music is subsequently played in response to the detected emotions.

## Real-Time Emotion Recognition System Based on Facial Expressions and EEG Using Machine Learning and Deep Neural Network Methods

A study was conducted to categorize the emotional expressions of physically disabled individuals and autistic children using two ways to identify emotions: facial landmarks and EEG signals. Two facial expression databases were created with a total of 30 participants (n=30) for automated maker placement in Emotion detection using facial landmarks, and another with a total of 55 participants for testing and validating the suggested methodology. All participants were classified according to their age (n=22.9).

In the first method, Emotion detection using facial landmarks, a database of face landmarks was compiled. For 20 minutes, the participants were asked to sit in front of a computer with a camera and express six distinct expressions in a controlled atmosphere (happiness, anger, fear, sadness, surprise, and disgust). Face feature extraction was achieved by using an HD camera to capture the subjects' faces, resulting in a grayscale image that simplified the facial imaging process. The participant's eyes are then recognized using a grayscale image, and 10 virtual markers (action units) are put on the participant's face at defined locations using a mathematical model. To detect the location of each virtual marker during the participants' emotional expressions, the Lucas-Kande optical flow algorithm is used. the study used a convolutional neural network to improve facial emotion detection in Facial landmarks categorization, as it is utilized in other computer fields such as face recognition. In order to obtain the greatest brain reaction while detecting emotions using EEG signals, video clips were generated utilizing emotional images from the International Affective Picture System for data collection. The video segments were designed to provoke the six predicted emotions. A small group of volunteers (n=19) with a mean age (n=22.9) were promoted based on the feeling they had while watching the films. To remove extraneous information from EEG signals, an amplitude range of 85 V was applied to the EEG signal voltage. Second, an infinite impulse response (IIR) filter of sixth order Butterworth was used. To reduce noise from the EEG signals, a filter with a cut-off frequency of [149] Hz was utilized. A long short-term memory (LSTM) network model was employed in EEG classification to train the emotional model and improve EEG signal emotion identification. It is utilized in deep learning and is well-suited to time series data to categorize, analyze, and predict, and make predictions and can process entire sequences as analog data. (EEG raw data) were given to the LSTM model. For the six videos, each participant generated roughly 118,000 recordings of EEG raw data from 14 EEG channels. The model had the best level of accuracy. It has two dropout layers, two dropout layers, and a dense layer. It has a fully linked hidden layer, three LSTM layers of 128, 64, and 32 neurons, two dropout layers, and a dense layer. The LSTM and dropout layers are used to learn characteristics from raw EEG signals. The dropout layer, on the other hand, is used to reduce overfitting by preventing too many units from "coadapting." Finally, the Softmax activation function is used by the dense layer for classification. The model is trained on 70% of the EEG data and tested on 30% of the data using 3-fold cross-validation. Each cycle of cross-validation uses 100 epochs. The Adam optimizer is used in the training phase and has a learning rate of 0.001. Moreover, the grid search method and fivefold cross-validation methods are employed to fine-tune feature dimension and threshold value.

The method used in the Facial Landmarks database validation attained the greatest accuracy of 99.81 percent. And, in the EEG signals database, the proposed technique had a higher emotional detection rate of 87.25 percent.

The accuracy in training data from 30 subjects that was not normalized was 89.04 percent, whereas the accuracy in normalized data was 96.93 percent. Normalized Testing Data from 55 Subjects had an accuracy of 93.02 percent. The gap and future work are that the system's precision and accuracy can be expanded by obtaining more data from more users. Approaches can also be used to extract more information from EEG waves. In addition to refining system techniques, putting participants in real-world settings where they can express their true feelings can help to improve the system's EEG accuracy.

