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MSc THESIS

# Music Recommendation System based on EEG Sentiment Analysis using ML Techniques.

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**ΕΘΝΙΚΟ ΚΑΙ ΚΑΠΟΔΙΣΤΡΙΑΚΟ ΠΑΝΕΠΙΣΤΗΜΙΟ ΑΘΗΝΩΝ**

**ΣΧΟΛΗ ΘΕΤΙΚΩΝ ΕΠΙΣΤΗΜΩΝ**
**ΤΜΗΜΑ ΠΛΗΡΟΦΟΡΙΚΗΣ ΚΑΙ ΤΗΛΕΠΙΚΟΙΝΩΝΙΩΝ**

**ΔΙΚΤΥΩΣΗ ΥΠΟΛΟΓΙΣΤΩΝ**

**ΔΙΠΛΩΜΑΤΙΚΗ ΕΡΓΑΣΙΑ**

# Σύστημα Μουσικής Σύστασης βασισμένο στην Ανάλυση Συναισθημάτων μέσω Δεδομένων Ηλεκτροεγκεφαλογράφου με χρήση Μηχανισμών Μάθησης Μηχανής.

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## ABSTRACT

Over the years, numerous studies have demonstrated that music can produce distinct effects and feelings on people. Although it is relatively easy to name different types of emotions, it remains difficult to relate them to the real emotions experienced by a person. In addition, there are many people who listen to a specific genre of music that they think it is enjoyable when in fact that genre might have a negative effect on them. The current thesis, will try to develop a music recommendation system that will base its output on emotions extracted from Electroencephalography (EEG) data so as to stay as close as possible to the human nature. The system, which is based on Machine Learning techniques, comprises the following features: (a) Processing of EEG data in order to perform various feature extraction methods; (b) perform data augmentation so as to enrich the current dataset; (c) make use of a proper dimensionality reduction method that will find correlations in the data and discard non-critical information; (d) implement classification methods that are able to predict emotion related labels (valence, arousal, dominance, liking); (e) map the predicted emotion related labels into real emotions (excited, happy, angry, sad) and (f) integrate the best models, with the use of a voting method, into a final music recommendation system.

**SUBJECT AREA**: Machine Learning

**KEYWORDS**: Music Recommendation System, Electroencephalography (EEG), Sentiment Analysis, Classification Algorithms, Feature Extraction Methods

# ΠΕΡΙΛΗΨΗ

Με την πάροδο των χρόνων, πολυάριθμες μελέτες έχουν δείξει ότι η μουσική μπορεί να παράγει ξεχωριστά αποτελέσματα και συναισθήματα στους ανθρώπους. Παρόλο που είναι σχετικά εύκολο να ονομαστούν διαφορετικοί τύποι συναισθημάτων, είναι δύσκολο να συσχετιστούν με τα πραγματικά συναισθήματα που βιώνει κάποιος. Επιπλέον, υπάρχει πληθώρα ανθρώπων που ακούν ένα συγκεκριμένο είδος μουσικής που θεωρούν ευχάριστο όταν στην πραγματικότητα αυτό το είδος μπορεί να έχει αρνητικό αντίκτυπο στους ίδιους. Απώτερος σκοπός της τρέχουσας διπλωματικής είναι η ανάπτυξη ενός συστήματος συστάσεων μουσικής βασιζόμενο σε συναισθήματα που εξάγονται από δεδομένα ηλεκτροεγκεφαλογράφου (EEG), ώστε να παραμείνουν όσο το δυνατόν πιο κοντά στην ανθρώπινη φύση. Το σύστημα αυτό, βασίζεται στις τεχνικές μάθησης μηχανών και περιλαμβάνει τα ακόλουθα χαρακτηριστικά: (α) Επεξεργασία δεδομένων EEG για την ανάπτυξη διαφόρων μεθόδων εξαγωγής χαρακτηριστικών, (β) εφαρμογή μεθόδων για αύξηση των δεδομένων ώστε να εμπλουτιστεί το τρέχον σύνολο τους, (γ) χρήση κατάλληλων μηχανισμών μείωσης των διαστάσεων των δεδομένων, οι οποίοι στοχεύουν στην εύρεση συσχετισμών στα δεδομένα με σκοπό την απομάκρυνση μη κρίσιμων πληροφορίων, (δ) εφαρμογή μεθόδων ταξινόμησης που είναι σε θέση να προβλέπουν τις σχετικές με το συναίσθημα ετικέτες (valence, arousal, dominance, liking), (ε) αντιστοίχηση των προβλεπόμενων σχετικά με το συναίσθημα ετικετών σε πραγματικά συναισθήματα (excited, happy, angry, sad) και (στ) ενσωμάτωση των καλύτερων μοντέλων με τη μέθοδο της ψηφοφορίας σε ένα τελικό σύστημα συστάσεων μουσικής.

**ΘΕΜΑΤΙΚΗ ΠΕΡΙΟΧΗ**: Μάθηση Μηχανής

**ΛΕΞΕΙΣ ΚΛΕΙΔΙΑ**: Σύστημα μουσικής σύστασης, Ηλεκτροεγκεφαλογράφημα (EEG), Ανάλυση συναισθημάτων, Αλγόριθμοι ταξινόμησης, Μέθοδοι εξαγωγής χαρακτηριστικών

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# PREFACE

The current thesis has been conducted for the master's program degree offered by the department of Informatics and Telecommunication from the National and Kapodistrian University of Athens. The main study of this thesis concerns the development of a music recommendation system which is based on EEG sentiment analysis using machine learning techniques. In the context of the present work, the proposed system has been implemented using Jupyter along with Python for the related algorithms and methods, as well as for the visualization of the experimental results. The choice of this topic is due to our interest in the field of Machine Learning and its numerous applications.

# 1. INTRODUCTION

Starting this thesis, readers will have to understand exactly what is the main problem we are trying to mitigate through this research. All media-services providers are trying to tailor the different suggestions they make to users based on their preferences. The big problem with this is that the only way to understand users' preferences is through either gathering and analyzing a large amount of data about different songs a user listens to, or questionnaires in which a user is asked to answer specific questions about their tastes and the kinds of music they enjoy listening to. Collecting and analyzing large volumes of data is usually very effective as a process of discovering user preferences. However, it remains time consuming and requires a large amount of computing resources when one considers the huge number of users consuming this type of music service. Additionally, many times users do not prefer to spend time on such surveys and procedures which naturally leads to ineffective suggestions to them.

Naturally, many efforts and research have been made to provide new and innovative solutions to these problems. This work is one of those attempts to alleviate these problems.

The best judge of which song or type of music a user likes is their brain. The brain, in conjunction with hearing, evokes a multitude of emotions. Sentiment or feeling is the strongest guide to what is desirable and what is not, and the case of error can be almost negligible. As a result, emotion can be used as a dominant axis in our proposed music recommendation system. The most basic and powerful emotions are the following four: happiness, sadness, angriness and relaxation. Therefore, they will also be considered and used in this work. In order to do so, data concerning brain activity or otherwise Electroencephalography (EEG) data should be collected, analyzed and processed using Machine Learning techniques and methods which are listed in the following chapters.

## 1.1 High Level Architecture

At this point, it is considered prudent to make a high level presentation of the architecture that this work will follow. All the components of the architecture are listed below and are discussed in more detail in *Chapter 4*.

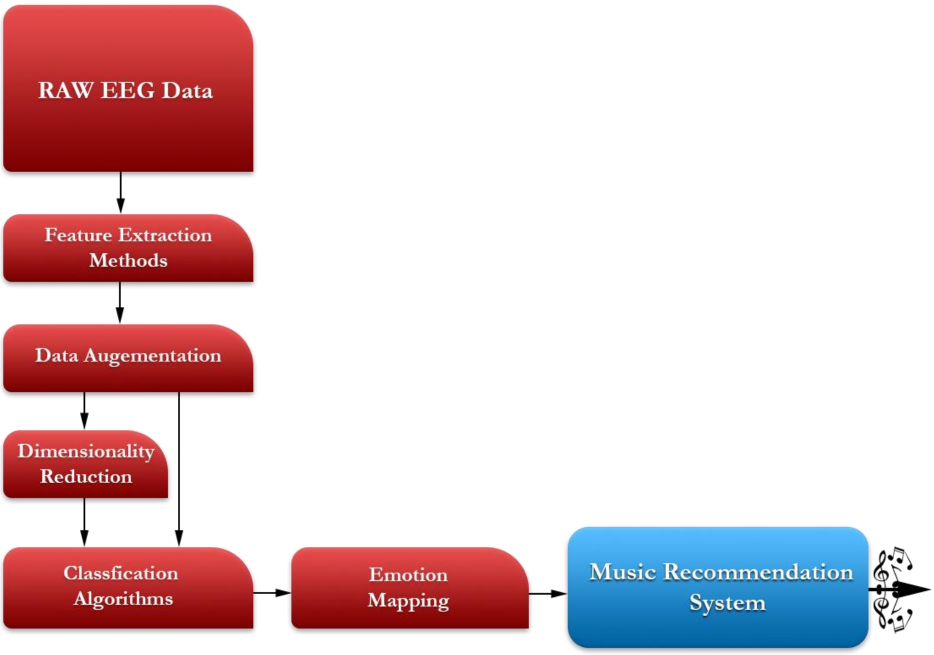


**Figure 1 High Level Architecture of the System**

**RAW EEG Data**

The first component of the architecture concerns the gathering of the RAW EEG Data. The current thesis will make use of the DEAP Database which is going to be presented in the following chapters.

**Feature Extraction Methods**

The second component of the architecture concerns the feature extraction stage. This component will be responsible for searching the best features which accurately describe the dataset and are intended to be informative and non-redundant. The methods that are going to be used are listed below:

- Discrete Wavelet Transform (**DWT**)
- Short Time Fourier Transform (**STFT**)
- Power Spectral Density (**PSD**)

**Data Augmentation**

Data augmentation is an essential component in this research. By using data augmentation on the output of the feature extraction methods we are able to significantly increase the diversity of data without actually collecting new one. As a result we were able to produce more accurate results.

**Dimensionality Reduction**

The feature vectors produced by the feature extraction and data augmentation stage contain a lot of random variables and carry a lot of information. However, it is of major importance to find a correlation between these variables and reduce the number of randomness under consideration. This procedure can be accomplished by implementing a dimensionality reduction method. In our case, we decide to perform an unsupervised linear transformation technique called Principal Component Analysis (PCA).

**Classification Algorithms**

This module has a vital role in this research. After identifying the appropriate feature vectors, it is time to perform and validate various classification methods in order to predict the class in which each one of the feature vector belongs to. The classes in our use case are emotion related labels. These labels are: valence, arousal, dominance and liking. The classification algorithms that are going to be used are presented below:

- Support Vector Machine (**SVM**)
- k-Nearest neighbors (**kNN**)
- Naïve Bayes (**NB**)
- Random Forest (**RF**)
- Multilayer Perceptron - Backpropagation (**MLP-BP**)

**Emotion Mapping**

Emotion mapping is the procedure in which emotion related labels predicted by the previous stage (Classification Algorithms) are mapped into the four basic and powerful emotions as previously described (happy, sad, angry, excited).

**Music Recommendation System**

The output of the machine learning framework presented above is a music recommendation system which is able to propose music and songs that suits the mood of the users. The current thesis will make use of the LAST.FM Database in order to retrieve the proposed music and songs.

# 2. VALIDATION METRICS

After implementing all different kind of Machine Learning methods and techniques, it is of major importance being able to validate the performance. In order to do so, we need to wisely select metrics that are going to be used. In our case, we decide to evaluate our results using Classification Accuracy, F1 Score and Binary Cross-Entropy.

**Classification Accuracy:** Classification accuracy is the ratio of number of correct predictions to the total number of input samples.

$$\boxed{Classification\ Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions}}$$

**F1 Score:** F1 Score is the Harmonic Mean between Precision and Recall and it declares how precise and robust a classifier is. The higher the F1 Score, the better is the performance of the model.

$$\boxed{F1\ Score = 2 * \frac{1}{\frac{1}{precision} + \frac{1}{recall}}}$$

- **Precision:** It is the number of correct positive results divided by the number of positive results predicted by the classifier.

$$\boxed{Precision = \frac{TruePositives}{TruePositives + FalsePositives}}$$

- **Recall:** It is the number of correct positive results divided by the number of all relevant samples.

$$\boxed{Recall = \frac{TruePositives}{TruePositives + FalseNegatives}}$$

**Binary Cross-Entropy:** Binary Cross-Entropy measures the performance of a binary classification model whose output is a probability values between 0 and 1. Binary Cross-entropy loss increases as the predicted probability diverges from the actual label.

$$\boxed{Binary\ Cross\_Entropy = -(ylog(p) + (1 - y)log(1 - p))}$$

- *p:* the predicted probability that observation O belongs to the class C.
- $y = \begin{cases} 1 & if\ observation\ O\ is\ classified\ correctly \\ 0 & otherwise \end{cases}$

# 3. DISCOVERING KNOWLEDGE

"*We are drowning in information but starved from knowledge*". John Naisbitt's famous quote describes precisely the problem that exists when it comes to discovering knowledge. Sometimes, it is rather easy to come up with a large volume of data. In our case, we discovered the DEAP database that contains plenty of data in order to perform our research. The difficult part is trying to identify patterns in this huge volume of information and exploit them towards enhancing decision making. There are three main families that try to discover knowledge through information; Unsupervised Learning, Supervised Learning and Semi-supervised Learning.

## 3.1 Supervised Learning

The focus of supervised learning methods is to train an algorithm to identify specific patterns apparent in a set of training datasets. The users in this case owns a dataset and knows in advance the patterns and/or trends that appear in it. The main goal is to use this information and train an algorithm so the latter is able to identify similar patterns and/or trends in new datasets. In this case, the validity of the original patterns is assumed a-priori; since, all of our data are labeled, Supervised Learning was the perfect candidate in our thesis.

# 4. METHODOLOGY

This chapter will provide a detailed analysis of all the methodology used in this thesis. We will analyze all the data sources, all the methods used for Feature Extraction, as well as the way data augmentation and dimensionality reduction mechanisms were performed. In addition, we will analyze all the classification methods used, how the mapping between emotion related labels with emotions was achieved, and finally, the music recommendation system.

## 4.1 Data Sources Identification

As previously stated, this section is all about identifying and accurately describing the data sources used in the current thesis.

### 4.1.1 DEAP Database

The DEAP database is a multimodal dataset for the analysis of human affective states. The electroencephalograpy (EEG) signals of 32 participants were recorded, using Biosemi ActiveTwo system, as each one of them watched 40 one-minute long excerpts of music videos. Participants rated each video in terms of the level of arousal, valence, like/dislike, dominance and familiarity. A novel method for stimuli selection was used, utilizing retrieval by affective tags from the last.fm website and video highlight detection. It is important to mention that the dataset is made publicly available.

### 4.1.2 Description of Dataset

In this section we will accurately describe the data used from the DEAP database in order to perform our experiments.

First, we have to describe the raw data used in our case. We have 32 participants and each one of them watched 40 one-minute long excerpts of music videos. Additionally, each participant had a three-second pre-trial relaxation baseline. Every participant labeled each music video with four emotion related labels; valence, arousal, dominance, liking and gave a decimal rating for each one of these labels between 1 and 9. Furthermore, a thresholding stage (using the mean value as the threshold) of the emotion related labels took place in order to decrease the complexity and increase the accuracy of the final results. As a result, each of the four emotion related labels were mapped to binary values. Arousal can be assigned to inactive or active, whereas valence can be assigned to unpleasant or pleasant accordingly. Dominance represents either a helpless and weak feeling (without control) or an empowered feeling (in control of everything). As for the liking emotion related label, it simply states if the participant likes or dislikes a music video. The sampling frequency for the EEG signals is 128 Hz and the device used for collecting them has 32 sensors/channels. To be able to provide more details about the data, we first need to describe the three different use cases considered in this thesis.

### 4.1.3 Description Of Use Cases

In this thesis we consider three different use cases in order to perform a more extensive and robust research and reach more mature results.

**Use Case 1 (UC1): Subject Independent**

In this use case, we are taking advantage of the users as a whole. In other words, we are not aiming at a personalized user experience but a generalized public opinion experience. This means that all raw data from all users are combined in a single file. Furthermore, we created four additional datafiles, one per emotion related label as described in *Chapter 4.1.2*.

As a result the datafiles are:

1. **Raw Data (EEG Signals) Aggregated from All Participants:**

| | | | | | | |
|---|---|---|---|---|---|---|
| 32<br>Participants | x | 40<br>Music Videos | x | 32<br>Sensors/Channels | x | 63s*128 *Hz*<br>Samples per Music Video |

2. **Valence Emotion Related datafile:**

| | | | | |
|---|---|---|---|---|
| 32<br>Participants | x | 40<br>Music Videos | x | 0/1<br>Valence Label |

3. **Arousal Emotion Related datafile:**

| | | | | |
|---|---|---|---|---|
| 32<br>Participants | x | 40<br>Music Videos | x | 0/1<br>Arousal Label |

4. **Dominance Emotion Related datafile:**

| | | | | |
|---|---|---|---|---|
| 32<br>Participants | x | 40<br>Music Videos | x | 0/1<br>Dominance Label |

5. **Liking Emotion Related datafile:**

| | | | | |
|---|---|---|---|---|
| 32<br>Participants | x | 40<br>Music Videos | x | 0/1<br>Liking Label |

**Use Case 2 (UC2): Gender Dependent**

In this use case, we are using two different kinds of input data separated by biological gender. The first one concerns all the male participants and the second one concerns all the female participants. Using this kind of separation we are able to provide user experience according to public opinion by the same biological gender. Similarly to UC1, we created eight additional datafiles, one per emotion related label both for males and females.

As a result the datafiles are:

1. **Raw Data (EEG Signals) Aggregated from both males and females:**

| | | | | | | |
|---|---|---|---|---|---|---|
| 17<br>Male Participants | x | 40<br>Music Videos | x | 32<br>Sensors/Channels | x | 63s*128 *Hz*<br>Samples per Music Video |

| | | | | | | |
|---|---|---|---|---|---|---|
| 15<br>Female Participants | x | 40<br>Music Videos | x | 32<br>Sensors/Channels | x | 63s*128 *Hz*<br>Samples per Music Video |

2. **Valence Emotion Related datafiles:**

| | | | | |
|---|---|---|---|---|
| 17<br>Male Participants | x | 40<br>Music Videos | x | 0/1<br>Valence Label |

| | | | | |
|---|---|---|---|---|
| 15<br>Female Participants | x | 40<br>Music Videos | x | 0/1<br>Valence Label |

3. **Arousal Emotion Related datafiles:**

| | | | | |
|---|---|---|---|---|
| 17<br>Male Participants | x | 40<br>Music Videos | x | 0/1<br>Arousal Label |

| | | | | |
|---|---|---|---|---|
| 15<br>Female Participants | x | 40<br>Music Videos | x | 0/1<br>Arousal Label |

4. Dominance Emotion Related datafiles:

| | | | | |
|---|---|---|---|---|
| 17<br>Male Participants | X | 40<br>Music Videos | X | 0/1<br>Dominance Label |

| | | | | |
|---|---|---|---|---|
| 15<br>Female Participants | X | 40<br>Music Videos | X | 0/1<br>Dominance Label |

5. Liking Emotion Related datafiles:

| | | | | |
|---|---|---|---|---|
| 17<br>Male Participants | X | 40<br>Music Videos | X | 0/1<br>Liking Label |

| | | | | |
|---|---|---|---|---|
| 15<br>Female Participants | X | 40<br>Music Videos | X | 0/1<br>Liking Label |

### Use Case 3: Subject Dependent

In this use case, we treat each participant as individual. This means that this dataset will provide a personalized experience based on the individual tastes that every participant has. Once again, we created additional datafiles for the individual emotion related labels for every participant. This means that we have 32 individual datafiles concerning emotion related labels.

As a result the datafiles are:

1. Raw Data (EEG Signals) for the individual participants (**x32 datafiles**):

| | | | | | |
|---|---|---|---|---|---|
| $\text{Participant}_1$ | 40<br>Music Videos | X | 32<br>Sensors/Channels | X | 63s*128 *Hz*<br>Samples per Music Video |

⋮

| | | | | | |
|---|---|---|---|---|---|
| $\text{Participant}_{32}$ | 40<br>Music Videos | X | 32<br>Sensors/Channels | X | 63s*128 *Hz*<br>Samples per Music Video |

2. Valence Emotion Related datafiles (**x32 datafiles**):

| | | | |
|---|---|---|---|
| $\text{Participant}_1$ | 40<br>Music Videos | X | 0/1<br>Valence Label |

⋮

| | | | |
|---|---|---|---|
| $\text{Participant}_{32}$ | 40<br>Music Videos | X | 0/1<br>Valence Label |

3. Arousal Emotion Related datafiles (**x32 datafiles**):

| | | | |
|---|---|---|---|
| $\text{Participant}_1$ | 40<br>Music Videos | X | 0/1<br>Arousal Label |

⋮

| | | | |
|---|---|---|---|
| $\text{Participant}_{32}$ | 40<br>Music Videos | X | 0/1<br>Arousal Label |

4. Dominance Emotion Related datafiles (**x32 datafiles**):

| | | | |
|---|---|---|---|
| $\text{Participant}_1$ | 40<br>Music Videos | X | 0/1<br>Dominance Label |

⋮

| | | | |
|---|---|---|---|
| $\text{Participant}_{32}$ | 40<br>Music Videos | X | 0/1<br>Dominance Label |

5. Liking Emotion Related datafiles (**x32 datafiles**):

| | | | |
|---|---|---|---|
| $\text{Participant}_1$ | 40 Music Videos | X | 0/1 Liking Label |

⋮

| | | | |
|---|---|---|---|
| $\text{Participant}_{32}$ | 40 Music Videos | X | 0/1 Liking Label |

## 4.2 Feature Extraction Methods

In this section all the feature extraction methods examined and deployed during the implementation of the current thesis will be analyzed in depth. The main target of this processing stage is to select and combine variables into features and effectively reducing the amount of data that must be processed, while still accurately and completely describing the original dataset. The following figure is an overview of the Feature Extraction Mechanism, which illustrates all the components needed in order to produce the feature vectors.

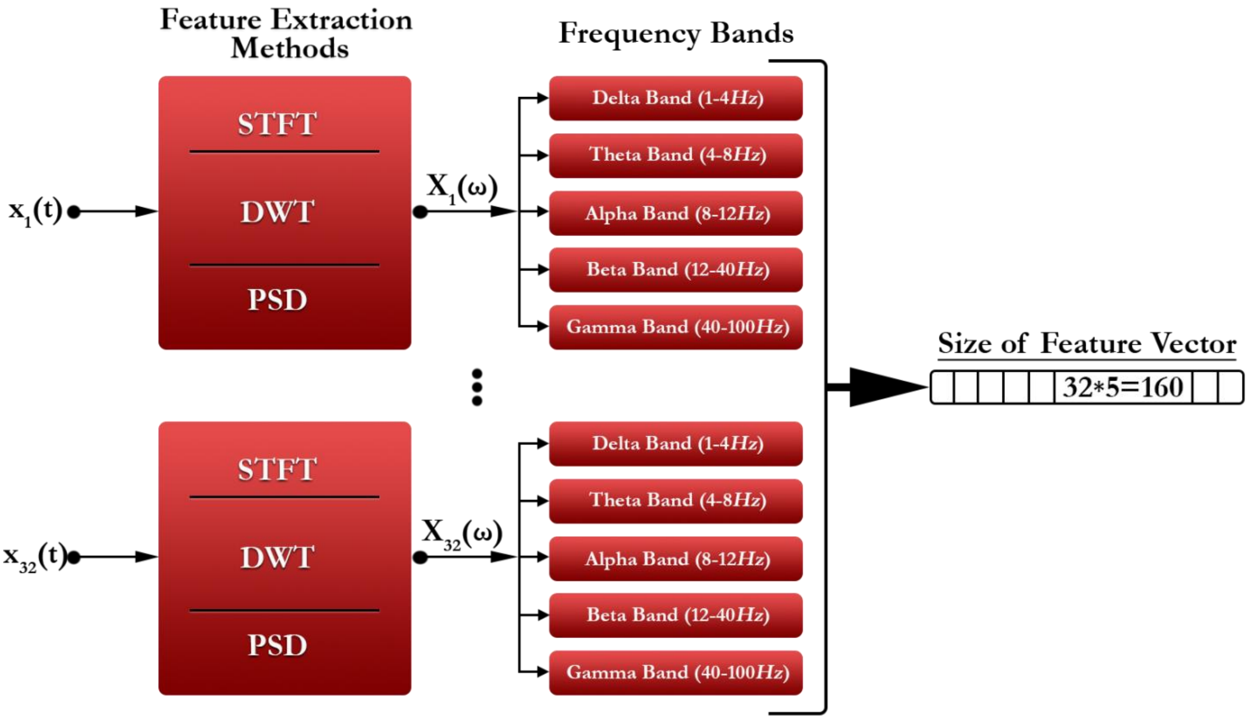


**Figure 2 Feature Extraction Methods Mechanism Overview**

According to the figure above, for each EEG signal $x_i(t)$ of each channel i (i ∈ {1,..,32}) three feature extraction methods (Discrete Wavelet Transform, Short Time Fourier Transform, Power Spectral Density) where applied so as to extract the main frequencies of the human EEG waves which are:

**Delta Band (1-4 Hz):** The slowest and highest amplitude brainwaves. Delta frequencies are stronger in the right brain hemisphere, and the sources of delta are typically localized in the thalamus.

**Theta Band (4–8 Hz):** Theta waves can be recorded from all over cortex, indicating that it is generated by a wide-ranging network involving medial prefrontal areas, central, parietal and medial temporal cortices. Theta brainwaves are generally associated with brain processes underlying mental workload or working memory.

**Alpha Band (8-12 Hz):** Alpha waves are defined as rhythmic oscillatory activity within the frequency range of 8–12 Hz. Alpha waves have several functional correlates reflecting sensory, motor and memory functions.

**Beta Band (12-40 Hz):** Oscillations within the 12-40 Hz range are commonly referred to as beta band activity. This frequency is generated both in posterior and frontal regions. Active, busy or anxious thinking and active concentration are generally known to correlate with higher beta power.

**Gamma Band (≥40 Hz):** At the moment, gamma frequencies are the black holes of EEG research as it is still unclear where exactly in the brain gamma frequencies are generated and what these oscillations reflect.

### 4.2.1 Discrete Wavelet Transform (DWT)

The first feature extraction applied to the raw EEG data is the Discrete Wavelet Transform (DWT). The DWT outputs coefficients which represent the degree of correlation between the analyzed signal and the wavelet function at different instances of time. As a result, DWT fully utilizes the time-frequency analysis by preserving the temporal information contained in the coefficients. In practice, the DWT is always implemented as a filter-bank, a very efficient way of splitting a signal into several frequency sub-bands.