## Using Bidirectional LSTM Recurrent Neural Networks to Disentangle Brain Activity from EEG Data

A study was conducted by Zhaoheng et al. (2017) to classify students’ confusion in watching online course videos from EEG data by applying Bidirectional LSTM Recurrent Neural Networks. They use three SVM classifiers with different kernel functions. They employ grid search to optimise the parameters C (1, 10, 100, 1000) and (103, 104) for each kernel, respectively. They also use a K Nearest Neighbor classifier as a baseline technique. They use various K parameter values ranging from 2 to 5 and select the one with the highest accuracy as the final result. To compare the outcomes of different neural networks, they classify the EEG data using Convolutional Neural Network, Deep Belief Network, and a single-layer LSTM Recurrent Neural Network (RNN-LSTM). They present a variable selection approach to find the most important feature in our Bidirectional LSTM model in order to assess which characteristic of the EEG dataset contributes the most to our model. Instead of incorporating all of the elements into the model, they omit one single feature. They then conduct the experiments with the remaining features. The results reveal that the Bidirectional LSTM model outperforms other machine learning algorithms in terms of performance and robustness as measured by cross-validation. With an accuracy of 73.3 percent, they can determine whether or not a pupil is confused. Furthermore, they discovered that the gamma 1 wave of the EEG signal is the most relevant component for identifying brain confusion. The findings indicate that machine learning has the potential to be a valuable tool for modelling and understanding brain function.

## EEG Signal Time-Frequency Analysis for Human Emotion Detection

A Paper was done by Murugappan et al. The purpose of this research is to present an emotion recognition system based on EEG (Electroencephalogram) signals. The primary goal of this research is to assess the efficacy of categorizing human emotions using two discrete wavelets transform (DWT)-based feature extraction methods using three statistical features. The EEG waves were acquired utilizing 63 biosensors using an audio-visual induction approach. In total, 6 healthy volunteers between the ages of 21 and 27 were used in this emotion recognition investigation. In this study, they employed three statistical parameters from EEG signals (energy, Resourcing Energy Efficiency (REE), and Root Mean Square (RMS)) to categorize four emotions (happy, disgust, surprise, and fear). For differentiating emotions, an unsupervised clustering method known as Fuzzy C-Means (FCM) clustering is used. As a result, wavelet-based feature extraction of EEG data in alpha band activity has been shown to be effective in detecting emotions from EEG signals. The results also support the use of “db4” wavelet transform-based feature extraction with proposed statistical features for assessing human emotions from EEG signals.

# Methods:

## sigmoid logistic regression:

For binary classification, logistic regression is a popular machine learning approach. Using a logit function, it forecasts the likelihood of a binary result. It's a type of linear regression in which the log function is used to predict the probability of an outcome. To transform the result to a categorical value, we apply the activation function (sigmoid). For example, logistic regression may be used to detect fraud, spam, cancer, and many other things. This is the equation of sigmoid logistic regression:

S(z)=

* + s(z)s(z) = output between 0 and 1 (probability estimate).
* z = input to the function (your algorithm’s prediction e.g., mx + b).
* e = base of natural log.

## Naive Bayes:

The Naïve Bayes is combined with a strong assumption that the qualities are conditionally independent, given the class, to create the Nave Bayes algorithm. Despite the fact that this independence requirement is frequently broken in practice, nave Bayes classification accuracy is generally competitive. Given its computing efficiency and a slew of other appealing characteristics, nave Bayes is commonly used in practice. This is the equation of naïve bayes:

P(c\x) =

* *P*(*c|x*) is the posterior probability of *class* (*target*) given *predictor* (*attribute*).
* *P*(*c*) is the prior probability of *class*.
* *P*(*x|c*) is the likelihood which is the probability of *predictor* given *class*.
* *P*(*x*) is the prior probability of *predictor*.

## random forest:

The **r**andom forest is a classification algorithm that uses numerous decision trees to classify data. When creating each individual tree, it employs bagging and feature randomization in order to generate an uncorrelated forest of trees whose committee prediction is more accurate than that of any one tree. This is the equation of random forest:

J(k,tk)= left +right

* Gleft right is the impurity (standard deviation in this case) of the left/right splits.
* Mleft right is the number of instance int left/right splits.