With this method we captured the signal of interest (the five Frequency bands mentioned above) with a few large magnitude of DWT coefficients, while the noise of the signal which results in smaller DWT coefficients (e.g. artifacts, environmental noise etc.) was removed. Taking the previous state into consideration, we have decided that DWT is a perfect candidate for the feature extraction stage and that is why we selected it in our research.

Finally, in order to conclude in a 1x5 feature vector for each one of the 32 EEG channels/sensors, we have calculated the Standard Deviation and Approximate Entropy of the calculated coefficients (see Annex I). This procedure was performed for each individual Frequency Band which is described in Chapter 4.2.

### 4.2.2 Short Time Fourier Transform (STFT)

The second method selected and applied to the initial raw EEG data is the Short Time Fourier Transform (STFT). STFT analysis is one of the techniques used in order to reveal the frequency contents of the EEG signals at each time point. STFT, also known as windowed Fourier, is applied to partition the EEG signal into several segments of short-time signals by shifting the time window with some overlapping. This process is called windowing. Therefore, the frequency spectrum was divided into frequency bins, whose size is dependent on the length of the window.

For the current thesis we have selected the “Hann” window. The Hanning window is a suitable STFT windowing function for analyzing EEG signals since it is characterized by its good frequency resolution. Furthermore, this type of window was selected for our thesis due to the fact that it is able to “smooth” data and return a friendly frequency representation of the signal that will be used for further analysis. The spectrogram resolution can be enhanced by modifying the length of the window; a large value of the window length provides a better frequency resolution, but poor time resolution. A shorter window length, however, provides the exact opposite outcome.

In conclusion, in order to result in a 1x5 feature vector for each one of the 32 EEG channels/sensors, we have calculated the Standard Deviation and the Approximate Entropy of the magnitude of the signal over time and frequency (see Annex I). This procedure was performed for each individual Frequency Band which were described in Chapter 4.2.

### 4.2.3 Power Spectral Density (PSD)

Last but not least Power Spectral Density (PSD) was selected as a feature extraction method and applied to the initial set of raw EEG Data. PSD is a suitable candidate for EEG signal processing due to the fact that it distributes the signal power over frequency and express the strength of the variations (energy) as a function of frequency. In other words, it shows at which frequencies variations are strong and at which frequencies variations are weak.

In the current thesis, among the various windows for calculating the PSD, soft-behaved Hanning-window was selected to analyze the unpredictable nature of brain signals. The Hanning window with the 256 samples window's length was chosen to achieve an acceptable frequency resolution. This window selection with a smoothing characteristic was found to be more appropriate because of the different and unpredictable nature of brain signals.

In conclusion, in order to result in a 1x5 feature vector for each one of the 32 EEG channels/sensors, we have calculated the Standard Deviation and Approximate Entropy of the magnitude of the signal over frequency (see Annex I). This procedure was performed for each individual Frequency Band which were described in Chapter 4.2.

## 4.3 Data Augmentation

Having a large dataset is of major importance for the performance of our algorithms. The dataset provided by the DEAP Database was rich enough for our experiments, but we wanted to try extending it, in order to conclude in more mature outputs. As a result, we implemented a rather simple data augmentation method to enrich our dataset. It is really important to mention that the data augmentation was performed on the feature vectors and not on the original RAW data in order to avoid any mistakes due to the unpredictable nature of EEG signals.

It is critical to carefully select the appropriate percentage of augmentation in order to enrich the dataset without creating redundancies and diminishing the effectiveness of the method. For these reasons, we resolved to augment our dataset by 20%.

Initially, we use a feature vector as an input for our mechanism. Then, we generated noise that was created using the Normal Distribution $N(\boldsymbol{\mu}, \boldsymbol{\sigma^2})$ where:

- $\boldsymbol{\mu} = \text{mean value} = 0$
- $\boldsymbol{\sigma} = \text{standard deviation} = [\,0.001, 0.01, 0.02, 0.05\,]$

Standard deviation can be assigned with four different values in order for the added noise to maintain its randomness and to eliminate possible repetitive patterns.
Moving on, we added the generated noise to the feature vector in order to create a completely new one that retains its similarity with the initial feature. We applied the procedure described above to the 20% of the feature vectors included in the initial dataset.

The figure presented below illustrates the mechanism used to achieve the data augmentation.

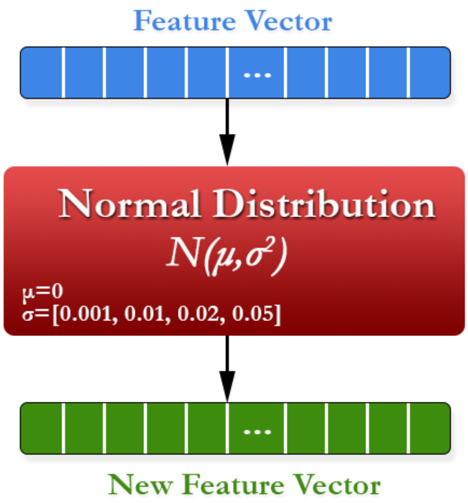


**Figure 3 Data Augmentation Mechanism Overview**

## 4.4 Dimensionality Reduction

In this section, we are going to discuss about the benefits of performing a dimensionality reduction method. As explained in Chapter 4.2, the feature vector that was produced using the three feature extraction methods has 160 ($\mathbf{5} * \mathbf{32}$) dimensions. Having so many dimensions increases the likelihood of correlations within the data. These correlations, produce redundancy in the information and reduce the quality of the dataset. Additionally, feature vectors with high dimensions increase the computational complexities. As a result we chose to perform a dimensionality reduction method in our data set in order to exploit all the advantages mentioned above.

The method that we selected to implement is the Principal Component Analysis (PCA) which is going to be discussed in more detail in the following chapter.

### 4.4.1 Principal component analysis (PCA)

Principal Component Analysis (PCA) is a widely used method in many research projects related to EEG signal analysis in order to reduce the dimension of the initial sensors' data. As already mentioned and explained in Chapter 4.4 there is of high importance, for the validity of our experimentation results to analyze and classify features, to find a balance between the variance of our data and their dimension. The target for the dimensionality reduction of our thesis is the creation of features with the following characteristics:

- **High Variance**: Features with high variance contains a useful information which is a requirement for building an effective Machine Learning Model.

- **Uncorrelated**: Features with high correlation are less useful and in certain cases downright harmful for our study.
- **Low Number of Features**: Too many features relative to observations would not only result in an overfit model that performs poorly out of sample but also in high computational complexity.

Taking all the above into consideration and after our experimentation phase we concluded in selecting PCA as a dimensionality reduction method due to the fact that it totally covers the required characteristics mentioned above. For our UCs we have selected the number of principal components which preserve around 98.8% or 99% of the total variance of the initial feature data. More details about the exact number of the principal components used in our experimentation will be given in Chapter 5.

The figure 4 illustrates in a high level view the process of the dimensionality reduction using PCA. As input data the initial features, derived from the three feature extraction methods analyzed in Chapter 4.2, were fed into the PCA component in order to decide upon the appropriate number of components that best describes our brain signal while ensuring that there will be no violations of the three principal targets presented above.


**Figure 4 Principal Component Analysis Mechanism Overview**

## 4.5 Classification Algorithms

In the current chapter all the Machine Learning algorithms chosen and deployed during the implementation of the current thesis project will be analyzed in depth. By the term classification we are referring to a technique of categorizing the provided data into a desired and distinct number of classes where we can assign a label to each class. As already mentioned and explained in Chapter 4.1.2, the classification problem that the current thesis addresses is a Supervised Binary Classification problem where for each feature vector (Chapter 4.2) a classification model had to map one by one the 4 emotion related labels (valence, arousal, dominance, liking) to a binary value (label). A classifier utilizes some training data so as to understand how given input variables relate to the class. After this stage the classifier is ready to predict the class (label) that each new sample belongs to.

Five machine learning algorithms were selected and compared, using the metrics described in Chapter 2, the Support Vector Machine (SVM), k-Nearest Neighbors (kNN), Naive Bayes (NB), Random Forest (RF) and Multilayer Perceptron with Backpropagation (MLP-BP). Each one of them will be explained in detail in the following chapters and the evaluation results will be presented in Chapter 5.

**Some General Terminology related to Machine Learning:**

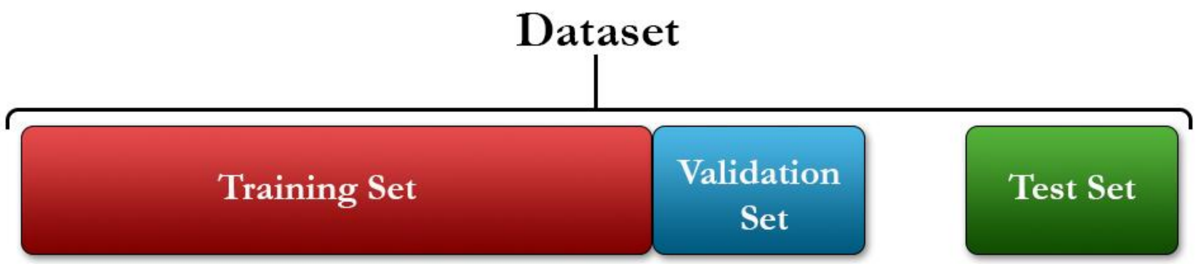


**Figure 5 Training, Validation and Test Data Sets**

**Classifier**: An algorithm that maps the input data to a specific category/class

**Training Set**: A large subset of the input data that is used in order to fit the classification model (most of the times is 80% of the initial dataset).

**Test Set**: The rest of the data (20%) of the initial dataset that will be used in order to evaluate our classification model is the Test Set. The test set is used to provide an unbiased evaluation of the final model fit on the training dataset.

**Validation Set**: The sample of data used to provide an unbiased evaluation of a model fit on the training dataset while tuning classification model hyperparameters.

**Classification model**: A classification model recognizes some patterns in the input values given for training. It predicts the class labels/categories the new data (test set).

**Binary Classification**: Classification task with two possible outcomes.

**Validation**: is a method used to tune the hyper-parameters of the model and is done on the validation set.

**Evaluation**: is a method used to test the final performance of the algorithm and is done on the test set.

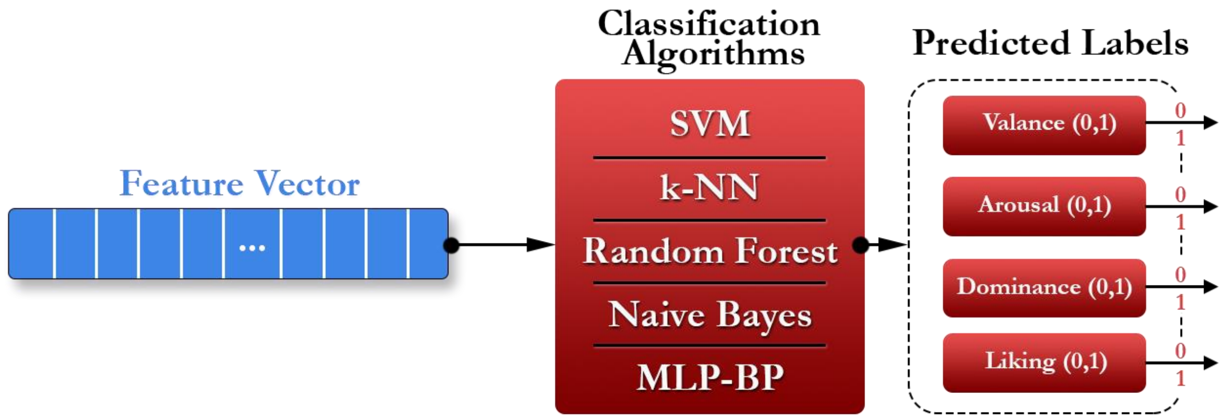


**Figure 6 Classification Algorithms Mechanism Overview**

### 4.5.1 Support Vector Machines (SVM)

The first and well known classification algorithm, examined during the implementation of our thesis, is the Support Vector Machine. Support Vector Machine abbreviated as SVM can be used for both regression and classification tasks.

The objective of the support vector machine algorithm is to find a hyperplane in an N-dimensional space (where N represents the number of features) that distinctly classifies the data points. By the term hyperplane we are referring to decision boundaries that help classify the data points. To separate the two classes of data points for each one of the emotion related labels, there are many possible hyperplanes that could be chosen. Our objective is to find a plane that has the maximum distance between data points of both classes. In order to better classify future data points we selected to maximize the margin distance.

The following figure illustrates an example of a non-linear classification problem solved using the SVM machine learning algorithm, where the circle with the green chromatic indication represents the hyperplane selected which better separates the data points belong to the two main classes (Class 1, 2).

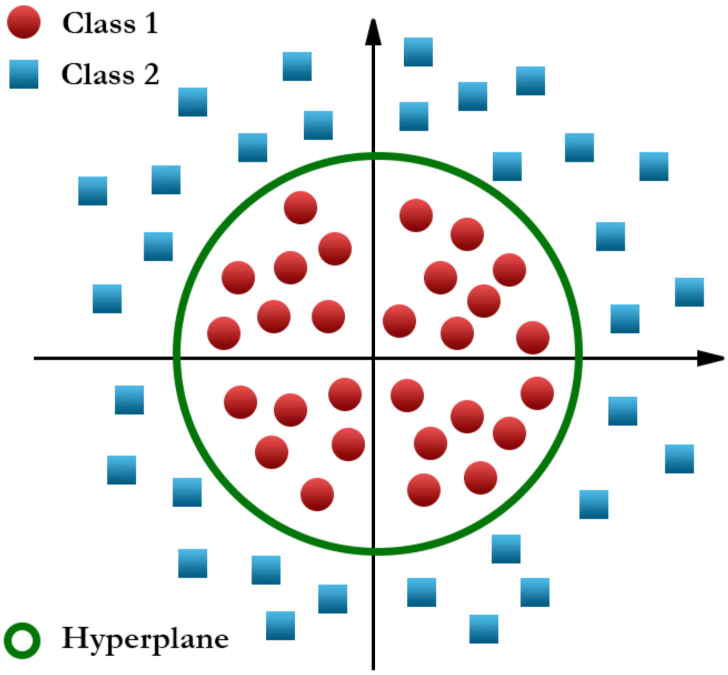


**Figure 7 SVM Example Scheme**

During the implementation of the SVM we had to decide upon the values of the core parameters related to the algorithm. More specifically, we had to tune the kernel, regularization, gamma and margin of SVM.

- **Kernel:** The function of kernel is to transform the input data into the required form. Different SVM algorithms use different types of kernel functions. These functions can be different types. While implementing SVM using scikit-learn library we experimented with three kernels the linear, polynomial and radial basis function (RBF). The right kernel is crucial, because if the transformation is incorrect, then the model can have very poor results.
- **Regularization:** The Regularization Parameter (in python it's called C) in the SVM optimization expresses the degree of importance that is being given to miss-classified data. If the C parameter value is higher, the optimization will choose smaller margin hyperplane, so training data miss-classification rate will be lower. On the other hand, if the C parameter value is low, then the margin will be large, even if there will be miss classified training data points.
- **Gamma:** The next important parameter for tuning is Gamma. The gamma parameter defines how far the influence of a single training point reaches. This means that higher Gamma value will consider only points close to the hyperplane and lower Gamma values will consider points at greater distance from the hyperplane.
- **Margin:** The last parameter is the margin. This distance from the decision surface (hyperplane) to the closest data point determines the margin of the SVM classifier. Higher margin results in a better classification model due to the fact that makes no low certainty classification decisions. According to the previous state the margin value should be always maximized.

### 4.5.2 k-Nearest neighbors (kNN)

The k-Nearest Neighbors algorithm or kNN is one of the simplest machine learning algorithms used in classification problems. kNN is based on the elementary state that similar data exist in close proximity. In kNN, K is the number of nearest neighbors. The number of neighbors is the core deciding factor in order to result in better performance. K is generally an odd number if the number of classes is 2.

In order for a new data point P to be classified to one of the two in total classes, firstly we find the k closest points to P and then classify this point based on the majority vote of its k neighbors. Each one of the closest neighbors, votes for its class and the class with the most votes is taken as the prediction for the point P. For our thesis, in order to find the k closest neighbors we selected the straight-line distance also called the Euclidean distance, which is a popular and familiar choice. To better summarize the kNN algorithm we used the three following simple steps:

- Calculate the Euclidean distance between the new data point and the rest of the data points
- Find the k nearest neighbors
- Vote for the label of the new data point

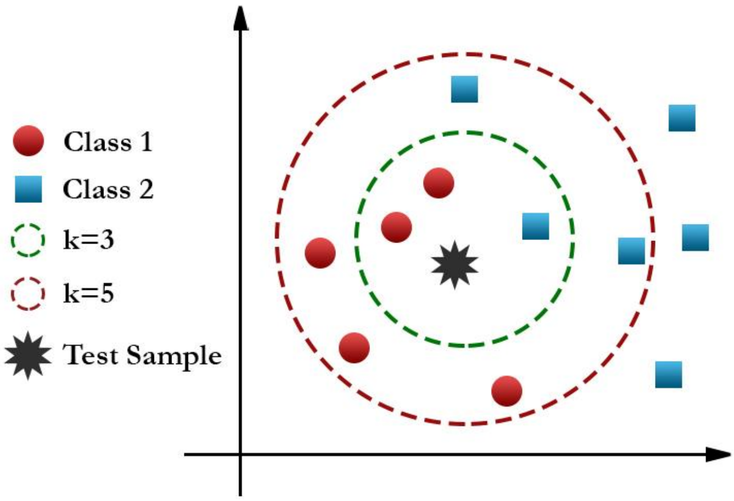


**Figure 8 k-NN Example Scheme**

Last but not least, the process of deciding upon the value of the K parameter is significant for our results. In the case of selecting a small number of neighbors, the noise will have a higher influence on the result, and a large number of neighbors make it computationally expensive. A small amount of neighbors will result in having low bias but high variance. On the other hand, a large number of neighbors will have a smoother decision boundary which means lower variance but higher bias. After experimenting with the K value we concluded in an even number which is keeping balance between variance and bias and also conduce to a better performance.

### 4.5.3 Naive Bayes (NB)

The third algorithm used in our thesis is the Naive Bayes (NB). NB is a probabilistic machine learning algorithm which is based on the Bayes Theorem. The goal of NB classifier is to determine the probability of the features occurring in each class, and to return the most likely class. This algorithm is called “Naive” because it makes a naive assumption that each feature is independent of other features, which is not true in real life.

Based on the Bayes Theorem the probability P(class|feature set) is the probability after the fact (posteriori), after considering all the given conditions. In our problem, it's the probability of classifying a feature for example to the binary class ‘1’, given a set of features that can be observed in class ‘1’. P(class) is called the prior, because it's all the information you know beforehand, the probability of being ‘0’ or ‘1’. P(feature set) is called evidence, because it's probability of what you are observing, the set of features. And P(feature set|class) is called the likelihood, meaning what is the probability of this belonging to class ‘1’, given this specific set of features. After calculating the probabilities for all classes the algorithm, in order to predict the class of each new (never seen before) example provided in test set, will pick the class that has higher probability.

### 4.5.4 Random Forest (RF)

The next machine learning algorithm used in our thesis, is the Random Forest. The random forest is based on a standard machine learning technique called a “decision tree”. A decision tree is a flowchart-like structure that uses a tree-like graph or model of decisions and their possible outputs. In a decision tree each node sets a query on an attribute, a branch represents the output of that condition and the leaf represents a class label. All the paths between root and leaves represent the classification rules. Considering what is already mentioned, decision tree is one way to display an algorithm that only contains conditional control statements. In a decision tree, an input is entered at the top and as it traverses down the tree the data gets bucketed into smaller and smaller sets.

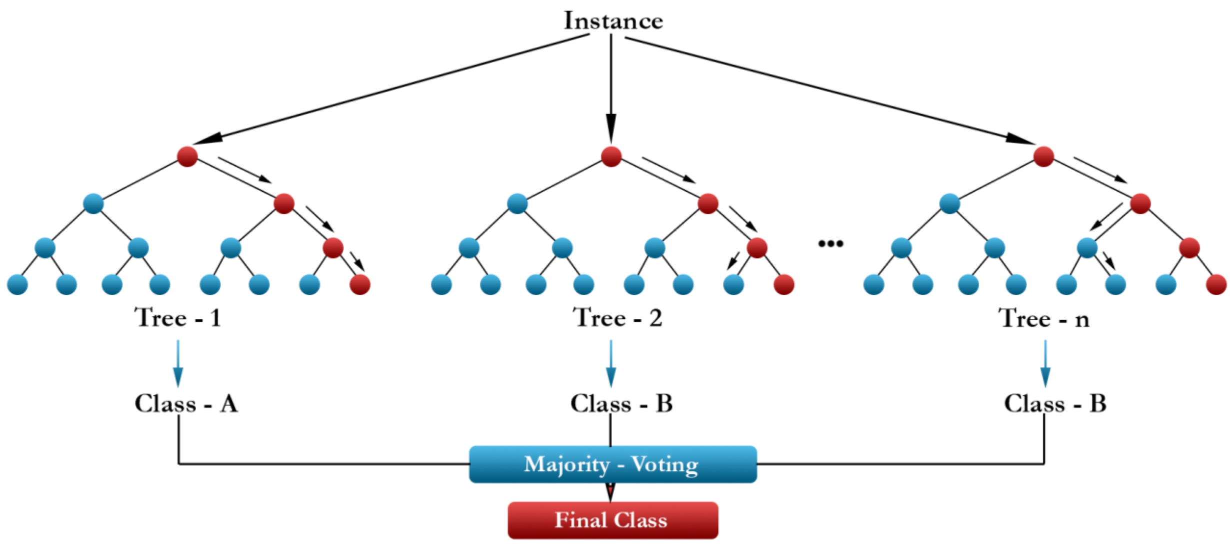


**Figure 9 Random Forest Example Scheme**

The random forest combines hundreds or thousands of decision trees, trains each one on a slightly different set of the observations, splitting nodes in each tree considering a limited number of the features. The final predictions of the random forest are made by averaging the predictions of each individual tree. The figure above illustrates a high level view of the Random Forest in order to better understand its logical steps. Figure 9 shows a RF which includes n decision trees, each one of them has conditional flows which result in a specific class. Finally, after all the decision trees result in a class, a majority voting concludes to the Final class selected for the feature.

### 4.5.5 Multilayer Perceptron - Backpropagation (MLP-BP)

The last Machine Learning Method selected is the Multilayer Perceptron with Backpropagation (MLP-BP). A multilayer perceptron (MLP) is a deep artificial neural network. It is composed of multiple layers of perceptrons. An MLP consists of at least three layers of nodes as presented in the figure below. More specifically, there is always an input layer which receives the input signal, an output layer that makes a decision or prediction about the input data, and in between there is a number of hidden layers that are the true computational engine of the MLP.

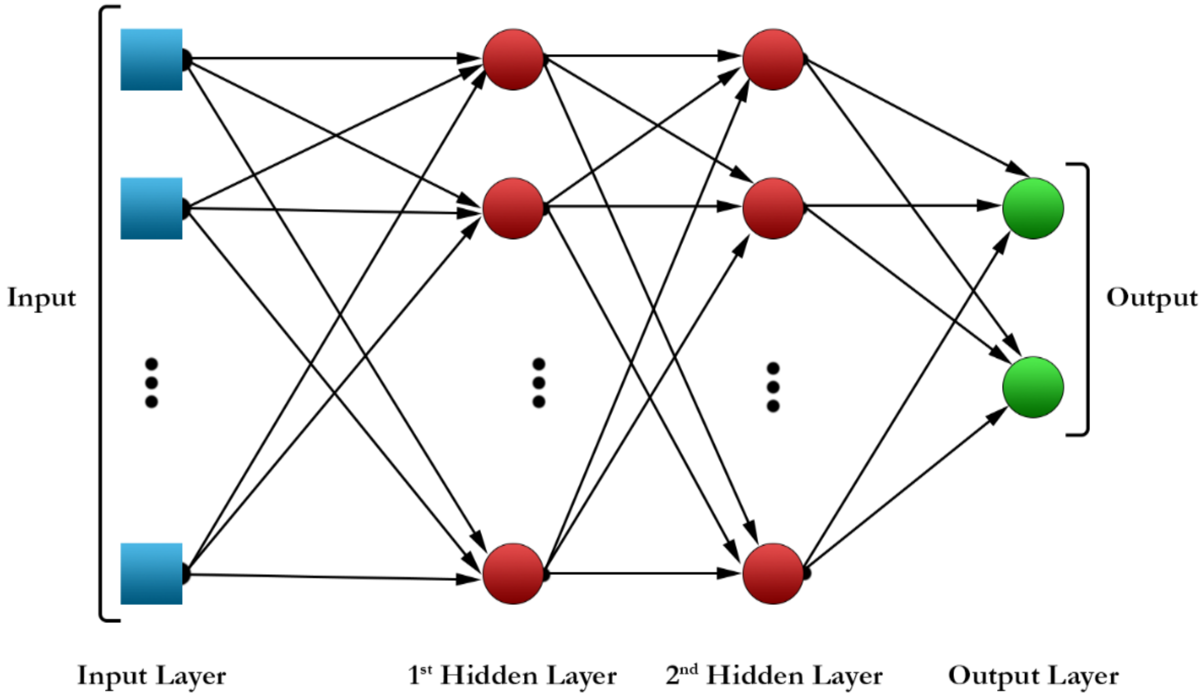


**Figure 10 MLP-BP Example Scheme**

MLPs are trained and learn to model the correlation (or dependencies) between those inputs and outputs. Training involves adjusting the weights and biases of each neuron (perceptron), of the model in order to minimize the error.
In a supervised classification problem, each input vector is associated with a label (ground truth). The output of the network gives a prediction, for each input fed to the neural network. In order to measure the performance of our classifier, the loss function should be defined. The loss will be high if the predicted class does not correspond to the ground truth class and it will be low otherwise. During the experimentation phase the main target was to better train the network. An optimization procedure was taken place during the current thesis, given the appropriate attention to the loss function and the optimizer. This procedure resulted in finding the values for the set of weights, which minimize the loss function. Backpropagation is used to make those weigh and bias adjustments relative to the error, and the error itself measured using Binary Cross Entropy.

## 4.6 Voting Classifier

In this chapter we are going to analyze in depth the Voting Classifier and the reason why we have chosen it as the final step of the classification phase towards sentiment analysis of the brain signals, which is the problem examined in our thesis.