## Extreme Gradient Boosting:

Because gradient boosting is a greedy method, it can easily overfit a training dataset. Regularization strategies that punish various sections of the algorithm and overall enhance the algorithm's performance by decreasing overfitting might help it. Extreme Gradient Boosting (XGBoost) is an open-source package that implements the gradient boosting technique in an efficient and effective manner. Although there were other open-source implementations of the technique before XGBoost, the introduction of XGBoost seemed to unleash the method's potency and make the applied machine learning community pay greater attention to gradient boosting in general. Shortly after its creation and initial release, XGBoost became the go-to approach for classification and regression issues in machine learning contests and was frequently the crucial component in winning solutions. This is the equation of extreme gradient boosting:

* **Residual**: is actual (observed) value — predicted value
* **Previous probability:** is the probability of an event calculated at a previous step. The initial probability is assumed to be 0.5 for every observation, which is used to build the first tree. For any subsequent trees, the previous probability is recalculated based on initial prediction and predictions from all prior trees, as shown in the process map.
* **Lambda**: is a regularization parameter. Increasing lambda disproportionately reduces the influence of small leaves (the ones with few observations) while having only a minor impact on larger leaves (the ones with many observations).

## K-nearest neighbor:

The K-Nearest Neighbour method is based on the Supervised Learning methodology and is one of the most basic Machine Learning algorithms. The K-NN method assumes that the new case/data and existing cases are comparable and places the new case in the category that is most comparable to the existing categories. The K-NN method saves all available data and classifies a new data point based on its similarity to the existing data. This implies that fresh data may be quickly sorted into a well-defined category using the K-NN method. The K-NN approach may be used for both regression and classification, though it is more commonly utilised for classification tasks. K-NN is a non-parametric method, which means it doesn't make any assumptions about the data. This is the equation of the k-nearest neighbors:

Pr(Y=j|X=x0)= ∑i∈N0 I(yi=j)

* X is a matrix of features from an observation
* Y is a class label
* Given a positive integer k, k-nearest neighbors look at the k observations closest to a test observation x0 and estimates the conditional probability that it belongs to class j using the formula.

## Decision Tree

A decision tree is a decision-making aid that employs a tree-like model of decisions and their potential results, such as chance event outcomes, resource costs, and utility. It's one approach to show an algorithm made up entirely of conditional control statements. Decision trees are a prominent technique in machine learning and are often used in operations research, particularly in decision analysis, to assist determine the best method for achieving a goal. This is the equation of decision tree:

gain(S,A)=Entropy(S)-(Sv)

* Suppose S is a set of instances
* A is an attribute
* Sv is the subset of S with A = v
* Values (A) is the set of all possible values of A

## Support vector classifier

SVM (Support Vector Machine) is a supervised machine learning technique that may be used to solve classification and regression problems. It is, however, mostly employed to solve categorization difficulties. Each data item is plotted as a point in n-dimensional space (where n is the number of features you have), with the value of each feature being the value of a certain coordinate in the SVM algorithm. Then we accomplish classification by locating the hyperplane that best distinguishes the two classes. This is the equation of Support vector classifier:

β0 + β1X1+ β2X2+…..+ βpXp=0

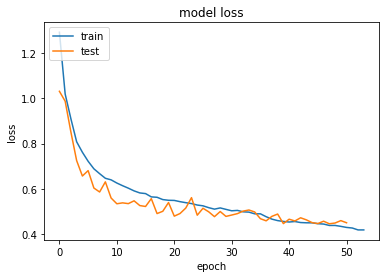
* β0 is the intercept
* β1 defining first axis
* β2 defining the second axis

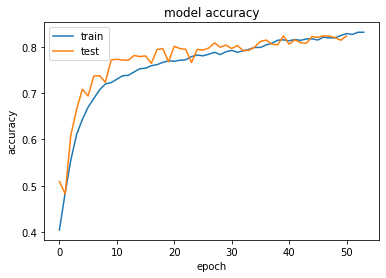
## Bert

Google's Bidirectional Encoder Representations from Transformers (BERT) is a Transformer-based machine learning approach for pre-training in natural language processing (NLP). Jacob Devlin and his Google colleagues built and released BERT in 2018. Google has been using BERT to better analyses user queries since 2019. BERT is a program that uses surrounding text to assist computers understand the meaning of ambiguous words in text

# Results

## CNN:

* For the image dataset we have used Deep Convolutional networks to classify images upon three emotions (sadness, happiness, neutrality), we have transformed the output to be label-coded furthermore, we have used Adam optimizer and seven convolutional layers with activation function of ELU and the result was 82% accuracy.
* 