Firstly, we need to justify the decision for using the Voting Classifier. After selecting and optimizing all the machine learning algorithms used for our classification problem we had to choose the machine learning model which better classifies the input data. Choosing the learner which results in better and more accurate results is not an easy process. However, it may proven more useful to chain or group classifiers together, using the techniques of voting, weighting, and combining in order to construct the most accurate classifier possible. Ensemble learners are classifiers which provide this functionality in a variety of ways. The Random Forest Classifier, which presented in Chapter 4.5.4 is an example of a voting classifier or ensemble learner, which uses numerous decision trees in a single predictive model.

Taking this into consideration, we examined the possibility of using a voting classifier in our analysis in order to determine whether this option is a more appropriate solution to our problem. We fine-tuned all the ML algorithms presented in Chapter 4.5 by selecting the best values for their parameters in order to achieve the best performance for each one of the 5 training models. Moving on, we combined the predictions of the 5 machine learning algorithms using the Voting Classifier. A voting classifier is not an actual classifier but a wrapper for a set of different ML algorithms that are trained and evaluated in parallel in order to exploit the different peculiarities of each one of them. The final output on a prediction is taken by majority vote according to the following strategy:

**Soft voting**: The probability vector for each predicted class (for all classifiers) are summed up and averaged. We have also assigned weights to each classifier, so as to ensure that the predictions of the classifiers that perform best would have greater possibility of selecting their output. The winning class is the one corresponding to the highest value. The formula for selecting the final class is presented below:

$$\boxed{final\_class = \boldsymbol{argmax}\left( \left( \frac{1}{N_{classifiers}} \right) * \sum_{i=1}^{5} P_i \right)}$$

where $P_i$ is the probability of classifier i for the chosen class.

The following figure represents the general scheme of the Voting Classifier used in our thesis so as to better understand its logical modules.

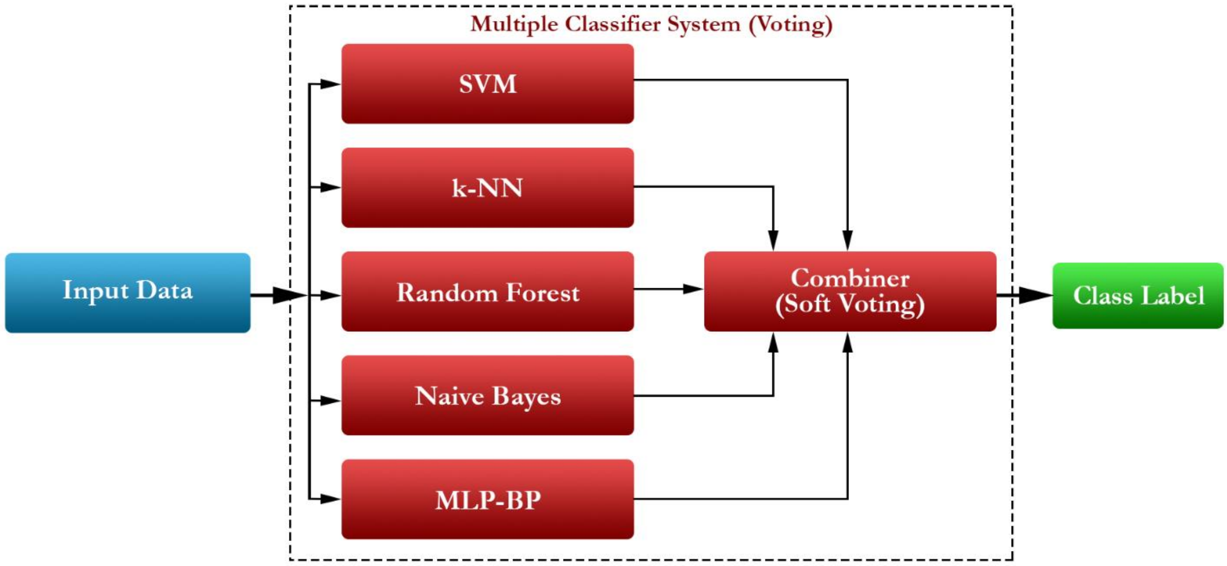


**Figure 11 Voting Classifier Scheme**

In conclusion, a voting classifier can be a good choice whenever a single strategy is not able to reach the desired accuracy threshold. A voting classifier allows the mixing of different classifiers, adopting a soft majority vote to decide which class must be considered as the "winning" one during the prediction process.

## 4.7 Emotion Mapping

Having introduced and explained all the techniques and methods for feature extraction, data augmentation, dimensionality reduction and classification it is time to explain how to perform the mapping from the emotion related labels predicted in Chapter 4.5 to the most basic and powerful emotions that presented in Chapter 1. For reminder, these are: happy, sad, excited and relaxed.

In order to perform the mapping we are going to use a scientific model. This model is based on Russell's circumplex model of emotions. As it is clear from the scientific model, the main two emotion related labels that we are going to use are valence and arousal. As we have already mentioned in Chapter 4.1.2, arousal and valence are binary variables which means that they can be assigned with 0 and 1 values. Based on Figure 2 presented below, the formulation for the mapping is rather simple.

- If valence = **1** and arousal = **1** then: **emotion→Happy**
- If valence = **1** and arousal = **0** then: **emotion→Relaxed**
- If valence = **0** and arousal = **0** then: **emotion→Sad**
- If valence = **0** and arousal = **1** then: **emotion→Angry**

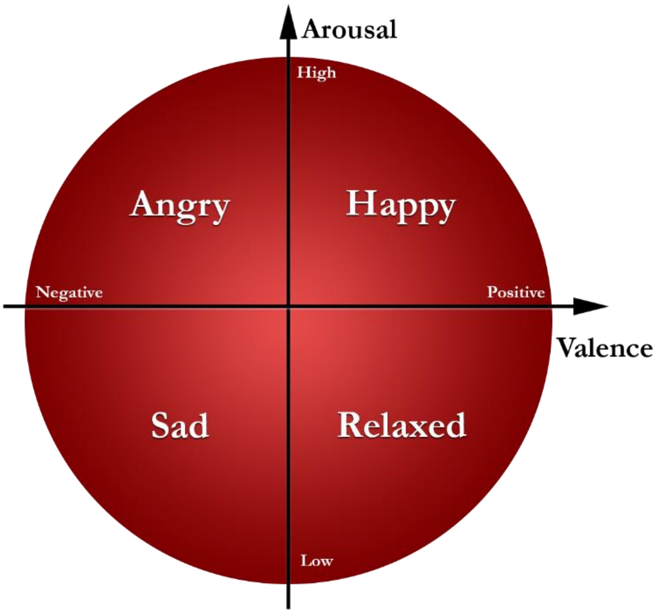


**Figure 12 Russell's circumplex model of emotions**

## 4.8 Music Recommendation System

In this final chapter of methodology we are going to introduce the music recommendation mechanism, we managed to implement using LAST.FM's database. It is important to mention that the music recommendation system will base its output on the voting classifier along with the emotion mapping mechanism that were described in chapter 4.6 and chapter 4.7 respectively. Since, Russell's circumplex model of emotions is using valence and arousal in order to perform the emotion mapping mechanism, we are going to use this output along with the remaining two emotion related labels (dominance, liking) in order to calculate a score, concerning the emotional resonance for the music videos. Furthermore, we implemented 3 different recommendation systems, one per UC. For reminder, all UCs were described in Chapter 4.1.3. The mathematical formula that we created in order to calculate the score for each music video is presented below:

$$\boxed{\boldsymbol{music\_video_{score}} = \sum_{i=0}^{K} \sum_{e} (b_{i_e} * a_e * weight_i)}$$

Where:

- $K$: the total number of participants watched the current music video.
- $e$: emotion set { happy, relaxed, sad, angry }
- $\mathrm{b}_{\mathrm{i}_\mathrm{e}}$: binary variable (0, 1) concerning if the participant i had or not the specific emotion $e$
- $a_e$: variable concerning the importance of the emotion. We used two different types of this variable in our UCs. More specifically:

  **UC1 and UC2:**

  1. $a_e = \mathbf{4}$ if $e$ $=$ happy
  2. $a_e = \mathbf{3}$ if $e$ $=$ relaxed
  3. $a_e = \mathbf{2}$ if $e$ $=$ sad
  4. $a_e = \mathbf{1}$ if $e$ $=$ angry

  **UC3:**

  5. $a_e = \mathbf{10}$ if $e$ $=$ happy
  6. $a_e = \mathbf{5}$ if $e$ $=$ relaxed
  7. $a_e = \mathbf{2}$ if $e$ $=$ sad
  8. $a_e = \mathbf{1}$ if $e$ $=$ angry

- $weight_i$: variable that takes into consideration the remaining two emotion related labels predicted by the voting algorithm (dominance, liking) of the participant i. More specifically:

  1. $weight_i = -1$ if dominance = 0 and liking = 0
  2. $weight_i = -1/2$ if dominance = 1 and liking = 0
  3. $weight_i = 1/2$ if dominance = 0 and liking = 1
  4. $weight_i = 1$ if dominance = 1 and liking = 1

The next step is to select the music videos with the highest scores in order to use them as reference for the recommendation list. The implemented mechanism for the recommendation list is described thoroughly below.

**Recommendation Mechanism:**

We selected the top 5 music videos with the highest computed score as a base for our recommendation list. For each of the 5 music videos we retrieve the $k_i$ most similar songs from the LAST.FM database. The retrieval was based on the genre, style and mood of the initial music video. Moving on, the $k_i$ variable was selected using the method presented below:

$$\boxed{\{k_i = \frac{k_{i-1}}{2}, k_1 = 16 \; and \; i = 2, \ldots, 5\}}$$

$k_1$: the initial value of k for the music video with the highest score

$i$: the index of each music video in the top 5 list.

At this point it should be noted that if there were no similar songs retrieved from the LAST.FM database, then the proposed recommendation list was based solely on the artist.

# 5. EXPERIMENTAL RESULTS

After analyzing and describing our complete methodology used for the implementation of this thesis, it is time to present our experimental results in order to validate our claims.

Firstly, it is really important to present the environment in which these experiments took place. All the experiments have been executed using the anaconda navigator platform 1.8.7 combined with Jupyter Notebook 5.5.0 and Python 3.6.8. The Operating System of our choice was Ubuntu 16.04 LTS.

Moving on, the system used for these experiments has the specification mentioned below:

- Intel Core i7-6800k @ 4.1GHz 6/12 - Core processor
- 32 GB 3000MHz of DDR4 Ram
- Nvidia GeForce GTX 1050 - Ti graphics card with 4GB of VRam

The following chapters will present all the experimental results of our research for all the UCs presented in Chapter 4.1.3

## 5.1 Subject Independent Experimentation and Results

The first results in this chapter are about the UC1. The following figures will present the accuracy and the f1 score (see Chapter 2) for all the algorithms used and described in Chapter 4.5

***Figures 13 - 20*** present the accuracy and the f1 score for all the algorithms using the Discrete Wavelet Transform Feature Extraction Method along with Standard Deviation (see Chapter 4.2.1)

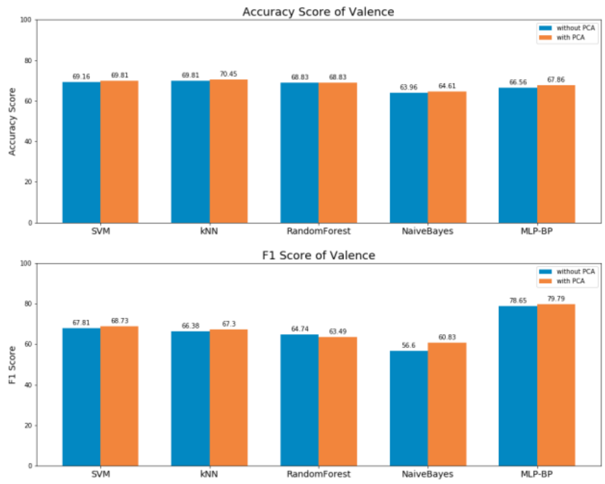


**Figure 13 Accuracy and f1 Score for Valence for all algorithms in UC1 using DWT and Standard Deviation for feature extraction**

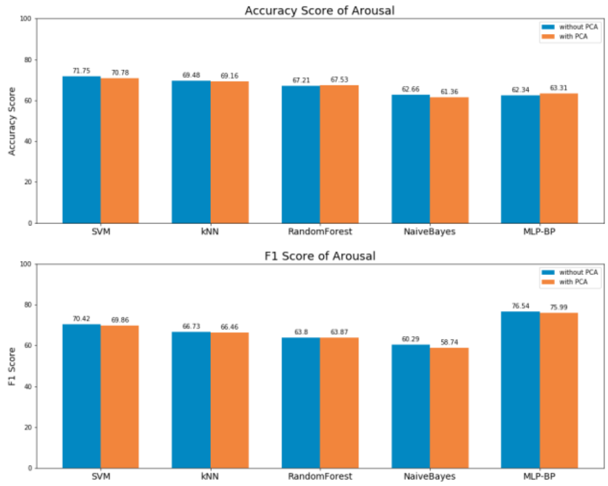


**Figure 14 Accuracy and f1 Score for Arousal for all algorithms in UC1 using DWT and Standard Deviation for feature extraction**

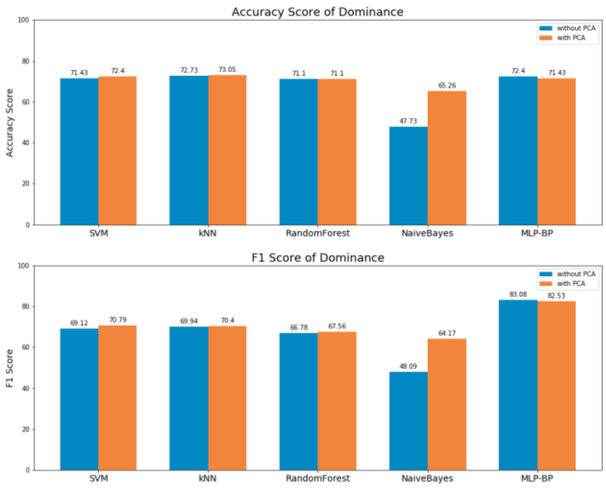


**Figure 15 Accuracy and f1 Score for Dominance for all algorithms in UC1 using DWT and Standard Deviation for feature extraction**

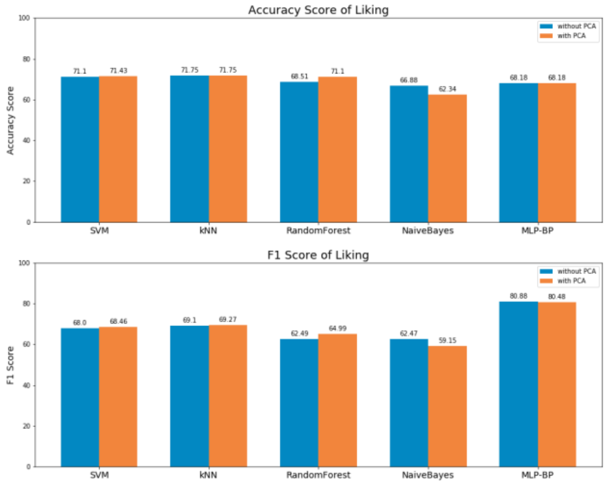


**Figure 16 Accuracy and f1 Score for Liking for all algorithms in UC1 using DWT and Standard Deviation for feature extraction**

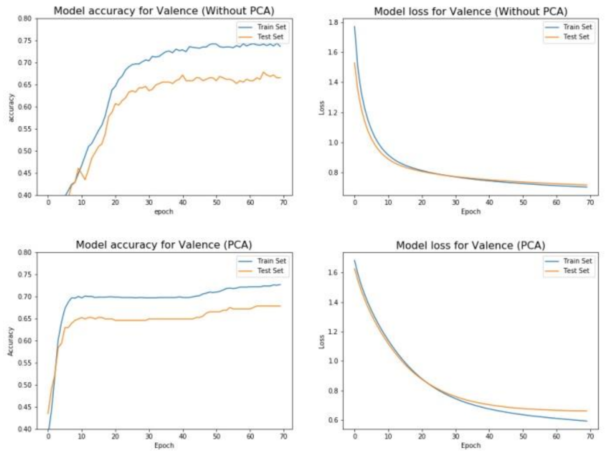


**Figure 17 Model Accuracy and Model Loss (binary Cross Entropy) for Valence for the MLP-BP Algorithm along with DWT and Standard Deviation for feature extraction in UC1**

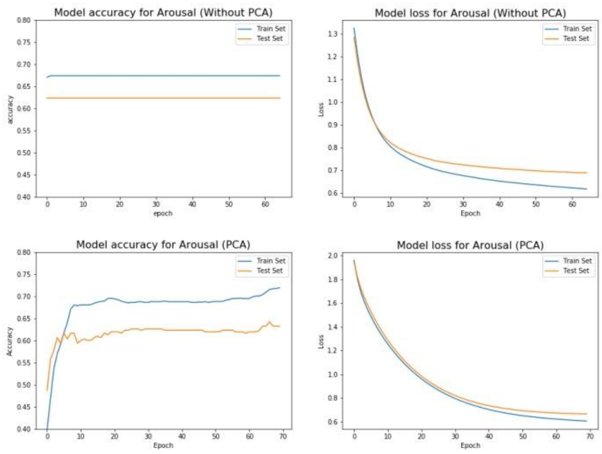


**Figure 18 Model Accuracy and Model Loss (binary Cross Entropy) for Arousal for the MLP-BP Algorithm along with DWT and Standard Deviation for feature extraction in UC1**

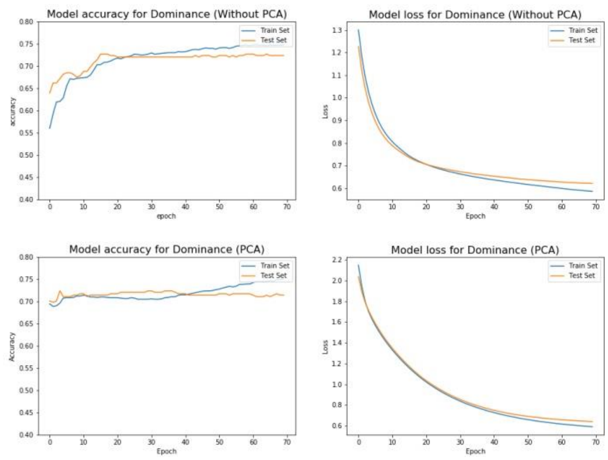


**Figure 19 Model Accuracy and Model Loss (binary Cross Entropy) for Dominance for the MLP-BP Algorithm along with DWT and Standard Deviation for feature extraction in UC1**

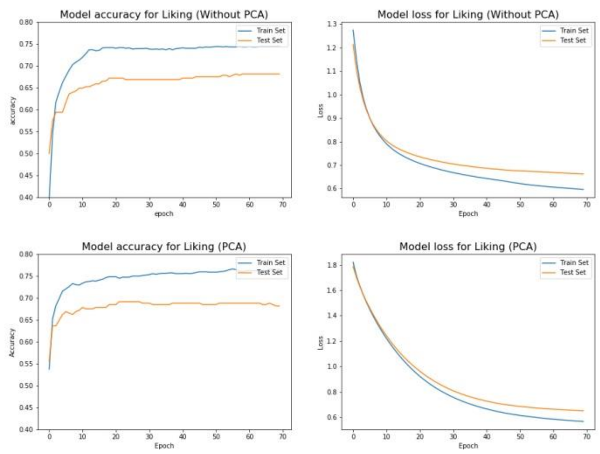


**Figure 20 Model Accuracy and Model Loss (binary Cross Entropy) for Liking using for the MLP-BP Algorithm along with DWT and Standard Deviation for feature extraction in UC1**

In order to sum up the results for accuracy and f1 score, we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 1 Feature Extraction Method: DWT with Standard Deviation in UC1**

| Feature Extraction Method: DWT with Standard Deviation | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=40) | | | |
| Algorithm | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| SVM | 69.16 / 67.81 | 71.75 / 70.42 | 71.43 / 69.12 | 71.1 / 68.0 | 69.81 / 68.73 | 70.78 / 69.86 | 72.4 / 70.79 | 71.43 / 68.46 |
| k-NN | 69.81 / 66.38 | 69.48 / 66.73 | 72.73 / 69.94 | 71.75 / 69.1 | 70.45 / 67.3 | 69.16 / 66.46 | 73.05 / 70.4 | 71.75 / 69.27 |
| RF | 68.83 / 64.74 | 67.21 / 63.8 | 71.1 / 66.78 | 68.51 / 62.49 | 68.83 / 63.49 | 67.53 / 63.87 | 71.1 / 67.56 | 71.1 / 64.99 |
| NB | 63.96 / 56.6 | 62.66 / 60.29 | 47.73 / 48.09 | 66.88 / 62.47 | 64.61 / 60.83 | 61.36 / 58.74 | 65.26 / 64.17 | 62.34 / 59.15 |
| MLP-BP | 66.56 / 78.65 | 62.34 / 76.54 | 72.4 / 83.08 | 68.18 / 80.88 | 67.86 / 79.79 | 63.31 / 75.99 | 71.43 / 82.53 | 68.18 / 80.48 |

Moving on, ***Figures 21 - 28*** present the accuracy and the f1 score for all the algorithms using the Discrete Wavelet Transform Feature Extraction Method along with Approximate Entropy (see Chapter 4.2.1)

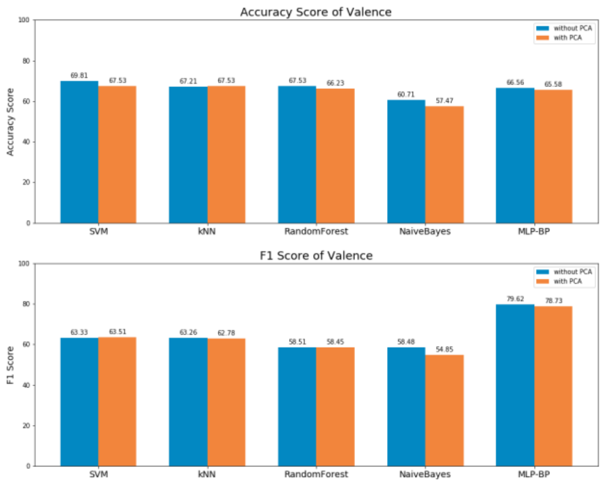


**Figure 21 Accuracy and f1 Score for Valence for all algorithms in UC1 using DWT and Approximate Entropy for feature extraction**

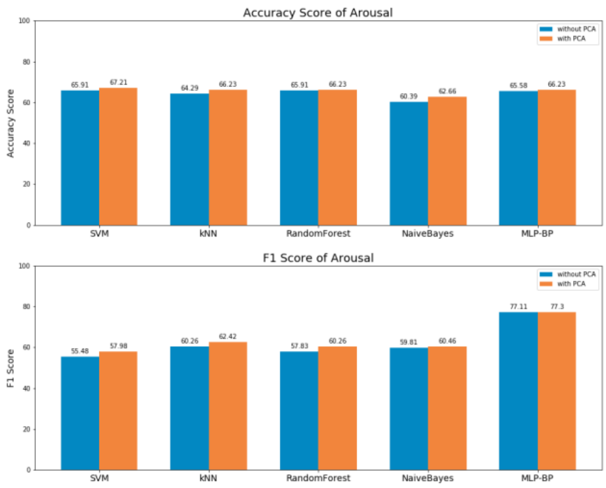


**Figure 22 Accuracy and f1 Score for Arousal for all algorithms in UC1 using DWT and Approximate Entropy for feature extraction**

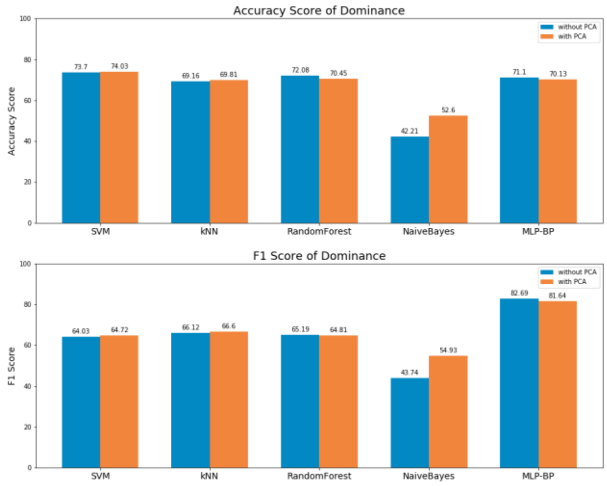


**Figure 23 Accuracy and f1 Score for Dominance for all algorithms in UC1 using DWT and Approximate Entropy for feature extraction**

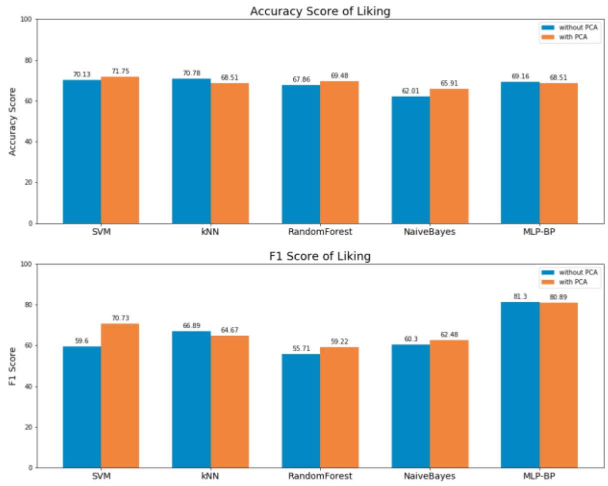


**Figure 24 Accuracy and f1 Score for Liking for all algorithms in UC1 using DWT and Approximate Entropy for feature extraction**

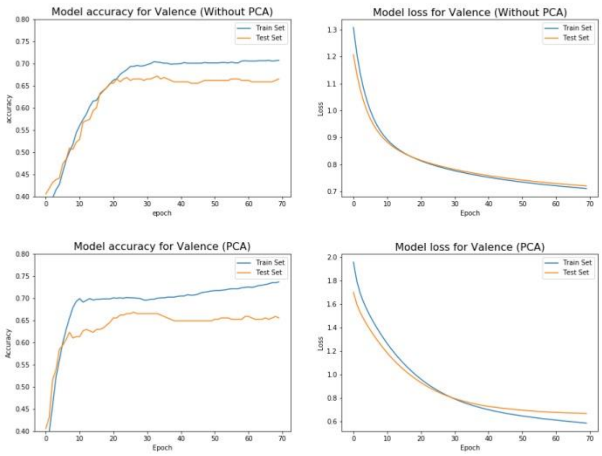


**Figure 25 Model Accuracy and Model Loss (binary Cross Entropy) for Valence for the MLP-BP Algorithm along with DWT and Approximate Entropy for feature extraction in UC1**

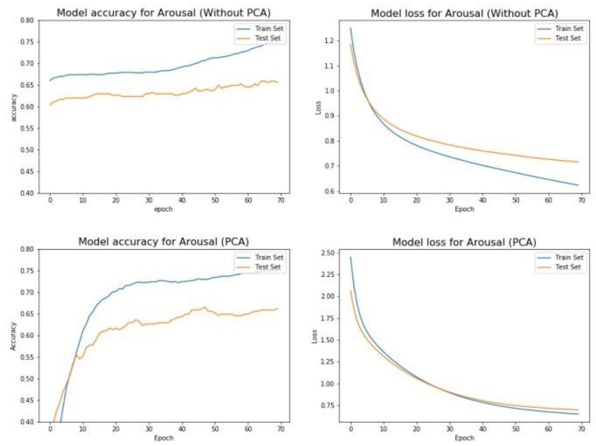


**Figure 26 Model Accuracy and Model Loss (binary Cross Entropy) for Arousal for the MLP-BP Algorithm along with DWT and Approximate Entropy for feature extraction in UC1**

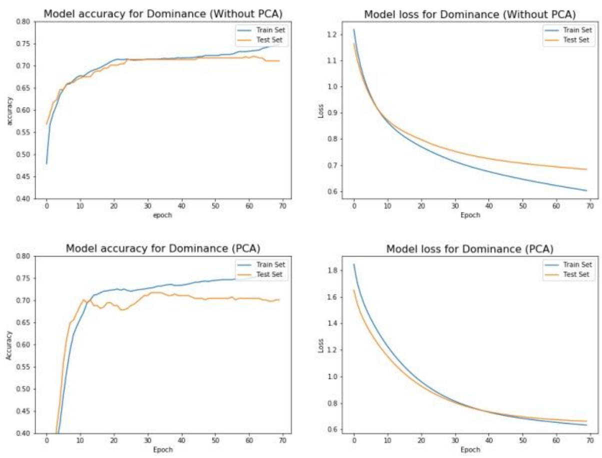


**Figure 27 Model Accuracy and Model Loss (binary Cross Entropy) for Dominance for the MLP-BP Algorithm along with DWT and Approximate Entropy for feature extraction in UC1**

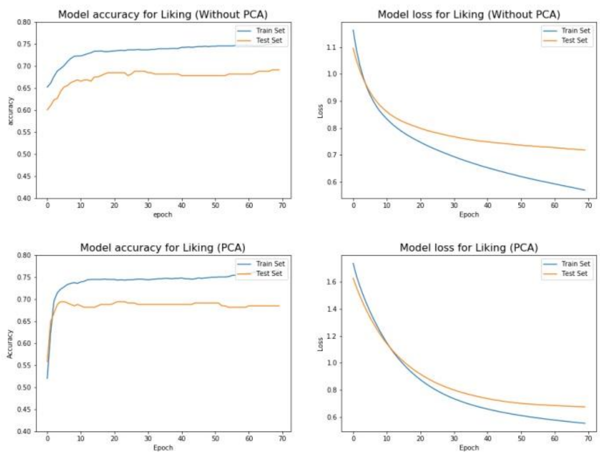


**Figure 28 Model Accuracy and Model Loss (binary Cross Entropy) for Liking using for the MLP-BP Algorithm along with DWT and Approximate Entropy for feature extraction in UC1**

In order to sum up the results for accuracy and f1 score, we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L**, Accuracy: **Acc**, f1 Score: **f1**

**Table 2 Feature Extraction Method: DWT with Approximate Entropy in UC1**

| Feature Extraction Method: DWT with Approximate Entropy | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=40) | | | |
| **Algorithm** | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| **SVM** | 69.81 / 63.33 | 65.91 / 55.48 | 73.7 / 64.03 | 70.13 / 59.6 | 67.53 / 63.51 | 67.21 / 57.98 | 74.03 / 64.72 | 71.75 / 70.73 |
| **k-NN** | 67.21 / 63.26 | 64.29 / 60.26 | 69.16 / 66.12 | 70.78 / 66.89 | 67.53 / 62.78 | 66.23 / 62.42 | 69.81 / 66.6 | 68.51 / 64.67 |
| **RF** | 67.53 / 58.51 | 65.91 / 57.83 | 72.08 / 65.19 | 67.86 / 55.71 | 66.23 / 58.45 | 66.23 / 60.26 | 70.45 / 64.81 | 69.48 / 59.22 |
| **NB** | 60.71 / 58.48 | 60.39 / 59.81 | 42.21 / 43.74 | 62.01 / 60.3 | 57.47 / 54.85 | 62.66 / 60.46 | 52.6 / 54.93 | 65.91 / 62.48 |
| **MLP-BP** | 66.56 / 79.62 | 65.58 / 77.11 | 71.1 / 82.69 | 69.16 / 81.3 | 65.58 / 78.73 | 66.23 / 77.3 | 70.13 / 81.64 | 68.51 / 80.89 |

Moving on, ***Figures 29 - 36*** present the accuracy and the f1 score for all the algorithms using the Power Spectral Density Feature Extraction Method along with Standard Deviation (see Chapter 4.2.3)

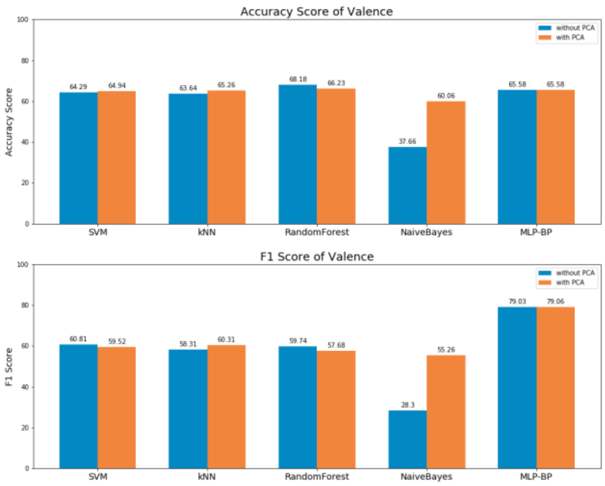


**Figure 29 Accuracy and f1 Score for Valence for all algorithms in UC1 using PSD and Standard Deviation for feature extraction**

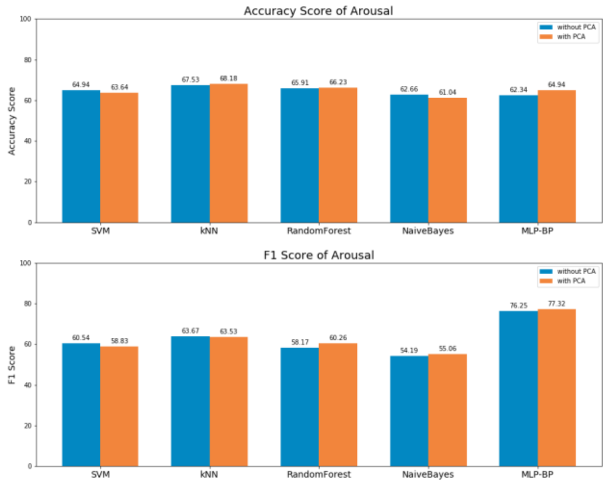


**Figure 30 Accuracy and f1 Score for Arousal for all algorithms in UC1 using PSD and Standard Deviation for feature extraction**

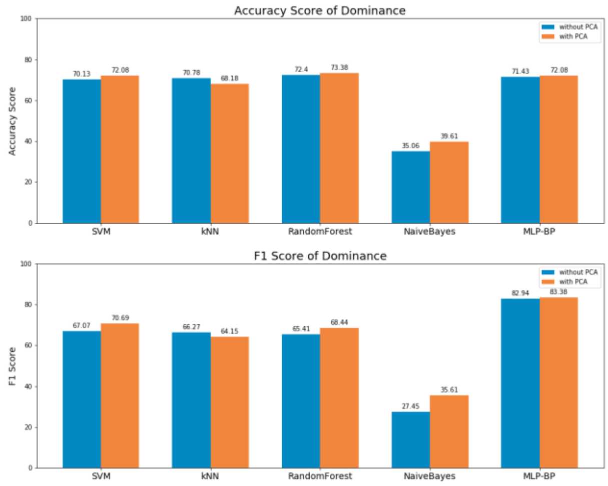


**Figure 31 Accuracy and f1 Score for Dominance for all algorithms in UC1 using PSD and Standard Deviation for feature extraction**

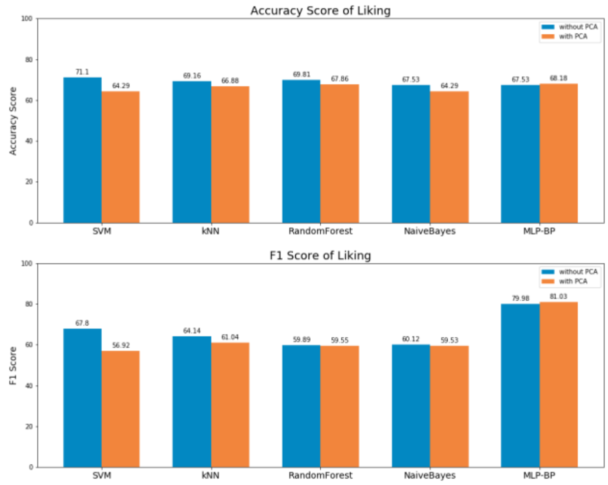


**Figure 32 Accuracy and f1 Score for Liking for all algorithms in UC1 using PSD and Standard Deviation for feature extraction**

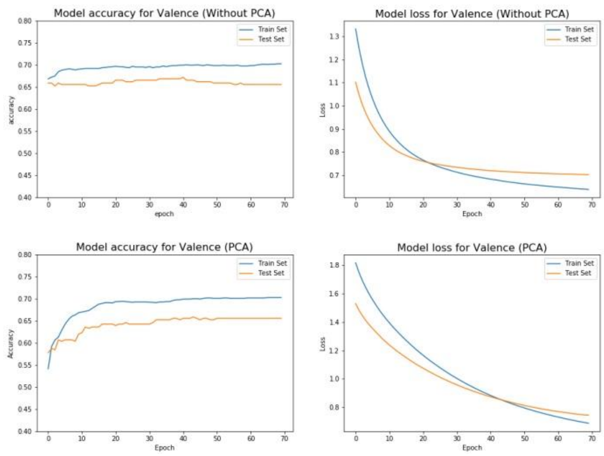


**Figure 33 Model Accuracy and Model Loss (binary Cross Entropy) for Valence for the MLP-BP Algorithm along with PSD and Standard Deviation for feature extraction in UC1**

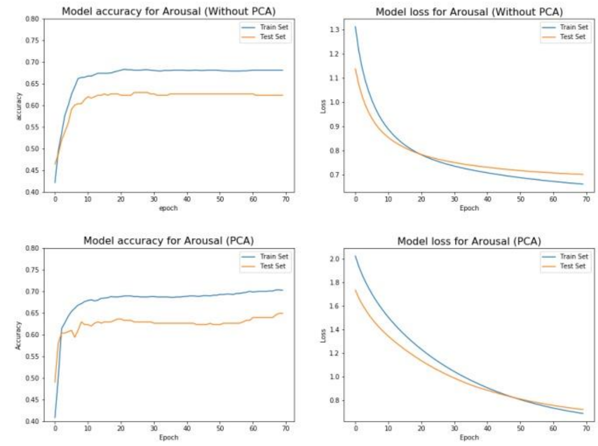


**Figure 34 Model Accuracy and Model Loss (binary Cross Entropy) for Arousal for the MLP-BP Algorithm along with PSD and Standard Deviation for feature extraction in UC1**

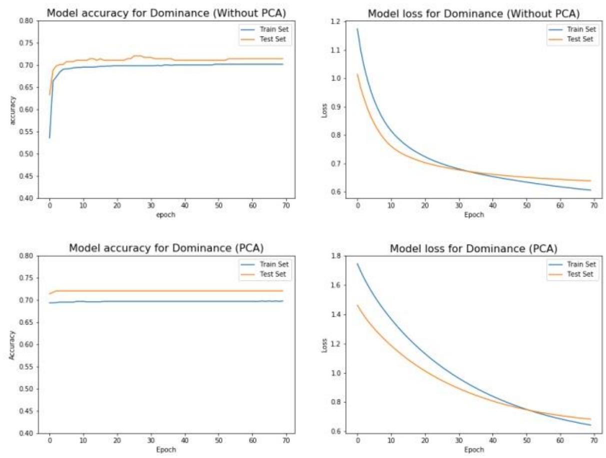


**Figure 35 Model Accuracy and Model Loss (binary Cross Entropy) for Dominance for the MLP-BP Algorithm along with PSD and Standard Deviation for feature extraction in UC1**

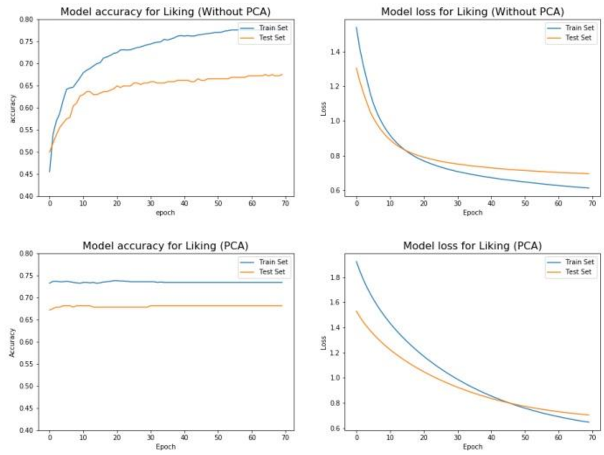


**Figure 36 Model Accuracy and Model Loss (binary Cross Entropy) for Liking using for the MLP-BP Algorithm along with PSD and Standard Deviation for feature extraction in UC1**

In order to sum up the results for accuracy and f1 score, we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 3 Feature Extraction Method: PSD with Standard Deviation in UC1**

| Feature Extraction Method: PSD with Standard Deviation | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=40) | | | |
| **Algorithm** | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| **SVM** | 64.29 / 60.81 | 64.94 / 60.54 | 70.13 / 67.07 | 71.1 / 67.8 | 64.94 / 59.52 | 63.64 / 58.83 | 72.08 / 70.69 | 64.29 / 59.62 |
| **k-NN** | 63.64 / 58.31 | 67.53 / 63.67 | 70.78 / 66.27 | 69.16 / 64.14 | 65.26 / 60.31 | 68.18 / 63.53 | 68.18 / 64.15 | 66.88 / 61.04 |
| **RF** | 68.18 / 59.74 | 65.91 / 58.17 | 72.4 / 65.41 | 69.81 / 59.89 | 66.23 / 57.68 | 66.23 / 60.26 | 73.38 / 68.44 | 67.86 / 59.55 |
| **NB** | 37.66 / 28.3 | 62.66 / 54.19 | 35.06 / 27.45 | 67.53 / 60.12 | 60.06 / 55.26 | 61.04 / 55.06 | 39.61 / 35.61 | 64.29 / 59.53 |
| **MLP-BP** | 66.58 / 79.03 | 62.34 / 76.25 | 71.43 / 82.94 | 67.53 / 79.98 | 65.58 / 79.06 | 64.94 / 77.32 | 72.08 / 83.38 | 68.51 / 81.03 |

Moving on, ***Figures 37 - 44*** present the accuracy and the f1 score for all the algorithms using the Power Spectral Density Feature Extraction Method along with Approximate Entropy (see Chapter 4.2.3)

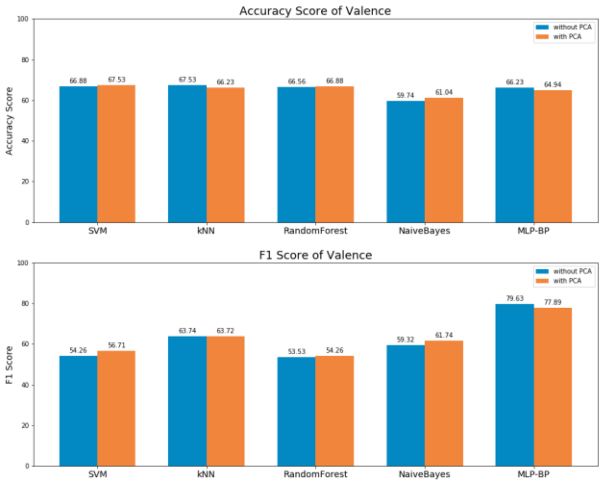


**Figure 37 Accuracy and f1 Score for Valence for all algorithms in UC1 using PSD and Approximate Entropy for feature extraction**

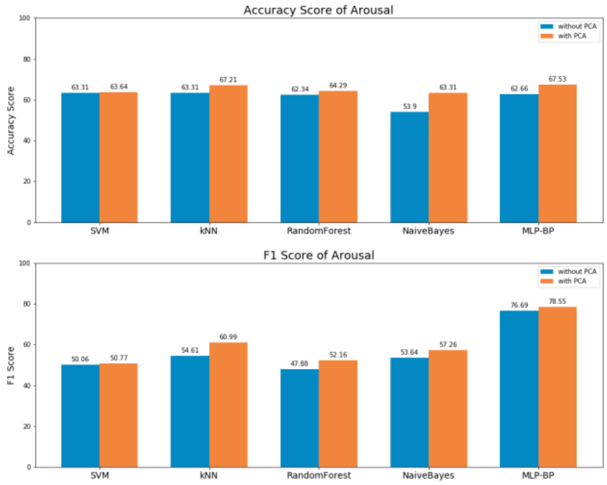


**Figure 38 Accuracy and f1 Score for Arousal for all algorithms in UC1 using PSD and Approximate Entropy for feature extraction**

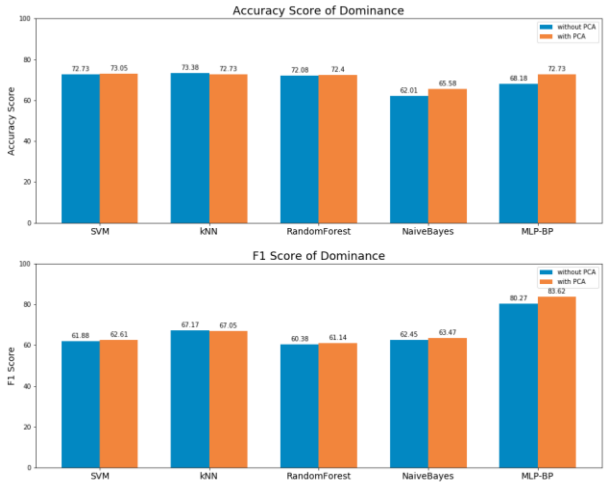


**Figure 39 Accuracy and f1 Score for Dominance for all algorithms in UC1 using PSD and Approximate Entropy for feature extraction**

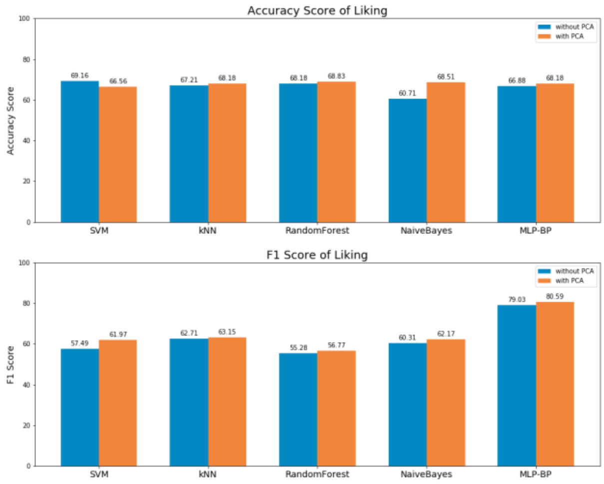


**Figure 40 Accuracy and f1 Score for Liking for all algorithms in UC1 using PSD and Approximate Entropy for feature extraction**

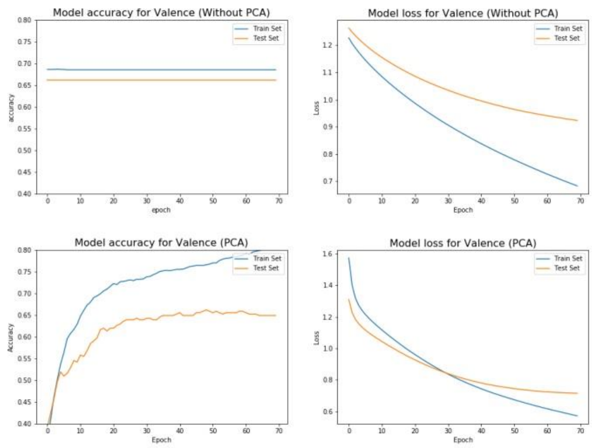


**Figure 41 Model Accuracy and Model Loss (binary Cross Entropy) for Valence for the MLP-BP Algorithm along with PSD and Approximate Entropy for feature extraction in UC1**

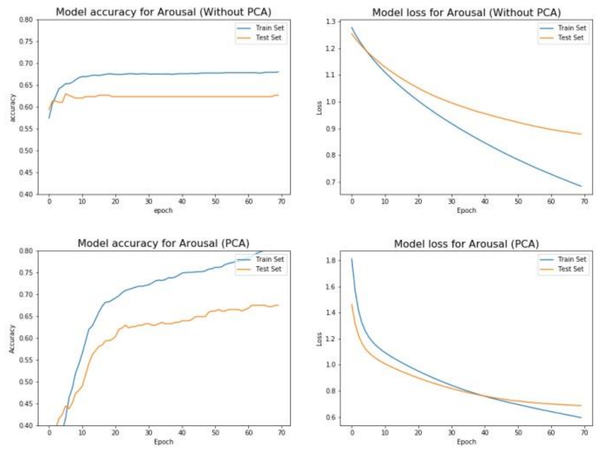


**Figure 42 Model Accuracy and Model Loss (binary Cross Entropy) for Arousal for the MLP-BP Algorithm along with PSD and Approximate Entropy for feature extraction in UC1**

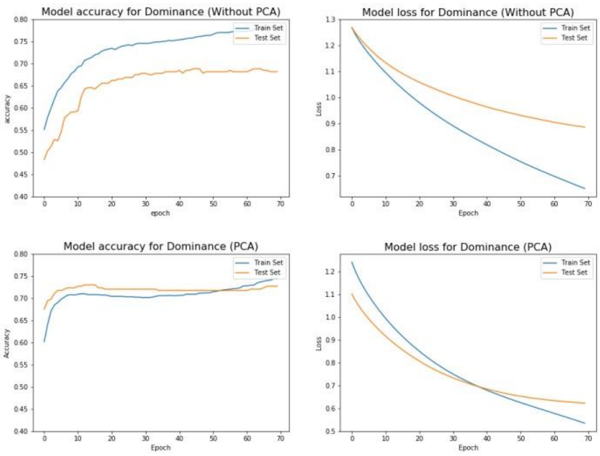


**Figure 43 Model Accuracy and Model Loss (binary Cross Entropy) for Dominance for the MLP-BP Algorithm along with PSD and Approximate Entropy for feature extraction in UC1**

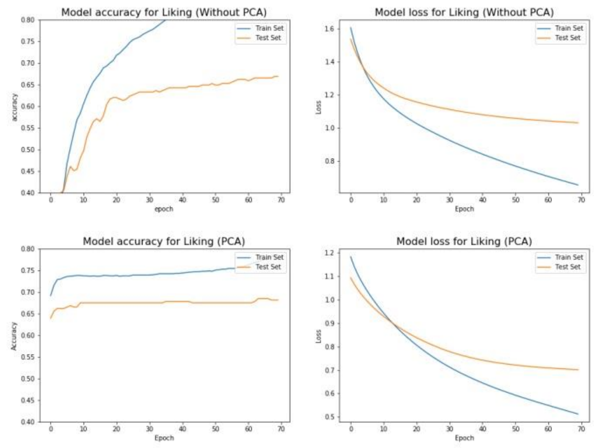


**Figure 44 Model Accuracy and Model Loss (binary Cross Entropy) for Liking using for the MLP-BP Algorithm along with PSD and Approximate Entropy for feature extraction in UC1**

In order to sum up the results for accuracy and f1 score, we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 4 Feature Extraction Method: PSD with Approximate Entropy in UC1**

| Feature Extraction Method: PSD with Approximate Entropy | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=40) | | | |
| Algorithm | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| SVM | 66.88 / 54.26 | 63.31 / 50.06 | 72.73 / 61.88 | 69.16 / 57.49 | 67.53 / 56.71 | 63.64 / 50.77 | 73.05 / 62.61 | 66.56 / 61.97 |
| k-NN | 67.53 / 63.74 | 63.31 / 54.61 | 73.38 / 67.17 | 67.21 / 62.71 | 66.23 / 63.72 | 67.21 / 60.99 | 72.73 / 67.05 | 68.18 / 63.15 |
| RF | 66.56 / 53.53 | 62.34 / 47.88 | 72.08 / 60.38 | 68.18 / 55.28 | 66.88 / 54.26 | 64.29 / 52.16 | 72.4 / 61.14 | 68.83 / 56.77 |
| NB | 59.74 / 59.32 | 53.9 / 53.64 | 62.01 / 62.45 | 60.71 / 60.31 | 61.04 / 61.74 | 63.31 / 57.26 | 65.58 / 63.47 | 68.51 / 62.17 |
| MLP-BP | 66.23 / 79.63 | 62.66 / 76.69 | 68.18 / 80.27 | 66.88 / 79.03 | 64.94 / 77.89 | 67.53 / 78.55 | 72.73 / 83.62 | 68.18 / 80.59 |

Moving on, ***Figures 45 - 52*** present the accuracy and the f1 score for all the algorithms using the Short Time Fourier Transform Feature Extraction Method along with Standard Deviation (see Chapter 4.2.2)

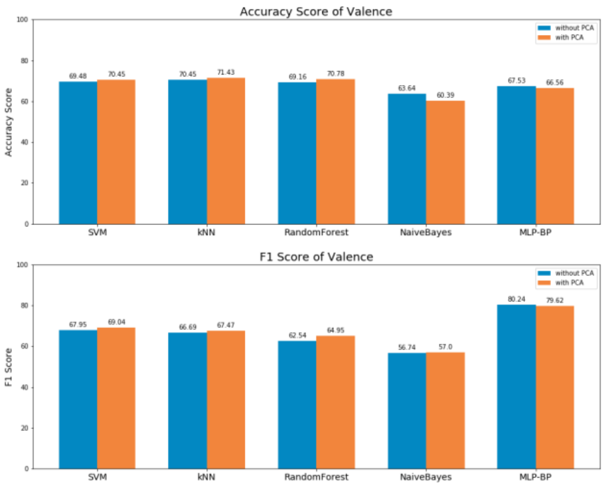


**Figure 45 Accuracy and f1 Score for Valence for all algorithms in UC1 using STFT and Standard Deviation for feature extraction**