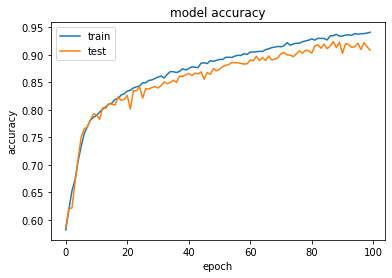


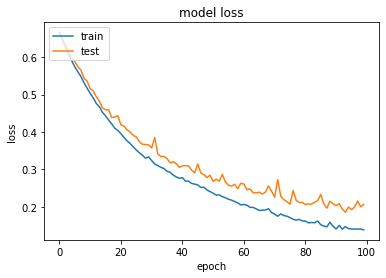
## BERT:

* Bert is a model used for natural language processing, so we have used Bert to classify the emotions (sadness, anger, joy, fear, surprise, love ) of people, to obtain high accuracy we used AdamW optimizer which yields better accuracy than its adversary, Adam optimizer, moreover, the accuracy for the first epoch was 92%

## Logistic Regression:

* For the EEG dataset to classify the confused and non-confused students we used Logistic regression for binary classification, and we have added neural networks to increase the accuracy. The Model uses Sigmoid activation function in a layer and four other ‘relu’ activation functioning layers to get higher accuracy. We have also used Early stopping function to avert from overfitting the data.



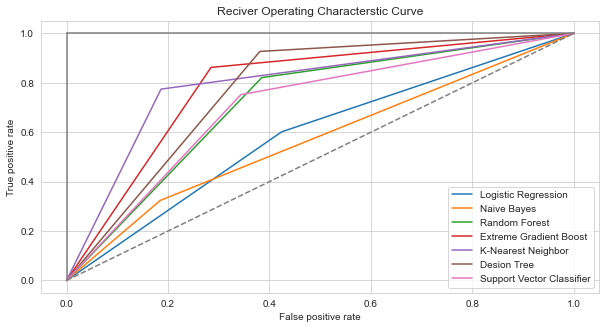
* 

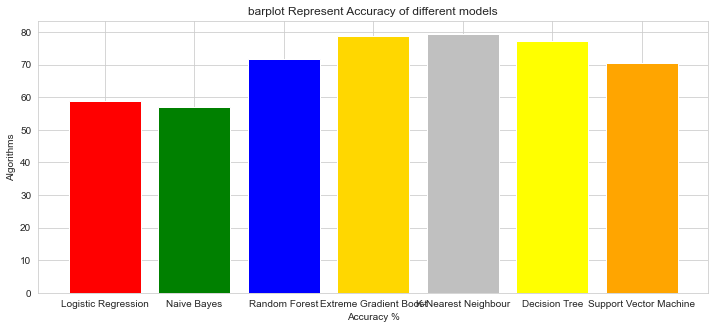
## XGBoost

The results from the XGBoost shows that the most important feature in prediction was Gamma Band among the EEG bands.

## Python built in models used on EEG:

* Naïve Bayes: Accuracy (55.5%)
* Random Forest classifier: accuracy (68%)
* XGBoost: 75% accuracy
* K-neighbor classifier: 85% accuracy
* Decision Tree classifier: 75% accuracy
* Support vector Classifier: 65% accuracy





# Conclusion

Deep-Learning and Machine-Learning are one of the most used technologies nowadays in many aspects. We used 8 models to extract, analyze and predict emotions through various signals. Emotion extraction is very important to develop many applications in the present and in the near future using Deep-Learning, Machine-Learning and Artificial Intelligence. It will help improve relationships, some emergencies and improving the teaching process as an example. EEG signals will be the easiest to extract emotion from then facial expressions while audio signals will take some time to extract accurate results from.