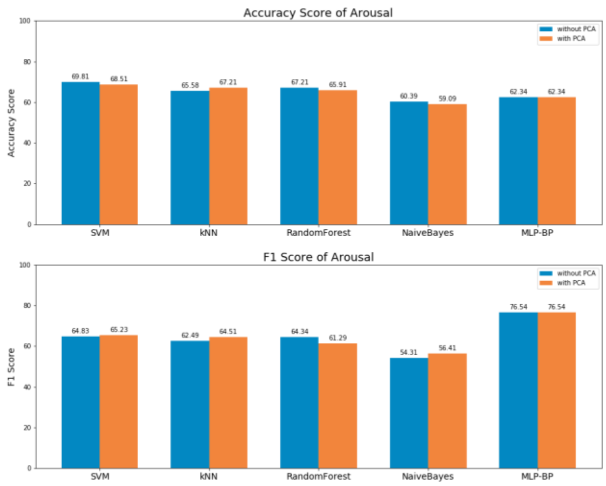


**Figure 46 Accuracy and f1 Score for Arousal for all algorithms in UC1 using STFT and Standard Deviation for feature extraction**

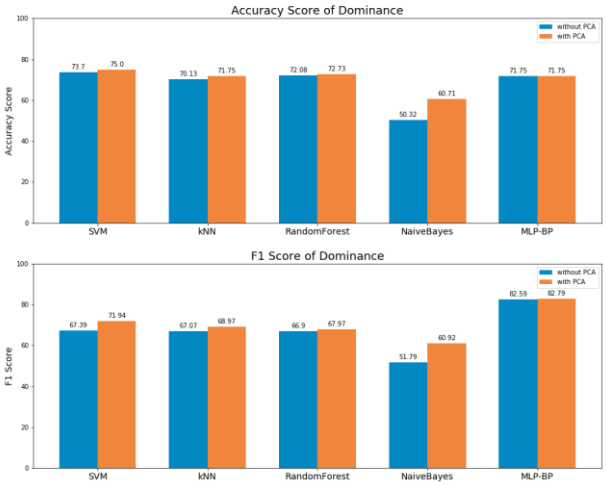


**Figure 47 Accuracy and f1 Score for Dominance for all algorithms in UC1 using STFT and Standard Deviation for feature extraction**

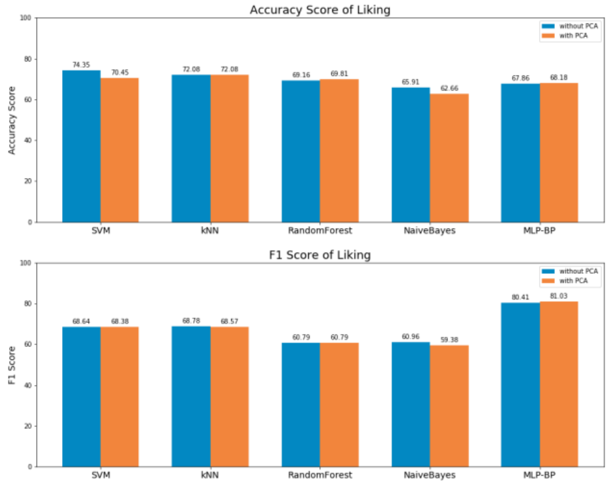


**Figure 48 Accuracy and f1 Score for Liking for all algorithms in UC1 using STFT and Standard Deviation for feature extraction**

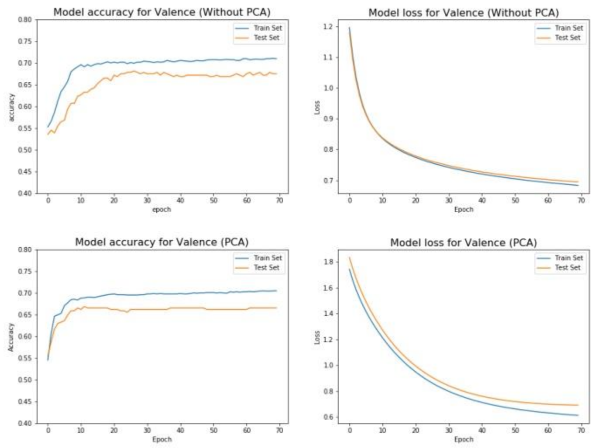


**Figure 49 Model Accuracy and Model Loss (binary Cross Entropy) for Valence for the MLP-BP Algorithm along with STFT and Standard Deviation for feature extraction in UC1**

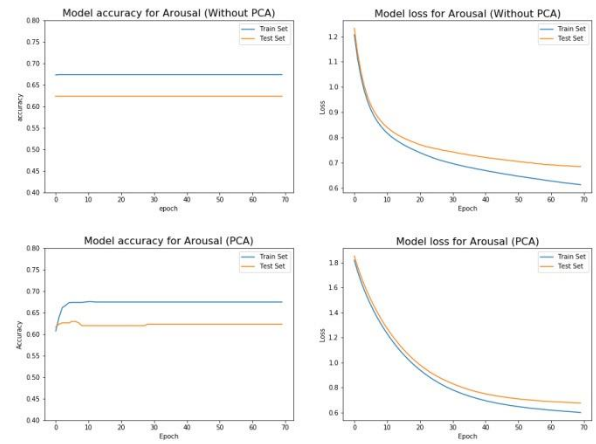


**Figure 50 Model Accuracy and Model Loss (binary Cross Entropy) for Arousal for the MLP-BP Algorithm along with STFT and Standard Deviation for feature extraction in UC1**

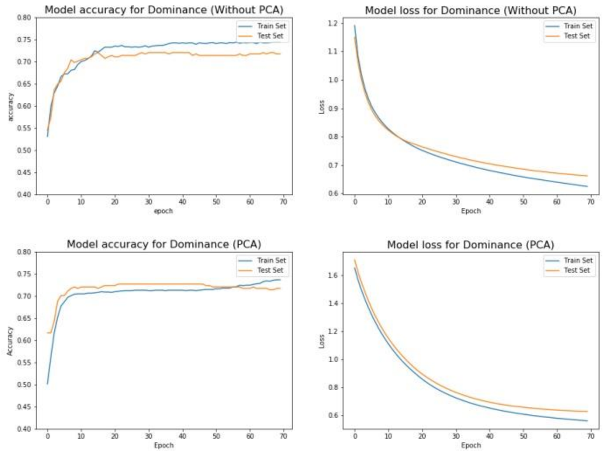


**Figure 51 Model Accuracy and Model Loss (binary Cross Entropy) for Dominance for the MLP-BP Algorithm along with STFT and Standard Deviation for feature extraction in UC1**

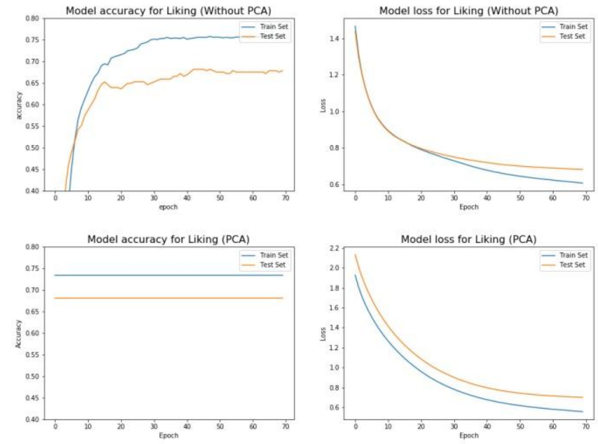


**Figure 52 Model Accuracy and Model Loss (binary Cross Entropy) for Liking using for the MLP-BP Algorithm along with STFT and Standard Deviation for feature extraction in UC1**

In order to sum up the results for accuracy and f1 score, we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 5 Feature Extraction Method: STFT with Standard Deviation in UC1**

| Feature Extraction Method: STFT with Standard Deviation | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=40) | | | |
| Algorithm | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| SVM | 69.48 / 67.95 | 69.81 / 64.83 | 73.7 / 67.39 | 74.35 / 68.64 | 70.45 / 69.04 | 68.51 / 65.23 | 75.0 / 71.94 | 70.45 / 68.38 |
| k-NN | 70.45 / 66.69 | 65.58 / 62.49 | 70.13 / 67.07 | 72.08 / 68.78 | 71.43 / 67.47 | 67.21 / 64.51 | 71.75 / 68.97 | 72.08 / 68.57 |
| RF | 69.16 / 62.54 | 67.21 / 64.34 | 72.08 / 66.9 | 69.16 / 60.79 | 70.78 / 64.95 | 65.91 / 61.29 | 72.73 / 67.97 | 69.81 / 60.79 |
| NB | 63.64 / 56.74 | 60.39 / 54.31 | 50.32 / 51.79 | 65.91 / 60.96 | 60.39 / 57.0 | 59.09 / 56.41 | 60.71 / 60.92 | 62.66 / 59.38 |
| MLP-BP | 67.53 / 80.24 | 62.34 / 76.54 | 71.75 / 82.59 | 67.86 / 80.41 | 66.56 / 79.62 | 62.64 / 76.54 | 71.75 / 82.79 | 68.18 / 81.03 |

Moving on, ***Figures 53 - 60*** present the accuracy and the f1 score for all the algorithms using the Short Time Fourier Transform Feature Extraction Method along with Approximate Entropy (see Chapter 4.2.2)

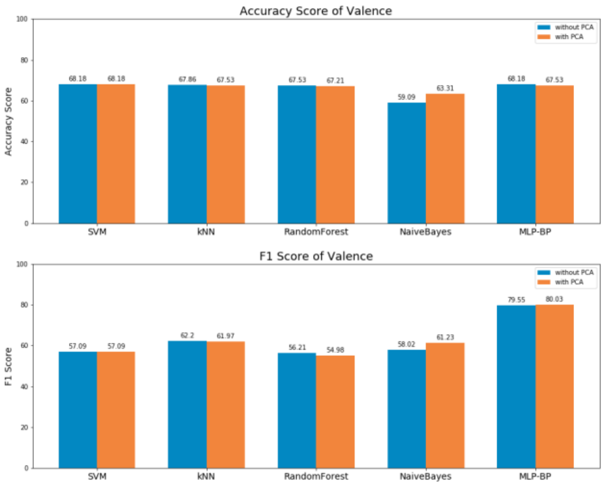


**Figure 53 Accuracy and f1 Score for Valence for all algorithms in UC1 using STFT and Approximate Entropy for feature extraction**


**Figure 54 Accuracy and f1 Score for Arousal for all algorithms in UC1 using STFT and Approximate Entropy for feature extraction**

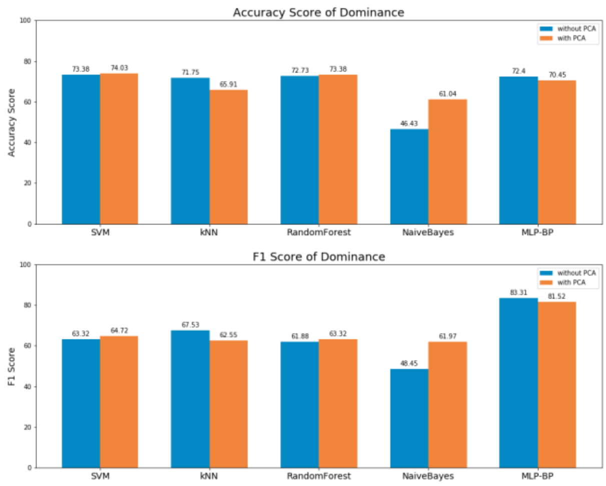


Figure 55 Accuracy and f1 Score for Dominance for all algorithms in UC1 using STFT and Approximate Entropy for feature extraction

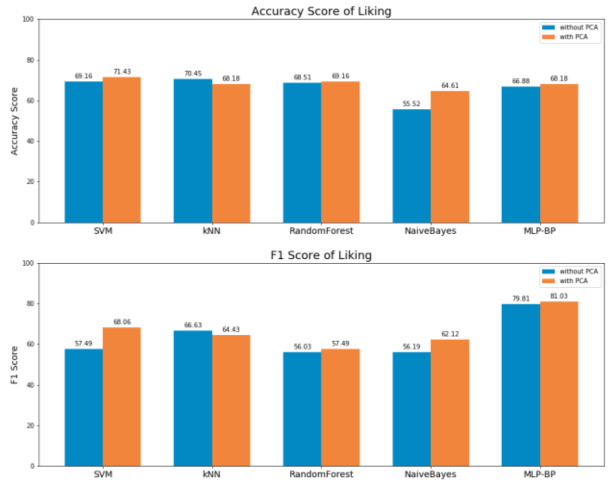


Figure 56 Accuracy and f1 Score for Liking for all algorithms using in UC1 STFT and Approximate Entropy for feature extraction

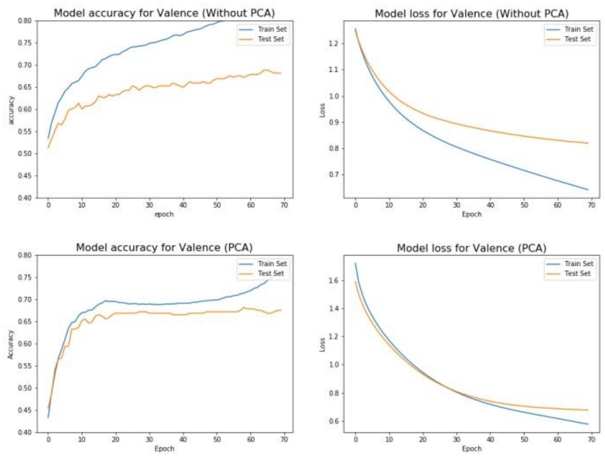


Figure 57 Model Accuracy and Model Loss (binary Cross Entropy) for Valence for the MLP-BP Algorithm along with STFT and Approximate Entropy for feature extraction in UC1

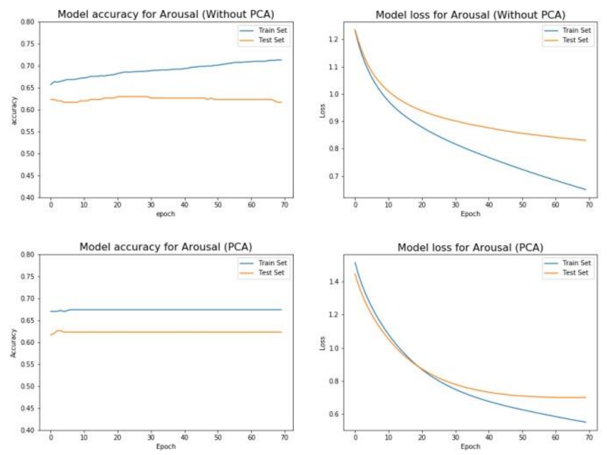


Figure 58 Model Accuracy and Model Loss (binary Cross Entropy) for Arousal for the MLP-BP Algorithm along with STFT and Approximate Entropy for feature extraction in UC1

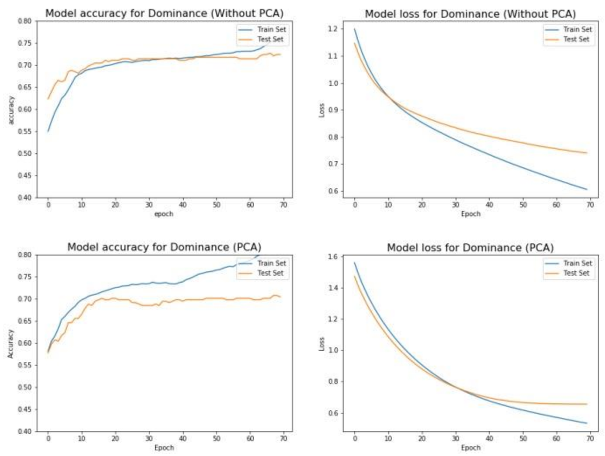


Figure 59 Model Accuracy and Model Loss (binary Cross Entropy) for Dominance for the MLP-BP Algorithm along with STFT and Approximate Entropy for feature extraction in UC1

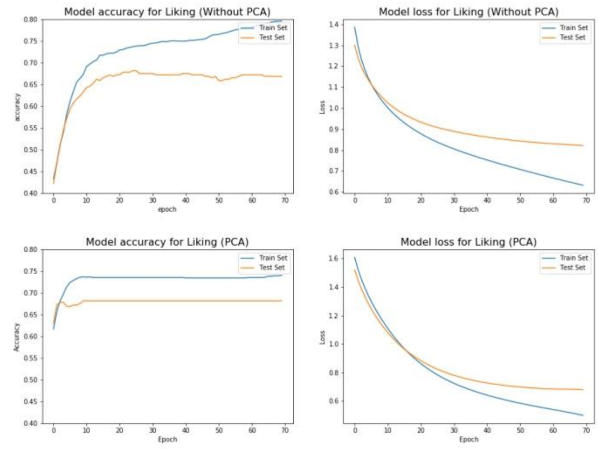


Figure 60 Model Accuracy and Model Loss (binary Cross Entropy) for Liking using for the MLP-BP Algorithm along with STFT and Approximate Entropy for feature extraction in UC1

In order to sum up the results for accuracy and f1 score, we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 6 Feature Extraction Method: STFT with Approximate Entropy in UC1**

| Feature Extraction Method: STFT with Approximate Entropy | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=40) | | | |
| **Algorithm** | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| **SVM** | 68.18 / 57.09 | 62.99 / 49.34 | 73.38 / 63.32 | 69.16 / 57.49 | 68.18 / 57.09 | 63.96 / 51.47 | 74.03 / 64.72 | 71.43 / 68.06 |
| **k-NN** | 67.86 / 62.2 | 62.01 / 56.33 | 71.75 / 67.53 | 70.45 / 66.63 | 67.53 / 61.97 | 64.61 / 59.82 | 65.91 / 62.55 | 68.18 / 64.43 |
| **RF** | 67.53 / 56.21 | 64.29 / 53.13 | 72.73 / 61.88 | 68.51 / 56.03 | 67.21 / 54.98 | 64.29 / 52.65 | 73.38 / 63.32 | 69.16 / 57.49 |
| **NB** | 59.09 / 58.02 | 56.82 / 56.24 | 46.43 / 48.45 | 55.52 / 56.19 | 63.31 / 61.23 | 61.04 / 55.35 | 61.04 / 61.97 | 64.61 / 62.12 |
| **MLP-BP** | 68.18 / 79.55 | 61.69 / 75.87 | 72.4 / 83.31 | 66.88 / 79.81 | 67.53 / 80.03 | 62.34 / 76.54 | 70.45 / 81.52 | 68.18 / 81.03 |

### 5.1.1 Voting Algorithm Results and Recommendation List

In this section, we are going to present the experimentation results for our voting algorithm in UC1. It is really important to mention that the results concern the emotion related labels only, since the voting algorithm with the method of soft voting (see Chapter 4.6) takes into consideration the weights assigned to each of the 5 algorithms in order to predict the emotion related label of each feature vector.

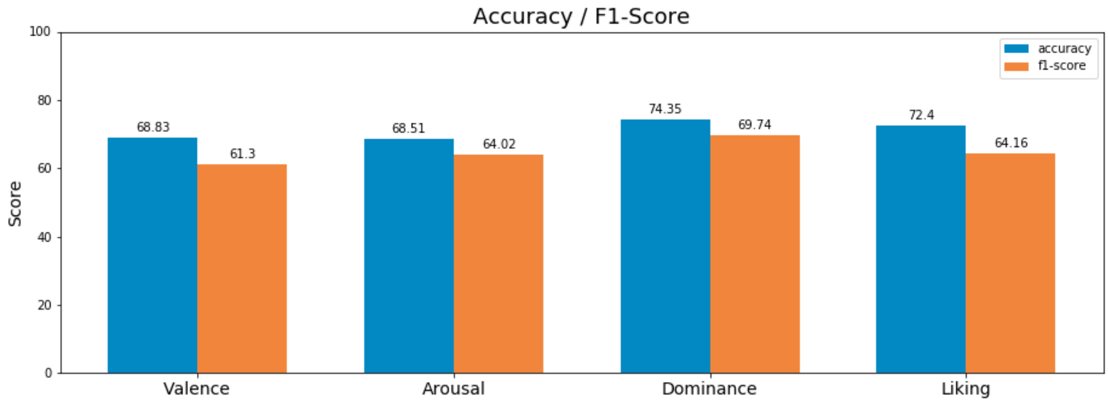


**Figure 61 Accuracy and f1 Score for emotion related labels for the voting algorithm in UC1 using STFT and standard deviation for feature extraction**

Based on the results presented above, we are going to construct the final recommendation list that was extracted from LAST.FM. We are going to use the method presented in Chapter 4.8.

**Recommendation List for all Participants**

**1. Blur , Beetlebum** https://www.last.fm/music/blur/_/beetlebum
**2. Blur , Parklife** https://www.last.fm/music/blur/_/parklife
**3. Oasis , Wonderwall** https://www.last.fm/music/oasis/_/wonderwall
**4. The Verve , Bitter Sweet Symphony** https://www.last.fm/music/the%2bverve/_/bitter%2bsweet%2bsymphony
**5. Franz Ferdinand , Take Me Out** https://www.last.fm/music/franz%2bferdinand/_/take%2bme%2bout
**6. The White Stripes , Seven Nation Army** https://www.last.fm/music/the%2bwhite%2bstripes/_/seven%2bnation%2barmy
**7. Oasis , Don't Look Back in Anger** https://www.last.fm/music/oasis/_/don%2527t%2blook%2bback%2bin%2banger
**8. Radiohead , Creep** https://www.last.fm/music/radiohead/_/creep
**9. Pulp , Common People** https://www.last.fm/music/pulp/_/common%2bpeople
**10. Kaiser Chiefs , Ruby** https://www.last.fm/music/kaiser%2bchiefs/_/ruby
**11. Supergrass , Alright** https://www.last.fm/music/supergrass/_/alright
**12. The Killers , Somebody Told Me** https://www.last.fm/music/the%2bkillers/_/somebody%2btold%2bme
**13. Beck , Loser** https://www.last.fm/music/beck/_/loser
**14. The Killers , Mr. Brightside** https://www.last.fm/music/the%2bkillers/_/mr.%2bbrightside
**15. R.E.M. , Losing My Religion** https://www.last.fm/music/r.e.m./_/losing%2bmy%2breligion
**16. Radiohead , Karma Police** https://www.last.fm/music/radiohead/_/karma%2bpolice
**17. The Jacksons , Blame It on the Boogie** https://www.last.fm/music/the%2bjacksons/_/blame%2bit%2bon%2bthe%2bboogie
**18. Michael Jackson , Billie Jean** https://www.last.fm/music/michael%2bjackson/_/billie%2bjean
**19. The Temptations , My Girl** https://www.last.fm/music/the%2btemptations/_/my%2bgirl
**20. The Supremes , You Can't Hurry Love** https://www.last.fm/music/the%2bsupremes/_/you%2bcan%2527t%2bhurry%2blove
**21. Jermaine Jackson , Let's Get Serious** https://www.last.fm/music/jermaine%2bjackson/_/let%2527s%2bget%2bserious
**22. Smokey Robinson and The Miracles , The Tracks Of My Tears**
https://www.last.fm/music/smokey%2brobinson%2band%2bthe%2bmiracles/_/the%2btracks%2bof%2bmy%2btears
**23. The Four Tops , I Can't Help Myself (Sugar Pie, Honey Bunch)**
https://www.last.fm/music/the%2bfour%2btops/_/i%2bcan%2527t%2bhelp%2bmyself%2b%2528sugar%2bpie%252c%2bhoney%2bbunch%2529
**24. The Miracles , Shop Around** https://www.last.fm/music/the%2bmiracles/_/shop%2baround
**25. Sia , Sweet Potato** https://www.last.fm/music/sia/_/sweet%2bpotato
**26. Sia , Numb** https://www.last.fm/music/sia/_/numb
**27. Birdy , Skinny Love** , https://www.last.fm/music/birdy/_/skinny%2blove
**28. A Fine Frenzy , Almost Lover** , https://www.last.fm/music/a%2bfine%2bfrenzy/_/almost%2blover
**29. Benny Benassi , Love Is Gonna Save Us** https://www.last.fm/music/benny%2bbenassi/_/love%2bis%2bgonna%2bsave%2bus
**30. Eric Prydz , Call On Me** https://www.last.fm/music/eric%2bprydz/_/call%2bon%2bme
**31. Box Car Racer , There Is** https://www.last.fm/music/box%2bcar%2bracer/_/there%2bis

## 5.2 Gender Dependent Experimentation and Results

The presented results in this chapter are about the UC2. The following figures will present the accuracy and the f1 score (see Chapter 2) for all the algorithms used and described in Chapter 4.5 for both males and females.

### 5.2.1 Experimentation Results for the Male Dataset

The following figures will present the experimental results concerning the **male dataset**.

***Figures 62 - 69*** present the accuracy and the f1 score for all the algorithms using the Discrete Wavelet Transform Feature Extraction Method along with Standard Deviation (see Chapter 4.2.1)

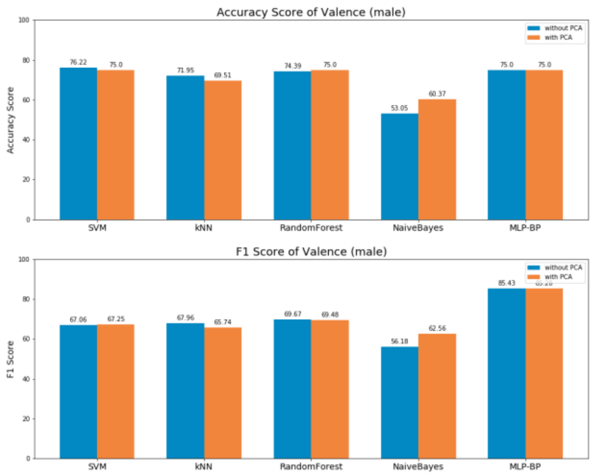


**Figure 62 Accuracy and f1 Score for Valence for all algorithms in UC2 (male dataset) using DWT and Standard Deviation for feature extraction**

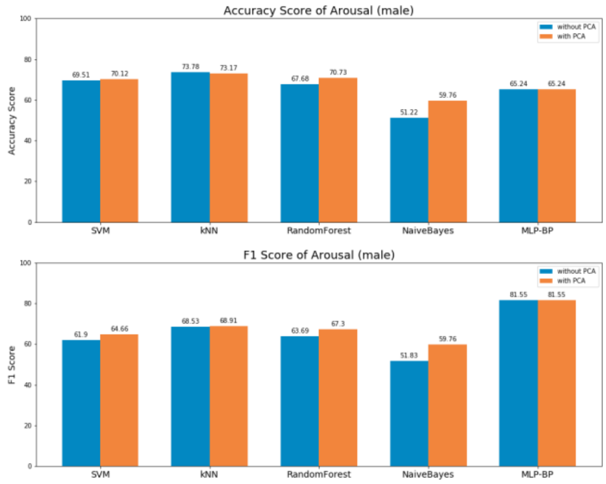


**Figure 63 Accuracy and f1 Score for Arousal for all algorithms in UC2 (male dataset) using DWT and Standard Deviation for feature extraction**

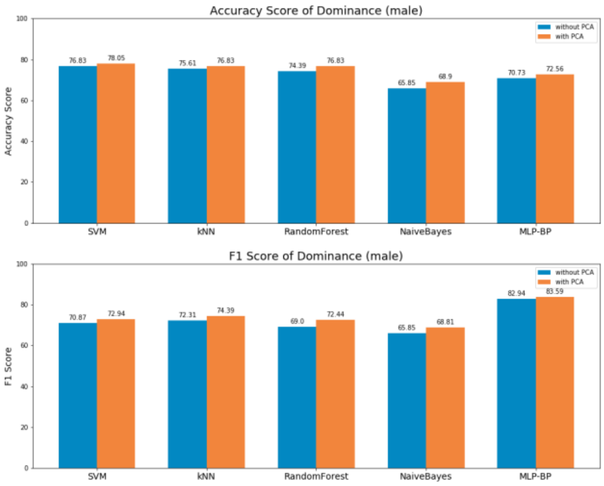


**Figure 64 Accuracy and f1 Score for Dominance for all algorithms in UC2 (male dataset) using DWT and Standard Deviation for feature extraction**

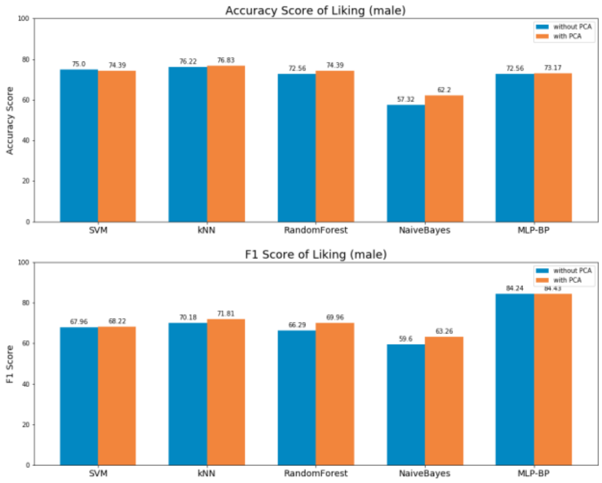


**Figure 65 Accuracy and f1 Score for Liking for all algorithms in UC2 (male dataset) using DWT and Standard Deviation for feature extraction**

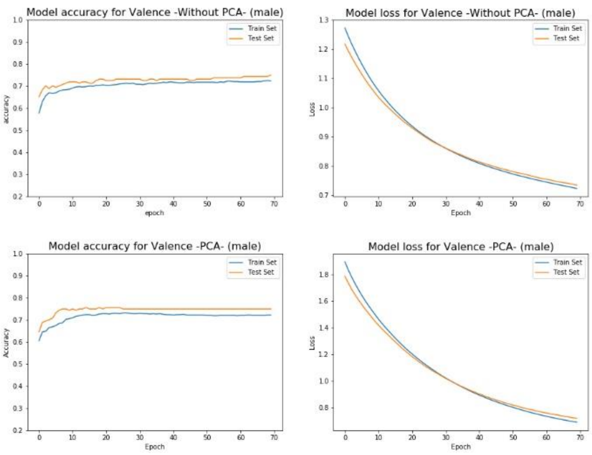


**Figure 66 Model Accuracy and Model Loss (binary Cross Entropy) for Valence for the MLP-BP Algorithm along with DWT and Standard Deviation for feature extraction in UC2 (male dataset)**

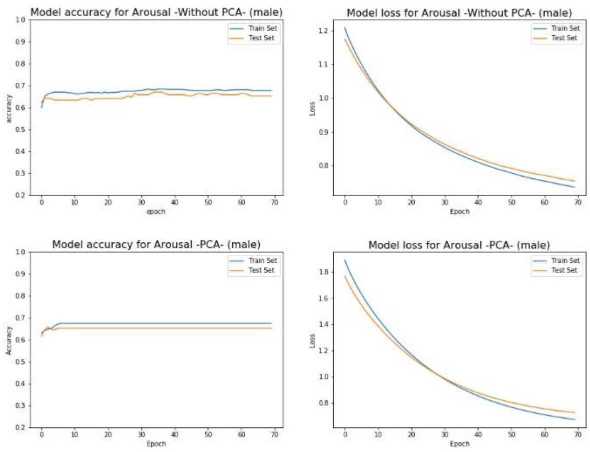


**Figure 67 Model Accuracy and Model Loss (binary Cross Entropy) for Arousal for the MLP-BP Algorithm along with DWT and Standard Deviation for feature extraction in UC2 (male dataset)**

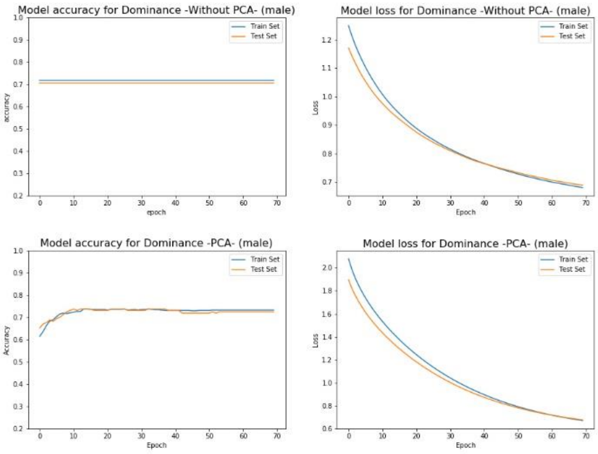


**Figure 68 Model Accuracy and Model Loss (binary Cross Entropy) for Dominance for the MLP-BP Algorithm along with DWT and Standard Deviation for feature extraction in UC2 (male dataset)**

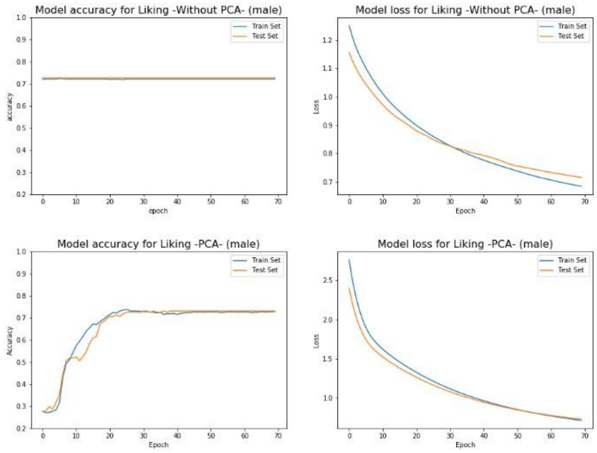


**Figure 69 Model Accuracy and Model Loss (binary Cross Entropy) for Liking using for the MLP-BP Algorithm along with DWT and Standard Deviation for feature extraction in UC2 (male dataset)**

In order to sum up the results for accuracy and f1 score, we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 7 Feature Extraction Method: DWT with Standard Deviation in UC2 (male dataset)**

| Feature Extraction Method: DWT with Standard Deviation | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=29) | | | |
| Algorithm | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| SVM | 76.22 / 67.06 | 69.51 / 61.9 | 76.83 / 70.87 | 75.0 / 67.96 | 75.0 / 67.25 | 70.12 / 64.66 | 78.05 / 72.94 | 74.39 / 68.22 |
| k-NN | 71.95 / 67.96 | 73.78 / 68.53 | 75.61 / 72.31 | 76.22 / 70.18 | 69.51 / 65.74 | 73.17 / 68.91 | 76.83 / 74.39 | 76.83 / 71.81 |
| RF | 74.39 / 69.67 | 67.68 / 63.69 | 74.39 / 69.0 | 72.56 / 66.29 | 75.0 / 69.48 | 70.73 / 67.3 | 76.83 / 72.44 | 74.39 / 69.96 |
| NB | 53.05 / 56.18 | 51.22 / 51.83 | 65.85 / 65.85 | 57.32 / 59.6 | 60.37 / 62.56 | 59.76/ 59.76 | 68.9 / 68.81 | 62.2 / 63.26 |
| MLP-BP | 75.0 / 85.43 | 65.24 / 81.55 | 70.73 / 82.94 | 72.56 / 84.24 | 75.0 / 85.28 | 65.24 / 81.55 | 72.56 / 83.59 | 73.17/ 84.43 |

Moving on, ***Figures 70 - 77*** present the accuracy and the f1 score for all the algorithms using the Discrete Wavelet Transform Feature Extraction Method along with Approximate Entropy (see Chapter 4.2.1)

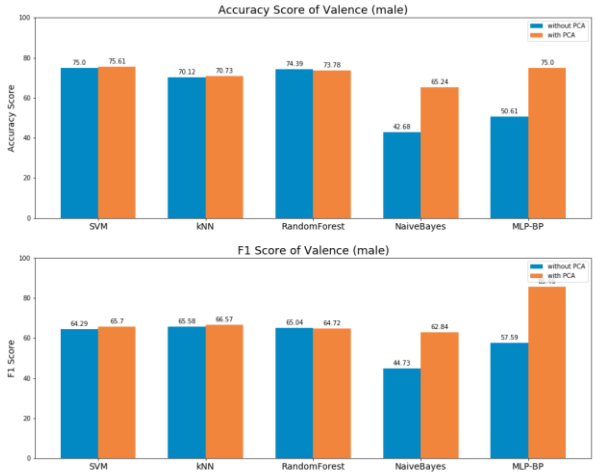


**Figure 70 Accuracy and f1 Score for Valence for all algorithms in UC2 (male dataset) using DWT and Approximate Entropy for feature extraction**

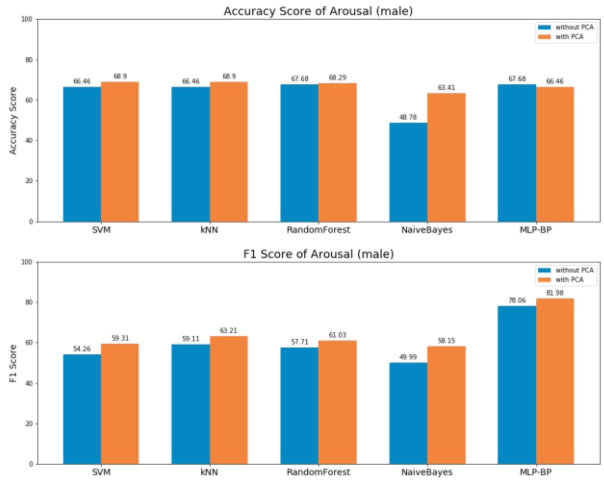


**Figure 71 Accuracy and f1 Score for Arousal for all algorithms in UC2 (male dataset) using DWT and Approximate Entropy for feature extraction**

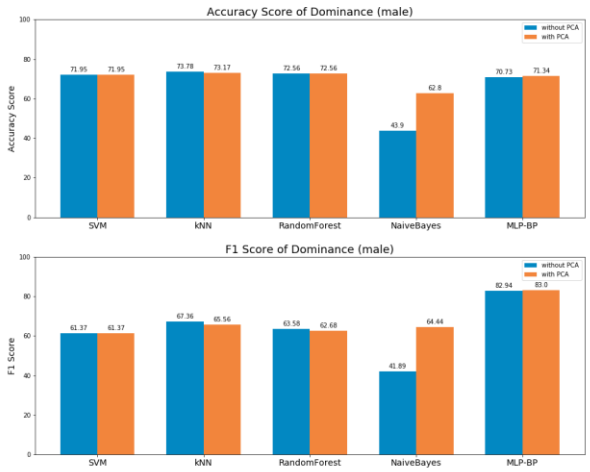


**Figure 72 Accuracy and f1 Score for Dominance for all algorithms in UC2 (male dataset) using DWT and Approximate Entropy for feature extraction**

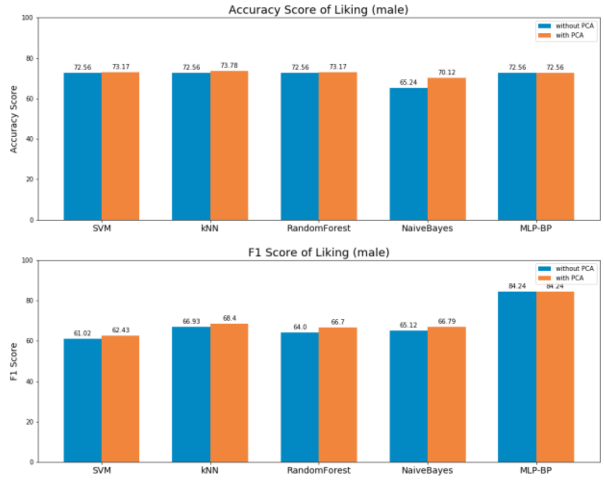


**Figure 73 Accuracy and f1 Score for Liking for all algorithms in UC2 (male dataset) using DWT and Approximate Entropy for feature extraction**

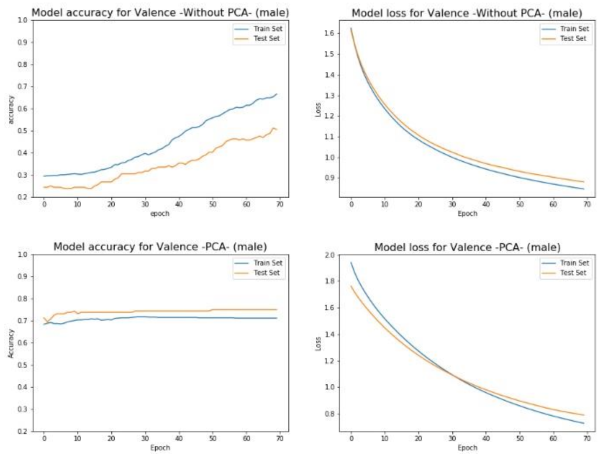


**Figure 74 Model Accuracy and Model Loss (binary Cross Entropy) for Valence for the MLP-BP Algorithm along with DWT and Approximate Entropy for feature extraction in UC2 (male dataset)**

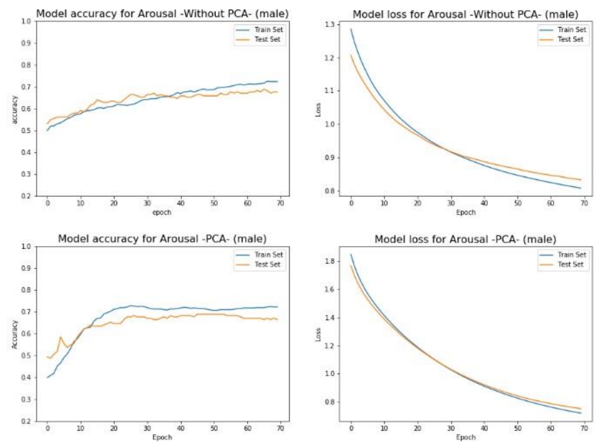


**Figure 75 Model Accuracy and Model Loss (binary Cross Entropy) for Arousal for the MLP-BP Algorithm along with DWT and Approximate Entropy for feature extraction in UC2 (male dataset)**

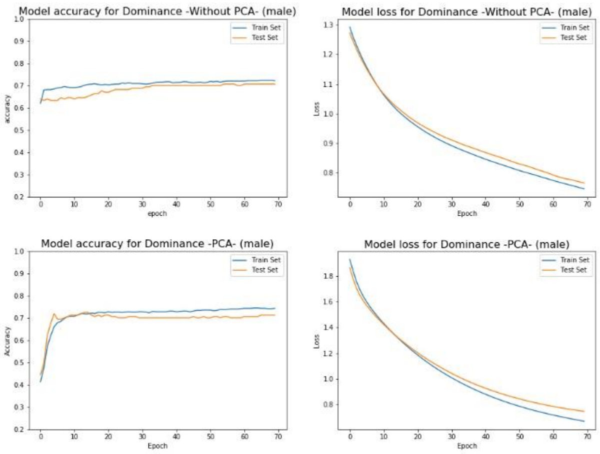


**Figure 76 Model Accuracy and Model Loss (binary Cross Entropy) for Dominance for the MLP-BP Algorithm along with DWT and Approximate Entropy for feature extraction in UC2 (male dataset)**

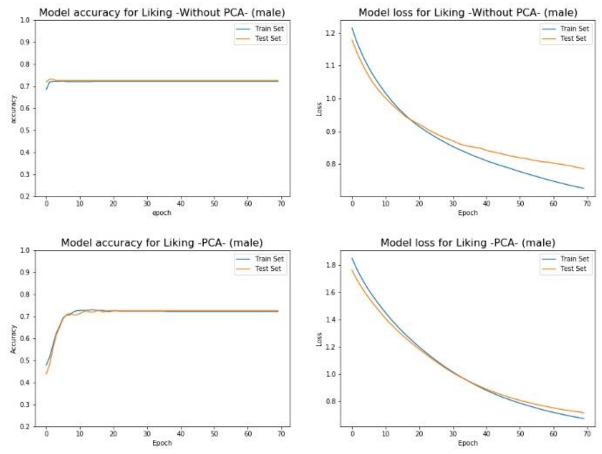


**Figure 77 Model Accuracy and Model Loss (binary Cross Entropy) for Liking using for the MLP-BP Algorithm along with DWT and Approximate Entropy for feature extraction in UC2 (male dataset)**

In order to sum up the results for accuracy and f1 score, we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 8 Feature Extraction Method: DWT with Approximate Entropy in UC2 (male dataset)**

| Feature Extraction Method: DWT with Approximate Entropy | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=29) | | | |
| Algorithm | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| SVM | 75.0 / 64.29 | 66.46 / 54.26 | 71.95 / 61.37 | 72.56 / 61.02 | 75.61 / 65.7 | 68.9 / 59.31 | 71.95 / 61.37 | 73.17 / 62.43 |
| k-NN | 70.12 / 65.58 | 66.46 / 59.11 | 73.78 / 67.36 | 72.56 / 66.93 | 70.73 / 66.57 | 68.9 / 63.21 | 73.17 / 65.56 | 73.78 / 68.4 |
| RF | 74.39 / 65.04 | 67.68 / 57.71 | 72.56 / 63.58 | 72.56 / 64.0 | 73.78 / 64.72 | 68.29 / 61.03 | 72.56 / 62.68 | 73.17 / 66.7 |
| NB | 42.68 / 44.73 | 48.78 / 49.99 | 43.9 / 41.89 | 65.24 / 65.12 | 65.24 / 62.84 | 63.41 / 58.15 | 62.8 / 64.44 | 70.12 / 66.79 |
| MLP-BP | 50.61 / 57.59 | 67.68 / 78.06 | 70.73 / 82.94 | 72.56 / 84.24 | 75.0 / 85.46 | 66.46 / 81.98 | 71.34 / 83.0 | 72.56 / 84.24 |

Moving on, ***Figures 78 - 85*** present the accuracy and the f1 score for all the algorithms using the Power Spectral Density Feature Extraction Method along with Standard Deviation (see Chapter 4.2.3)

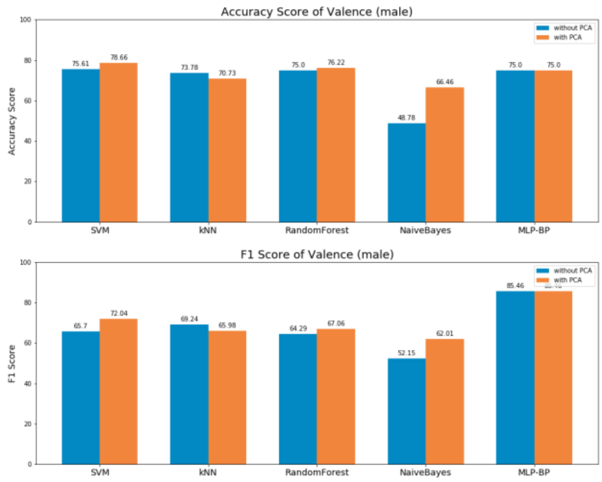


**Figure 78 Accuracy and f1 Score for Valence for all algorithms in UC2 (male dataset) using PSD and Standard Deviation for feature extraction**

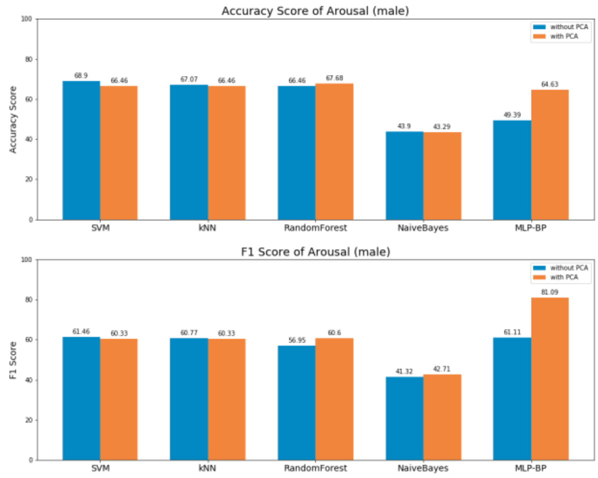


**Figure 80 Accuracy and f1 Score for Arousal for all algorithms in UC2 (male dataset) using PSD and Standard Deviation for feature extraction**

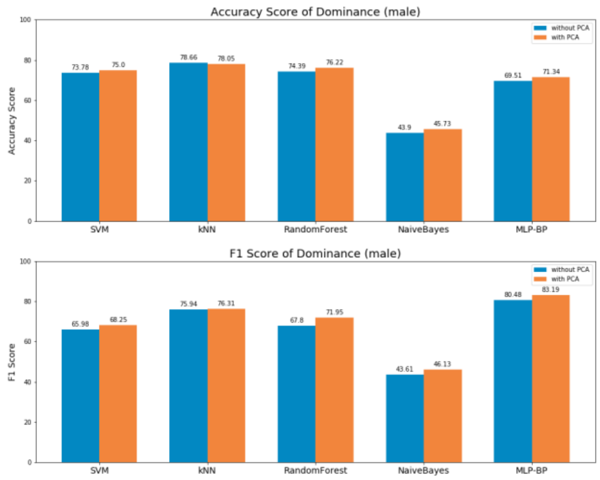


**Figure 79 Accuracy and f1 Score for Dominance for all algorithms in UC2 (male dataset) using PSD and Standard Deviation for feature extraction**

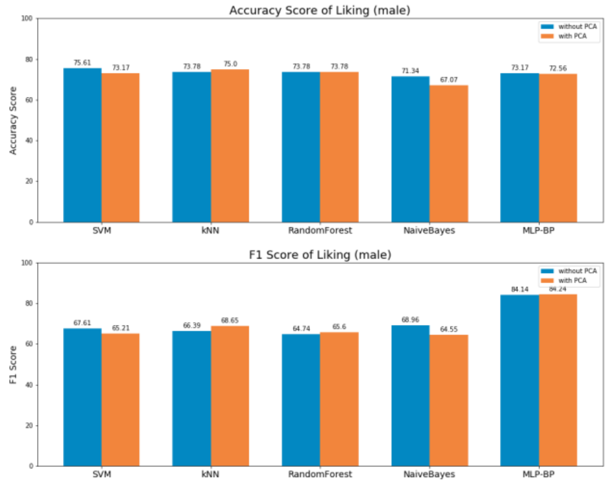


**Figure 81 Accuracy and f1 Score for Liking for all algorithms in UC2 (male dataset) using PSD and Standard Deviation for feature extraction**

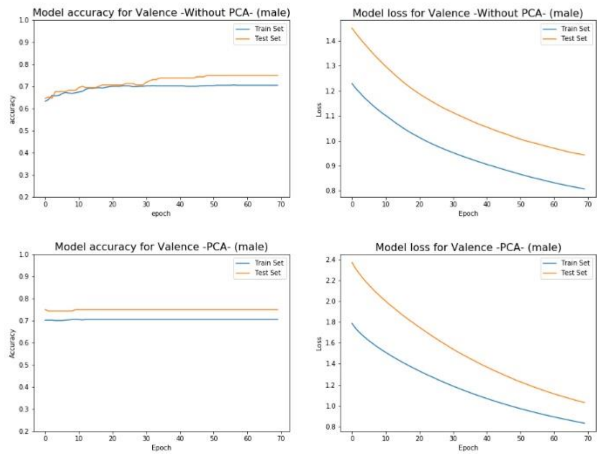


**Figure 82 Model Accuracy and Model Loss (binary Cross Entropy) for Valence for the MLP-BP Algorithm along with PSD and Standard Deviation for feature extraction in UC2 (male dataset)**

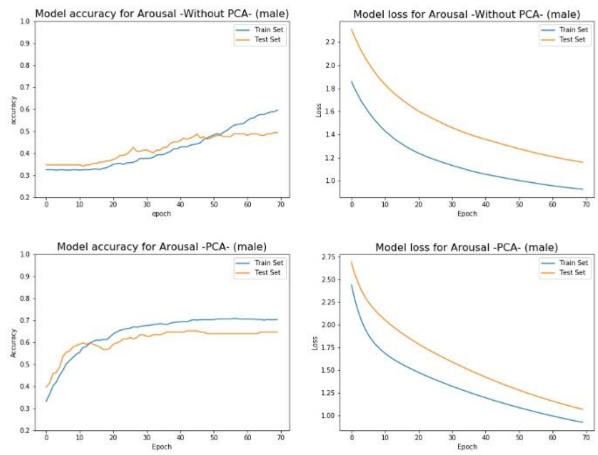


**Figure 83 Model Accuracy and Model Loss (binary Cross Entropy) for Arousal for the MLP-BP Algorithm along with PSD and Standard Deviation for feature extraction in UC2 (male dataset)**