# Reference list

Brownlee, J. (2020, August 15). *A Gentle Introduction to the Gradient Boosting Algorithm for Machine Learning*. Machine Learning Mastery. https://machinelearningmastery.com/gentle-introduction-gradient-boosting-algorithm-machine-learning/

*Development of a Real-Time Emotion Recognition System Using Facial Expressions and EEG based on machine learning and deep neural network methods*. (2020, January 1). ScienceDirect. https://www.sciencedirect.com/science/article/pii/S235291482030201X

Dobilas, S. (2021, April 25). *XGBoost: Extreme Gradient Boosting — How to Improve on Regular Gradient Boosting?* Medium. https://towardsdatascience.com/xgboost-extreme-gradient-boosting-how-to-improve-on-regular-gradient-boosting-5c6acf66c70a

*Extracting the features of emotion from EEG signals and classify using affective computing*. (2017, March 1). IEEE Conference Publication | IEEE Xplore. https://ieeexplore.ieee.org/document/8300118

Fraser, B. (2020, April 15). *A pragmatic dive into Random Forests and Decision Trees with Python*. Medium. https://towardsdatascience.com/a-pragmatic-dive-into-random-forests-and-decision-trees-with-python-a850f6ed4ed

Gannouni, S. (2021a, March 29). *Emotion detection using electroencephalography signals and a zero-time windowing-based epoch estimation and relevant electrode identification*. Scientific Reports. https://www.nature.com/articles/s41598-021-86345-5

Gannouni, S. (2021b, March 29). *Emotion detection using electroencephalography signals and a zero-time windowing-based epoch estimation and relevant electrode identification*. Scientific Reports. https://www.nature.com/articles/s41598-021-86345-5

*K-Nearest Neighbor(KNN) Algorithm for Machine Learning - Javatpoint*. (2017). Www.Javatpoint.Com. https://www.javatpoint.com/k-nearest-neighbor-algorithm-for-machine-learning

Libretexts. (2020a, August 17). *3: K-Nearest Neighbors (KNN)*. Statistics LibreTexts. https://stats.libretexts.org/Bookshelves/Computing\_and\_Modeling/RTG%3A\_Classification\_Methods/3%3A\_K-Nearest\_Neighbors\_(KNN)

Libretexts. (2020b, August 17). *3: K-Nearest Neighbors (KNN)*. Statistics LibreTexts. https://stats.libretexts.org/Bookshelves/Computing\_and\_Modeling/RTG%3A\_Classification\_Methods/3%3A\_K-Nearest\_Neighbors\_(KNN)

Lutkevich, B. (2020, January 27). *BERT language model*. SearchEnterpriseAI. https://searchenterpriseai.techtarget.com/definition/BERT-language-model

Murugappan, M. (2008). *Time-Frequency Analysis of EEG Signals for Human Emotion Detection*. SpringerLink. https://link.springer.com/chapter/10.1007/978-3-540-69139-6\_68?error=cookies\_not\_supported&code=16433820-8f22-4bdd-b386-1dcbbfd6451b

*NCBI - WWW Error Blocked Diagnostic*. (2019). NCBI. https://misuse.ncbi.nlm.nih.gov/error/abuse.shtml

Ray, S. (2020, December 23). *Understanding Support Vector Machine(SVM) algorithm from examples (along with code)*. Analytics Vidhya. https://www.analyticsvidhya.com/blog/2017/09/understaing-support-vector-machine-example-code/

*The Relevance of Voice Quality Features in Speaker Independent Emotion Recognition*. (2007, April 1). IEEE Conference Publication | IEEE Xplore. https://ieeexplore.ieee.org/abstract/document/4218026

Sirohi, K. (2020, March 13). *Support Vector Machine (Detailed Explanation) - Towards Data Science*. Medium. https://towardsdatascience.com/support-vector-machine-support-vector-classifier-maximal-margin-classifier-22648a38ad9c

Wikipedia contributors. (2021a, March 20). *Decision tree*. Wikipedia. https://en.wikipedia.org/wiki/Decision\_tree

Wikipedia contributors. (2021b, June 1). *BERT (language model)*. Wikipedia. https://en.wikipedia.org/wiki/BERT\_(language\_model)

William Pao, a&s International. (2017, October 12). *The many applications of emotion recognition*. Milesight. https://www.asmag.com/showpost/23883.aspx

Yiu, T. (2021, May 27). *Understanding Random Forest - Towards Data Science*. Medium. https://towardsdatascience.com/understanding-random-forest-58381e0602d2

Zhuang, N. (2017, August 16). *Emotion Recognition from EEG Signals Using Multidimensional Information in EMD Domain*. Hindawi. https://www.hindawi.com/journals/bmri/2017/8317357/