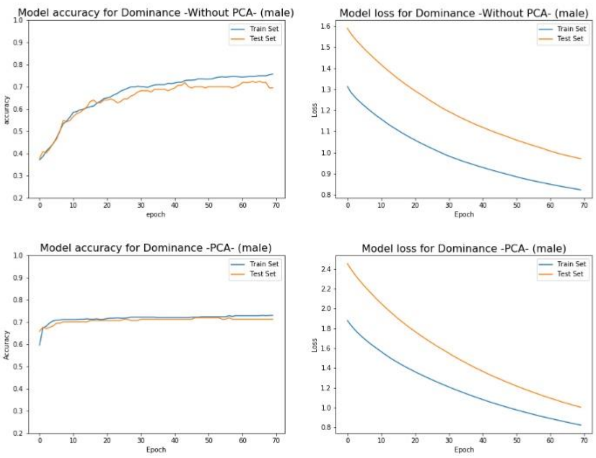


**Figure 84 Model Accuracy and Model Loss (binary Cross Entropy) for Dominance for the MLP-BP Algorithm along with PSD and Standard Deviation for feature extraction in UC2 (male dataset)**

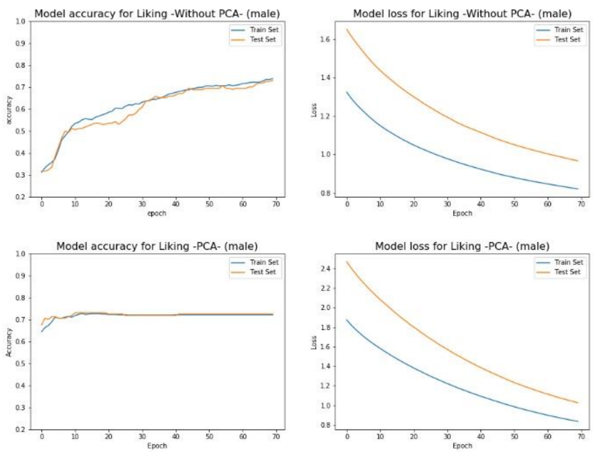


**Figure 85 Model Accuracy and Model Loss (binary Cross Entropy) for Liking using for the MLP-BP Algorithm along with PSD and Standard Deviation for feature extraction in UC2 (male dataset)**

In order to sum up the results for accuracy and f1 score, we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 9 Feature Extraction Method: PSD with Standard Deviation in UC2 (male dataset)**

| Feature Extraction Method: PSD with Standard Deviation | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=29) | | | |
| Algorithm | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| SVM | 75.61 / 65.7 | 68.9 / 61.46 | 73.78 / 65.98 | 75.61 / 67.61 | 78.66 / 72.04 | 66.46 / 60.33 | 75.0 / 68.25 | 73.17 / 65.21 |
| k-NN | 73.78 / 69.24 | 67.07 / 60.77 | 78.66 / 75.94 | 73.78 / 66.39 | 70.73 65.98 | 66.46 / 60.33 | 78.05 / 76.31 | 75.0 / 68.65 |
| RF | 75.0 / 64.29 | 66.46 / 56.95 | 74.39 / 67.8 | 73.78 / 64.74 | 76.22 / 67.06 | 67.68 / 60.6 | 76.22 / 71.95 | 73.78 / 65.6 |
| NB | 48.78 / 52.15 | 43.9 / 41.32 | 43.9 / 43.61 | 71.34 / 68.96 | 66.46 / 62.01 | 43.29 / 42.71 | 45.73 / 46.13 | 67.07 / 65.55 |
| MLP-BP | 75.0 / 85.46 | 49.39 / 61.11 | 69.51 / 80.48 | 73.17 / 84.14 | 75.0 / 85.46 | 64.63 / 81.09 | 71.34 / 83.19 | 72.56 / 84.24 |

Moving on, ***Figures 86 - 93*** present the accuracy and the f1 score for all the algorithms using the Power Spectral Density Feature Extraction Method along with Approximate Entropy (see Chapter 4.2.3)

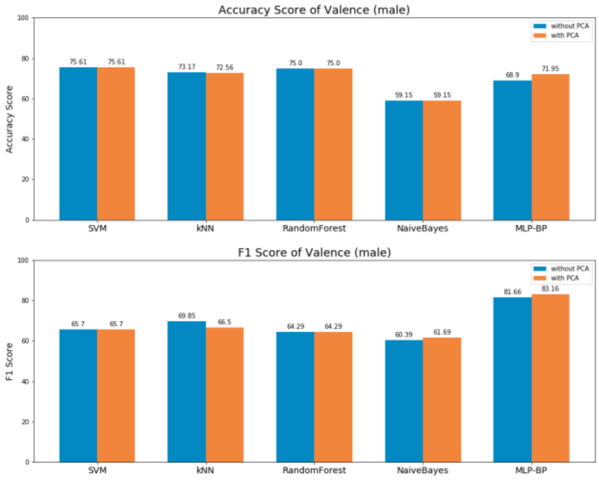


**Figure 86 Accuracy and f1 Score for Valence for all algorithms in UC2 (male dataset) using PSD and Approximate Entropy for feature extraction**

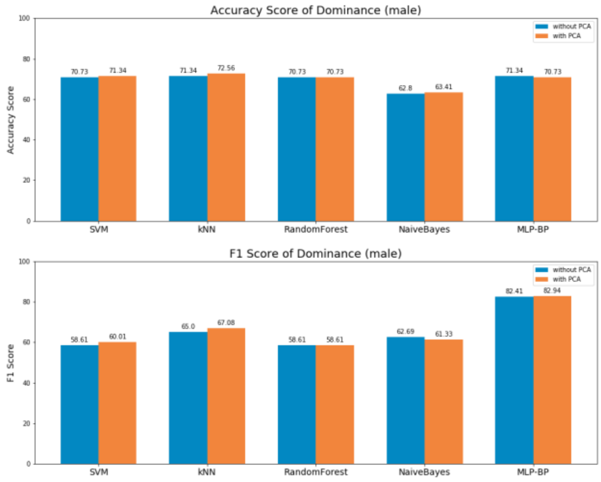


**Figure 87 Accuracy and f1 Score for Dominance for all algorithms in UC2 (male dataset) using PSD and Approximate Entropy for feature extraction**

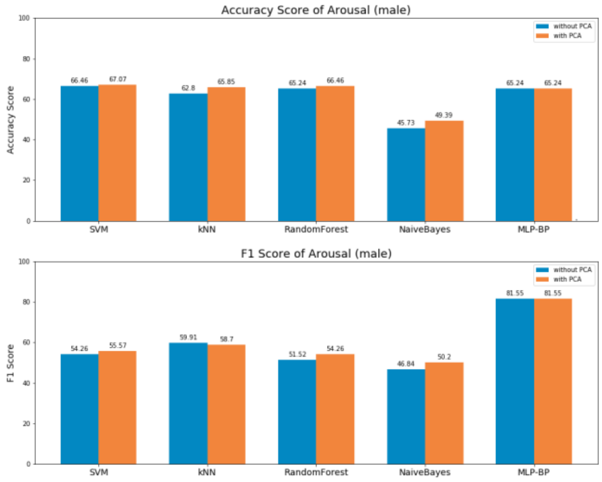


**Figure 88 Accuracy and f1 Score for Arousal for all algorithms in UC2 (male dataset) using PSD and Approximate Entropy for feature extraction**

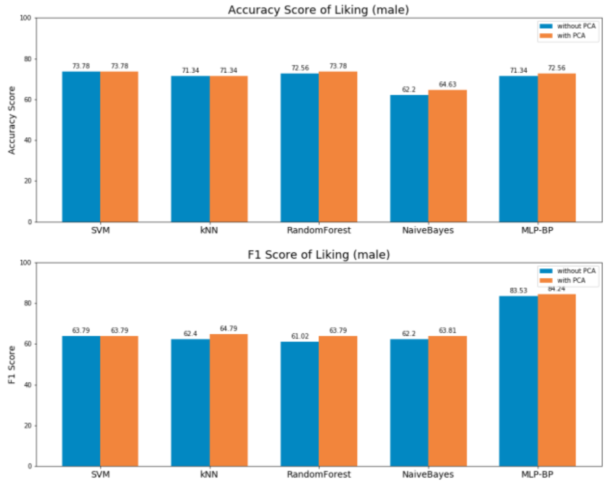


**Figure 89 Accuracy and f1 Score for Liking for all algorithms in UC2 (male dataset) using PSD and Approximate Entropy for feature extraction**

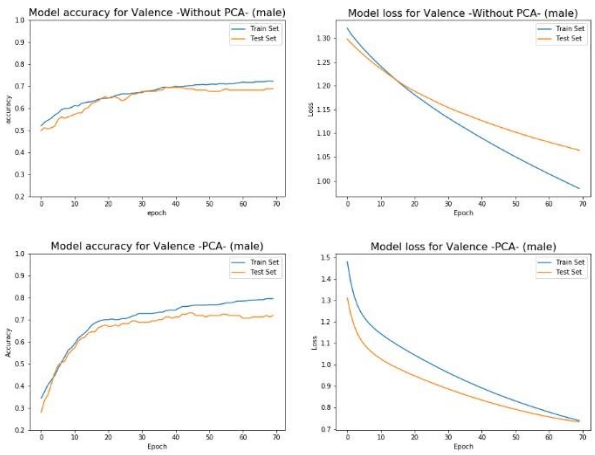


**Figure 90 Model Accuracy and Model Loss (binary Cross Entropy) for Valence for the MLP-BP Algorithm along with PSD and Approximate Entropy for feature extraction in UC2 (male dataset)**

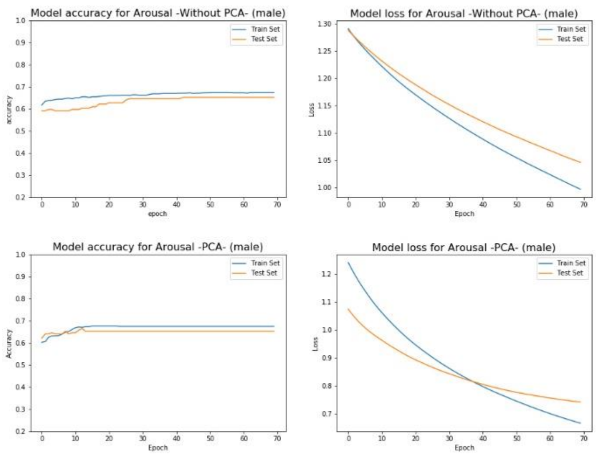


**Figure 91 Model Accuracy and Model Loss (binary Cross Entropy) for Arousal for the MLP-BP Algorithm along with PSD and Approximate Entropy for feature extraction in UC2 (male dataset)**

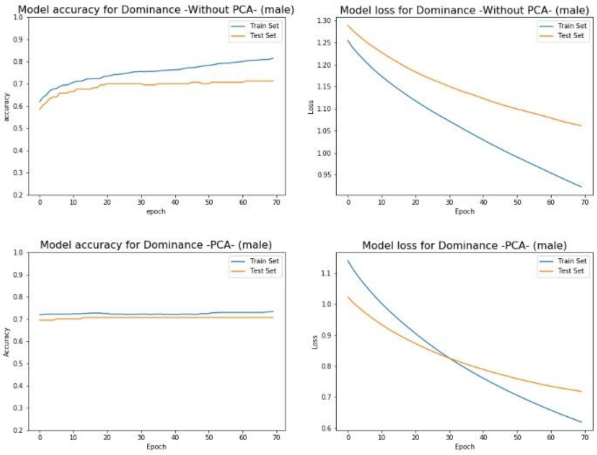


**Figure 92 Model Accuracy and Model Loss (binary Cross Entropy) for Dominance for the MLP-BP Algorithm along with PSD and Approximate Entropy for feature extraction in UC2 (male dataset)**

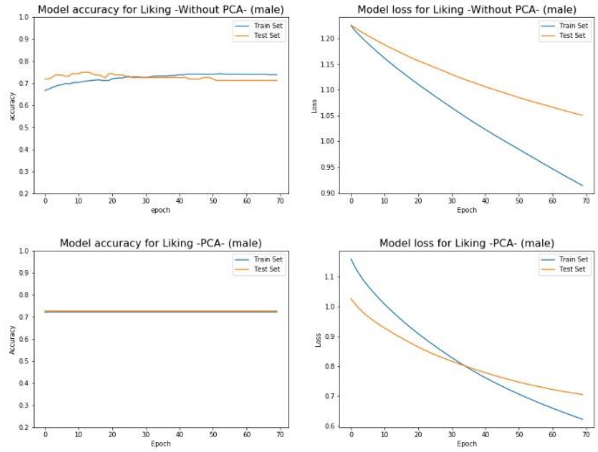


**Figure 93 Model Accuracy and Model Loss (binary Cross Entropy) for Liking using for the MLP-BP Algorithm along with PSD and Approximate Entropy for feature extraction in UC2 (male dataset)**

In order to sum up the results for accuracy and f1 score, we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 10 Feature Extraction Method: PSD with Approximate Entropy in UC2 (male dataset)**

| Feature Extraction Method: PSD with Approximate Entropy | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=29) | | | |
| **Algorithm** | **V Acc / f1 %** | **A Acc / f1 %** | **D Acc / f1 %** | **L Acc / f1 %** | **V Acc / f1 %** | **A Acc / f1 %** | **D Acc / f1 %** | **L Acc / f1 %** |
| **SVM** | 75.61 / 65.7 | 66.46 / 54.26 | 70.73 / 58.61 | 73.78 / 63.79 | 75.61 / 65.7 | 67.07 / 55.57 | 71.34 / 60.01 | 73.78 / 63.79 |
| **k-NN** | 73.17 / 69.85 | 62.8 / 59.91 | 71.34 / 65.0 | 71.34 / 62.4 | 72.56 / 66.5 | 65.85 / 58.7 | 72.56 / 67.08 | 71.34 / 64.79 |
| **RF** | 75.0 / 64.29 | 65.24 51.52 | 70.73 / 58.61 | 72.56 / 61.02 | 75.0 / 64.29 | 66.46 / 54.26 | 70.73 / 58.61 | 73.78 / 63.79 |
| **NB** | 59.15 / 60.39 | 45.73 / 46.84 | 62.8 / 62.69 | 62.2 / 62.2 | 59.15 / 61.69 | 49.39 / 50.2 | 63.41 / 61.33 | 64.63 / 63.81 |
| **MLP-BP** | 68.9 / 81.66 | 65.24 / 81.55 | 71.34 / 82.41 | 71.34 / 85.53 | 71.95 / 83.16 | 65.24 / 81.55 | 70.73 / 82.94 | 72.56 / 84.24 |

Moving on, ***Figures 94 - 101*** present the accuracy and the f1 score for all the algorithms using the Short Time Fourier Transform Feature Extraction Method along with Standard Deviation (see Chapter 4.2.2)

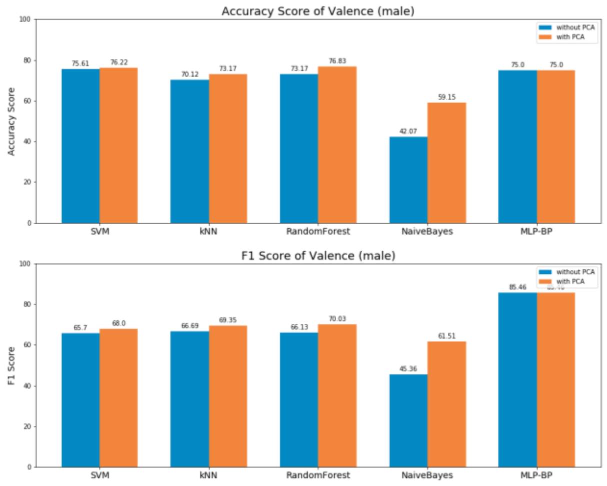


Figure 94 Accuracy and f1 Score for Valence for all algorithms in UC2 (male dataset) using STFT and Standard Deviation for feature extraction

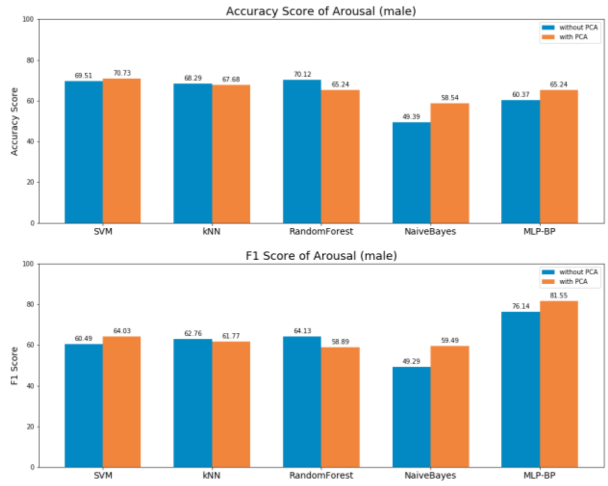


Figure 96 Accuracy and f1 Score for Arousal for all algorithms in UC2 (male dataset) using STFT and Standard Deviation for feature extraction

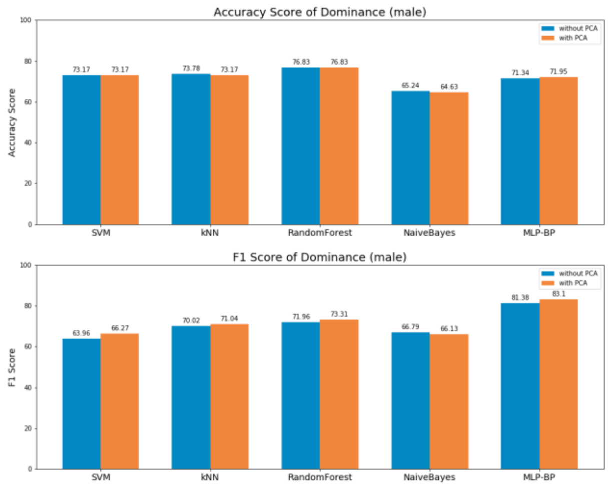


Figure 95 Accuracy and f1 Score for Dominance for all algorithms in UC2 (male dataset) using STFT and Standard Deviation for feature extraction

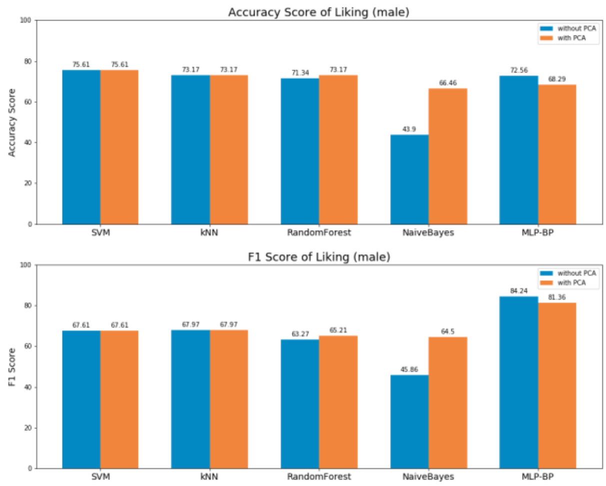


Figure 97 Accuracy and f1 Score for Liking for all algorithms in UC2 (male dataset) using STFT and Standard Deviation for feature extraction

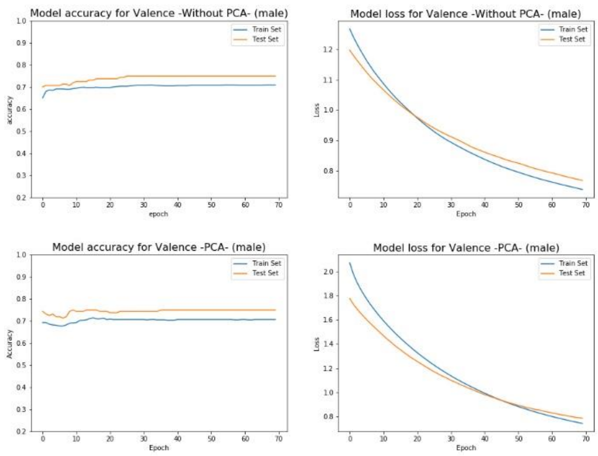


Figure 98 Model Accuracy and Model Loss (binary Cross Entropy) for Valence for the MLP-BP Algorithm along with STFT and Standard Deviation for feature extraction in UC2 (male dataset)

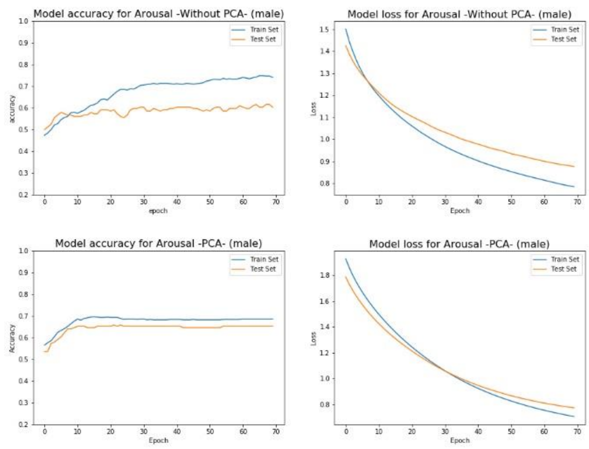


Figure 99 Model Accuracy and Model Loss (binary Cross Entropy) for Arousal for the MLP-BP Algorithm along with STFT and Standard Deviation for feature extraction in UC2 (male dataset)

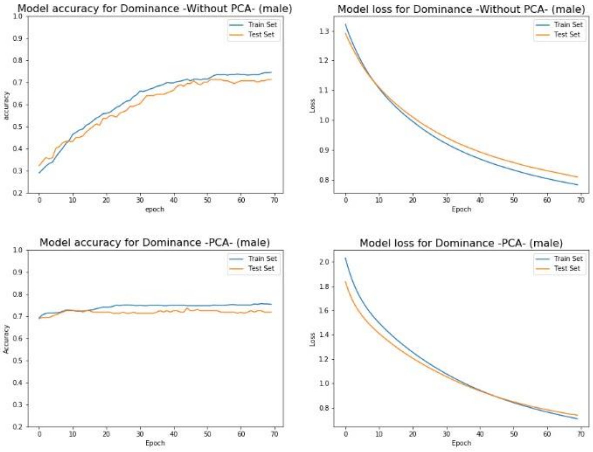


**Figure 100 Model Accuracy and Model Loss (binary Cross Entropy) for Dominance for the MLP-BP Algorithm along with STFT and Standard Deviation for feature extraction in UC2 (male dataset)**

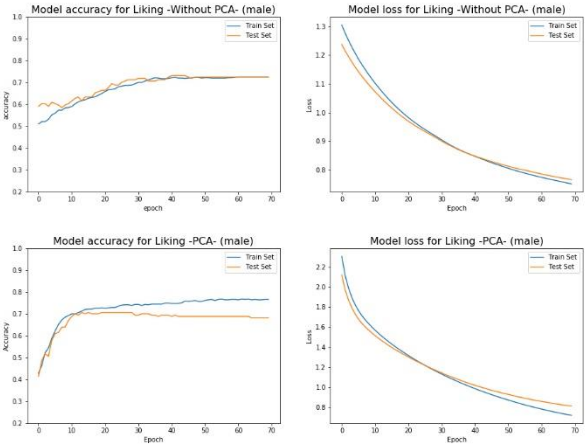


**Figure 101 Model Accuracy and Model Loss (binary Cross Entropy) for Liking using for the MLP-BP Algorithm along with STFT and Standard Deviation for feature extraction in UC2 (male dataset)**

In order to sum up the results for accuracy and f1 score, we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 11 Feature Extraction Method: STFT with Standard Deviation in UC2 (male dataset)**

| Feature Extraction Method: STFT with Standard Deviation | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=29) | | | |
| **Algorithm** | **V Acc / f1 %** | **A Acc / f1 %** | **D Acc / f1 %** | **L Acc / f1 %** | **V Acc / f1 %** | **A Acc / f1 %** | **D Acc / f1 %** | **L Acc / f1 %** |
| **SVM** | 75.61 / 65.7 | 69.51 / 60.49 | 73.17 / 63.96 | 75.61 / 67.61 | 76.22 / 68.0 | 70.73 / 64.03 | 73.17 / 66.27 | 75.61 / 67.61 |
| **k-NN** | 70. 12/ 66.69 | 68.29 / 62.76 | 73.78 / 70.02 | 73.17 / 67.97 | 73.17 / 69.35 | 67.68 / 61.77 | 73.17 / 71.04 | 73.17 / 67.97 |
| **RF** | 73.17 / 66.13 | 70.12 / 64.13 | 76.83 / 71.96 | 71.34 / 63.27 | 76.83 / 70.03 | 65.24 / 58.89 | 76.83 / 73.31 | 73.17 / 65.21 |
| **NB** | 42.07 / 45.36 | 49.39 / 49.29 | 65.24 / 66.79 | 43.9 / 45.86 | 59.15 / 61.51 | 58.54 / 59.49 | 64.63 / 66.13 | 66.46 / 64.5 |
| **MLP-BP** | 75.0 / 85.46 | 60.37 / 76.14 | 71.34 / 81.38 | 72.56 / 84.24 | 75.0 / 85.46 | 65.24 / 81.55 | 71.95 / 83.1 | 68.29 / 81.36 |

Moving on, ***Figures 102 - 109*** present the accuracy and the f1 score for all the algorithms using the Short Time Fourier Transform Feature Extraction Method along with Approximate Entropy (see Chapter 4.2.2)

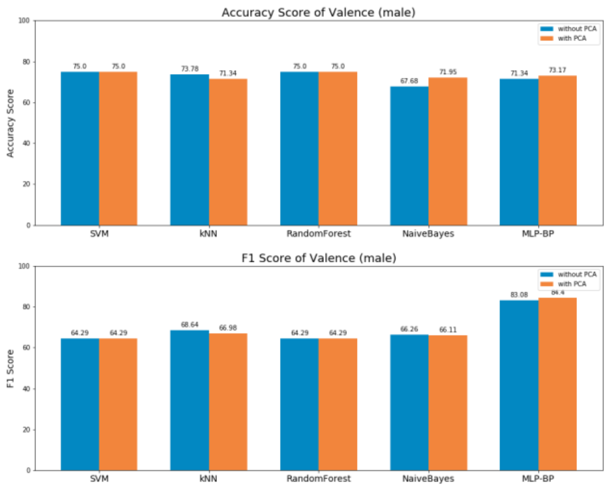


**Figure 102 Accuracy and f1 Score for Valence for all algorithms in UC2 (male dataset) using STFT and Approximate Entropy for feature extraction**

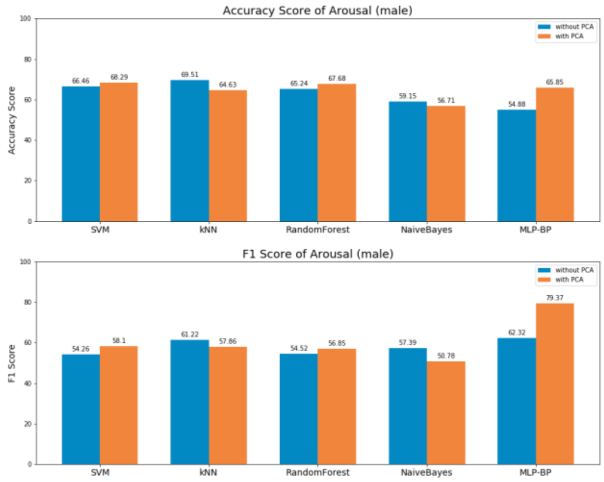


**Figure 103 Accuracy and f1 Score for Arousal for all algorithms in UC2 (male dataset) using STFT and Approximate Entropy for feature extraction**

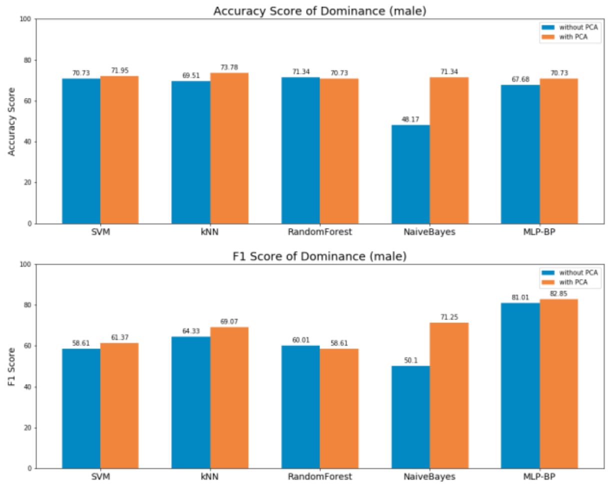


**Figure 104 Accuracy and f1 Score for Dominance for all algorithms in UC2 (male dataset) using STFT and Approximate Entropy for feature extraction**

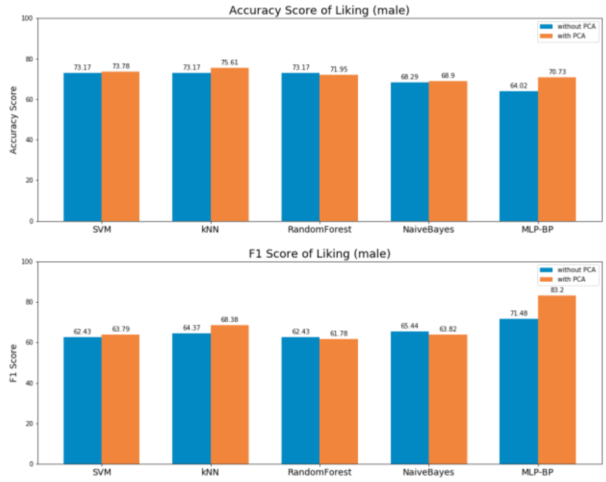


**Figure 105 Accuracy and f1 Score for Liking for all algorithms in UC2 (male dataset) using STFT and Approximate Entropy for feature extraction**

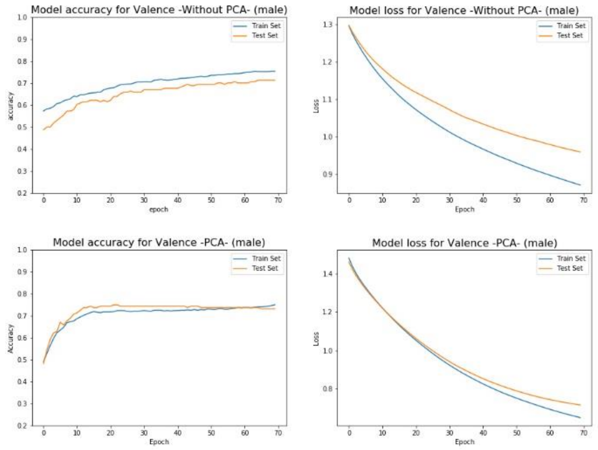


**Figure 106 Model Accuracy and Model Loss (binary Cross Entropy) for Valence for the MLP-BP Algorithm along with STFT and Approximate Entropy for feature extraction in UC2 (male dataset)**

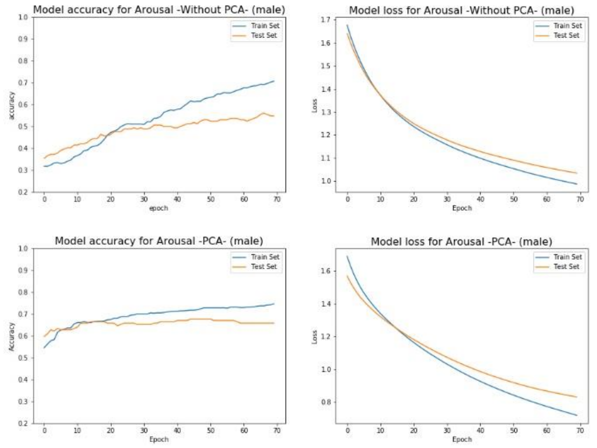


**Figure 107 Model Accuracy and Model Loss (binary Cross Entropy) for Arousal for the MLP-BP Algorithm along with STFT and Approximate Entropy for feature extraction in UC2 (male dataset)**

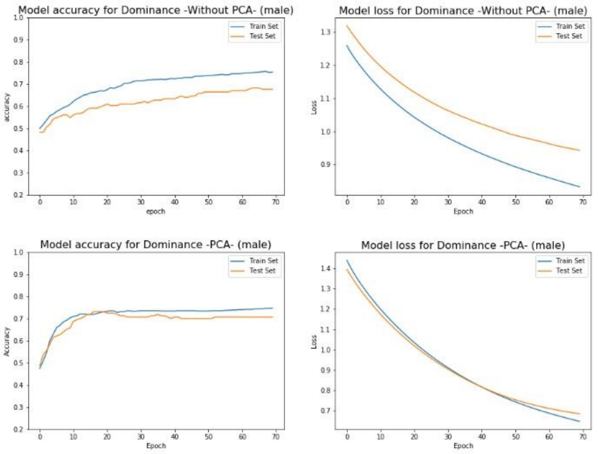


**Figure 108 Model Accuracy and Model Loss (binary Cross Entropy) for Dominance for the MLP-BP Algorithm along with STFT and Approximate Entropy for feature extraction in UC2 (male dataset)**

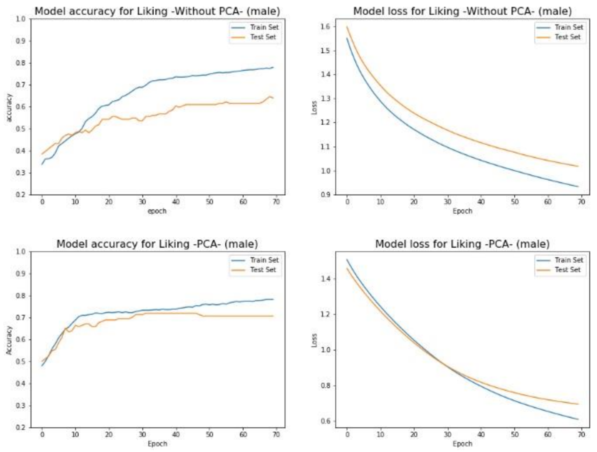


**Figure 109 Model Accuracy and Model Loss (binary Cross Entropy) for Liking using for the MLP-BP Algorithm along with STFT and Approximate Entropy for feature extraction in UC2 (male dataset)**

In order to sum up the results for accuracy and f1 score we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 12 Feature Extraction Method: STFT with Approximate Entropy in UC2 (male dataset)**

| Feature Extraction Method: STFT with Approximate Entropy | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=29) | | | |
| **Algorithm** | **V Acc / f1 %** | **A Acc / f1 %** | **D Acc / f1 %** | **L Acc / f1 %** | **V Acc / f1 %** | **A Acc / f1 %** | **D Acc / f1 %** | **L Acc / f1 %** |
| **SVM** | **75.0 / 64.29** | **66.46 / 54.26** | **70.73 / 58.61** | **73.17 / 62.43** | **75.0 / 64.29** | **68.29 / 58.1** | **71.95 / 61.37** | **73.78 / 63.79** |
| **k-NN** | **73.78 / 68.64** | **69.51 / 61.22** | **69.51 / 64.33** | **73.17 / 64.37** | **71.34 / 66.98** | **64.63 / 57.86** | **73.78 / 69.07** | **75.61 / 68.38** |
| **RF** | **75.0 / 64.29** | **65.24 / 54.52** | **71.34 / 60.01** | **73.17 / 62.43** | **75.0 / 64.29** | **67.68 / 56.85** | **70.73 / 58.61** | **71.95 / 61.78** |
| **NB** | **67.68 / 66.26** | **59.15 / 57.39** | **48.17 / 50.1** | **68.29 / 65.44** | **71.95 / 66.11** | **56.71 / 50.78** | **71.34 / 71.25** | **68.9 / 63.82** |
| **MLP-BP** | **71.34 / 83.08** | **54.88 / 62.32** | **67.68 / 81.01** | **64.02 / 71.48** | **73.17 / 84.4** | **65.85 / 79.37** | **70.73 / 82.55** | **70.73 / 83.2** |

### 5.2.2 Experimentation Results for the Female Dataset

The following figures will present the experimental results concerning the **female dataset**.

***Figures 110 - 117*** present the accuracy and the f1 score for all the algorithms using the Discrete Wavelet Transform Feature Extraction Method along with Standard Deviation (see Chapter 4.2.1)

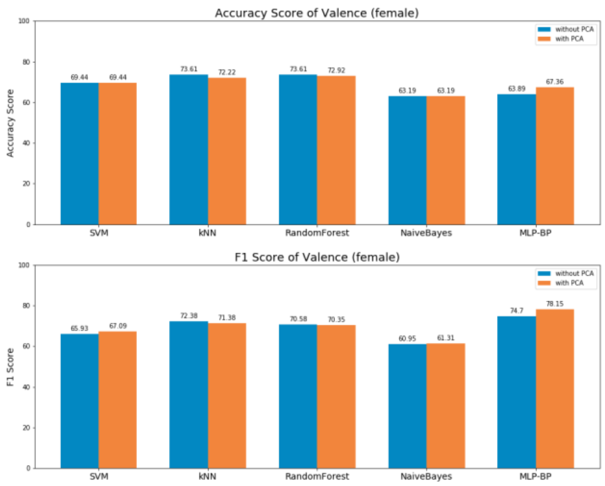


Figure 110 Accuracy and f1 Score for Valence for all algorithms in UC2 (female dataset) using DWT and Standard Deviation for feature extraction

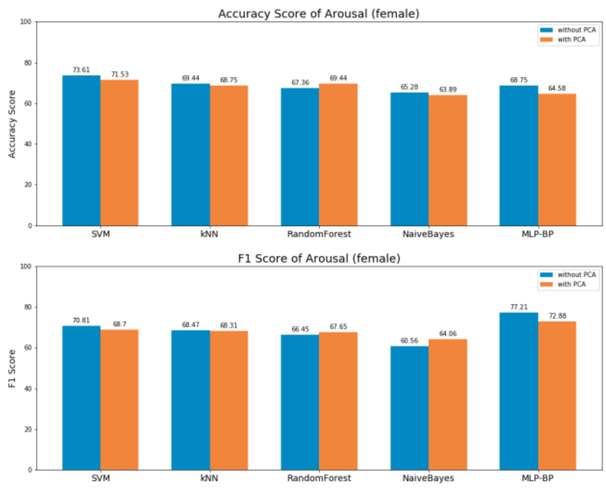


Figure 112 Accuracy and f1 Score for Arousal for all algorithms in UC2 (female dataset) using DWT and Standard Deviation for feature extraction

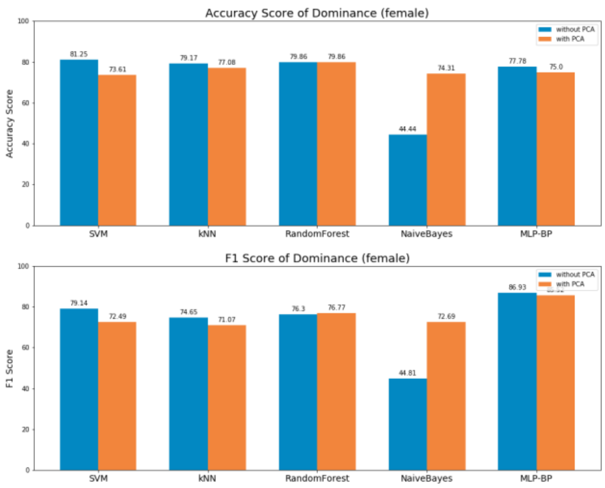


Figure 111 Accuracy and f1 Score for Dominance for all algorithms in UC2 (female dataset) using DWT and Standard Deviation for feature extraction

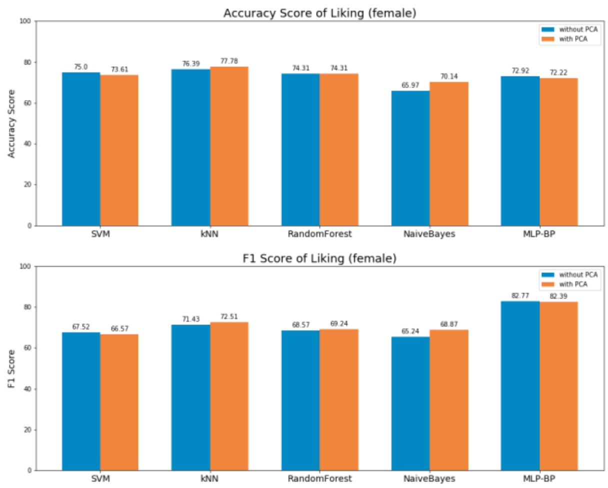


Figure 113 Accuracy and f1 Score for Liking for all algorithms in UC2 (female dataset) using DWT and Standard Deviation for feature extraction

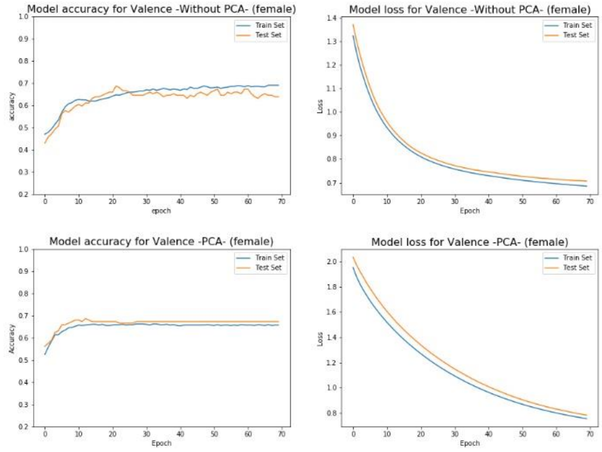


Figure 114 Model Accuracy and Model Loss (binary Cross Entropy) for Valence for the MLP-BP Algorithm along with DWT and Standard Deviation for feature extraction in UC2 (female dataset)

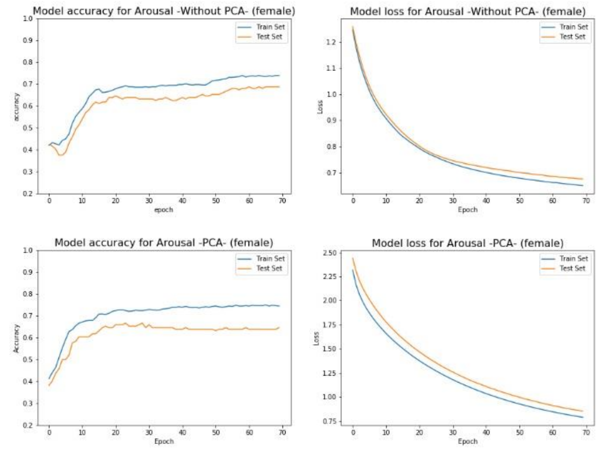


Figure 115 Model Accuracy and Model Loss (binary Cross Entropy) for Arousal for the MLP-BP Algorithm along with DWT and Standard Deviation for feature extraction in UC2 (female dataset)

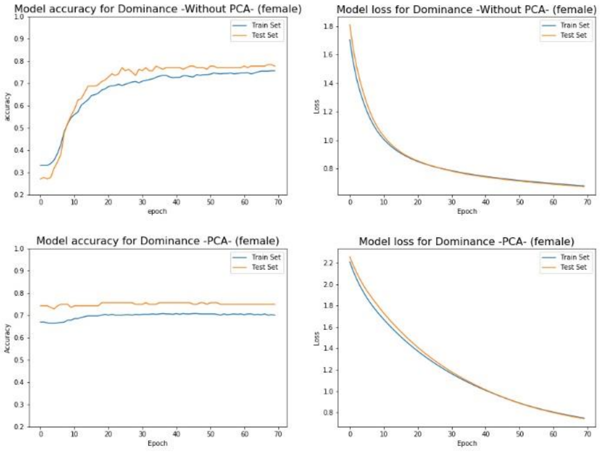


**Figure 116 Model Accuracy and Model Loss (binary Cross Entropy) for Dominance for the MLP-BP Algorithm along with DWT and Standard Deviation for feature extraction in UC2 (female dataset)**

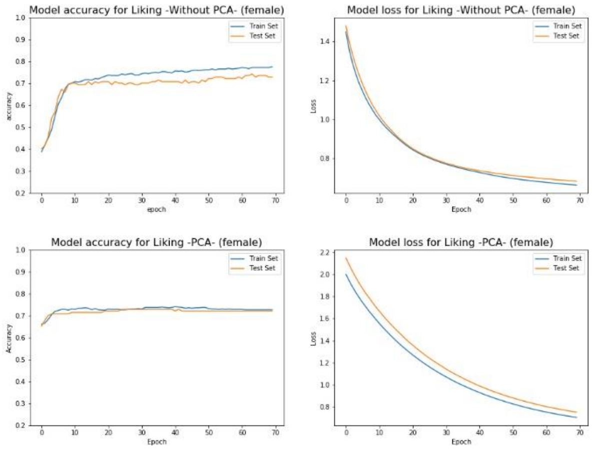


**Figure 117 Model Accuracy and Model Loss (binary Cross Entropy) for Liking using for the MLP-BP Algorithm along with DWT and Standard Deviation for feature extraction in UC2 (female dataset)**

In order to sum up the results for accuracy and f1 score, we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 13 Feature Extraction Method: DWT with Standard Deviation in UC2 (female dataset)**

| **Feature Extraction Method: DWT with Standard Deviation** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **No PCA** | | | | **With PCA (Components=18)** | | | |
| **Algorithm** | **V Acc / f1 %** | **A Acc / f1 %** | **D Acc / f1 %** | **L Acc / f1 %** | **V Acc / f1 %** | **A Acc / f1 %** | **D Acc / f1 %** | **L Acc / f1 %** |
| **SVM** | **69.44 / 65.93** | **71.75 / 70.42** | **81.25 / 79.14** | **75.0 / 67.52** | **69.44 / 67.09** | **70.78 / 69.86** | **73.61 / 72.49** | **73.61 / 66.57** |
| **k-NN** | **73.61 / 72.38** | **69.48 / 66.73** | **79.17 / 74.65** | **76.39 / 71.43** | **72.22 / 71.38** | **69.16 / 66.46** | **77.08 / 71.07** | **77.78 / 72.51** |
| **RF** | **73.61 / 70.58** | **67.21 / 63.8** | **79.86 / 76.3** | **74.31 / 68.57** | **72.92 / 70.35** | **67.53 / 63.87** | **79.86 / 76.77** | **74.31 / 69.24** |
| **NB** | **63.19 / 60.95** | **62.66 / 60.29** | **44.44 / 44.81** | **65.97 / 65.24** | **63.19 / 63.31** | **61.36 / 58.74** | **74.31 / 72.69** | **70.14 / 68.87** |
| **MLP-BP** | **63.89 / 74.7** | **65.58 / 76.91** | **77.78 / 86.93** | **72.92 / 82.77** | **67.36 / 78.15** | **62.34 / 76.54** | **75.0 / 85.52** | **72.22 / 82.39** |

Moving on, ***Figures 118 - 125*** present the accuracy and the f1 score for all the algorithms using the Discrete Wavelet Transform Feature Extraction Method along with Approximate Entropy (see Chapter 4.2.1)

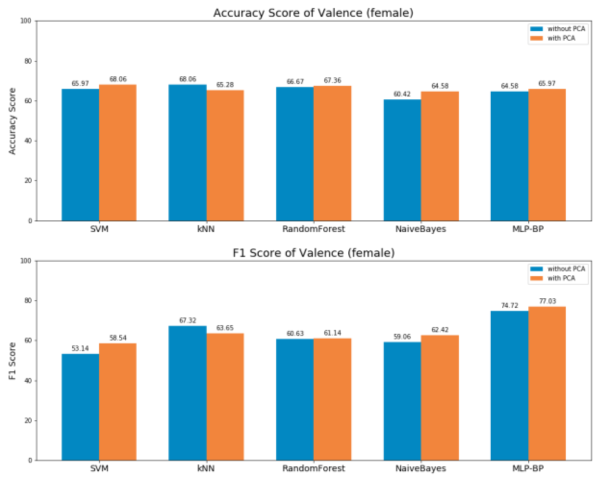


Figure 118 Accuracy and f1 Score for Valence for all algorithms in UC2 (female dataset) using DWT and Approximate Entropy for feature extraction

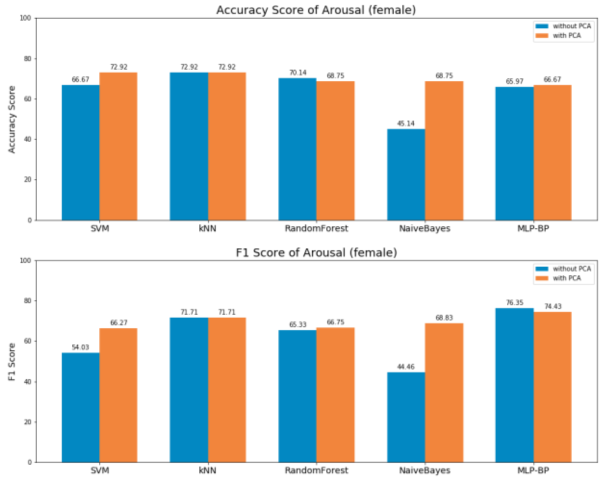


Figure 119 Accuracy and f1 Score for Arousal for all algorithms in UC2 (female dataset) using DWT and Approximate Entropy for feature extraction

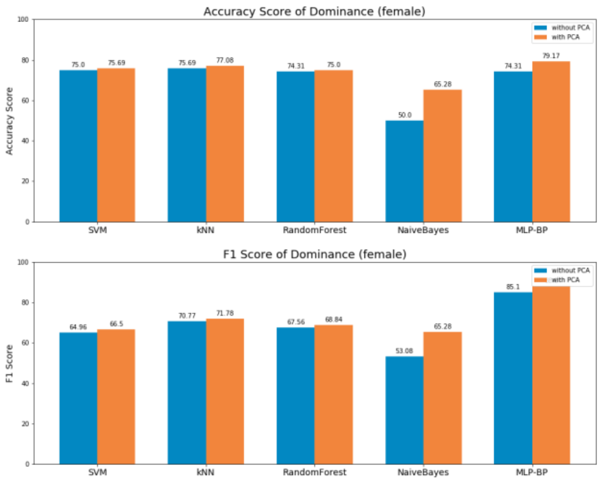


Figure 120 Accuracy and f1 Score for Dominance for all algorithms in UC2 (female dataset) using DWT and Approximate Entropy for feature extraction

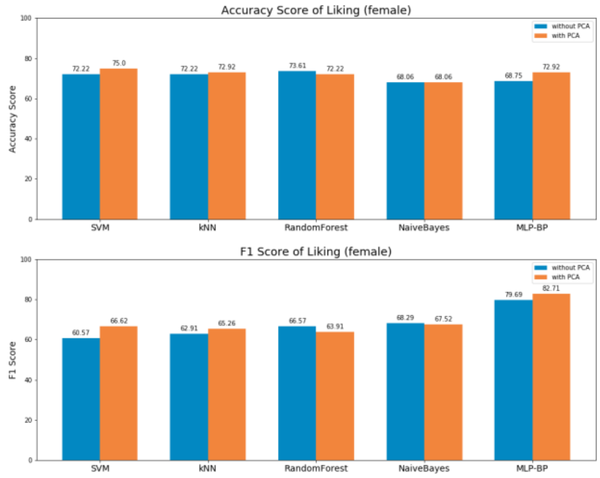


Figure 121 Accuracy and f1 Score for Liking for all algorithms in UC2 (female dataset) using DWT and Approximate Entropy for feature extraction

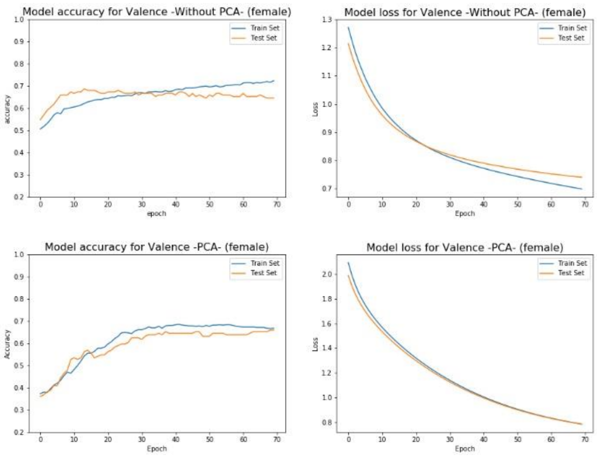


Figure 122 Model Accuracy and Model Loss (binary Cross Entropy) for Valence for the MLP-BP Algorithm along with DWT and Approximate Entropy for feature extraction in UC2 (female dataset)

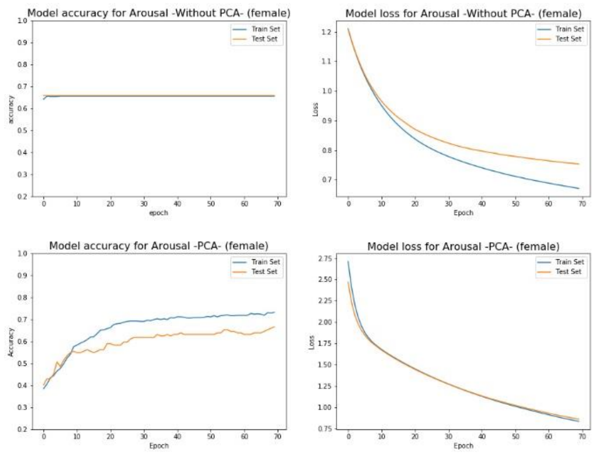


Figure 123 Model Accuracy and Model Loss (binary Cross Entropy) for Arousal for the MLP-BP Algorithm along with DWT and Approximate Entropy for feature extraction in UC2 (female dataset)

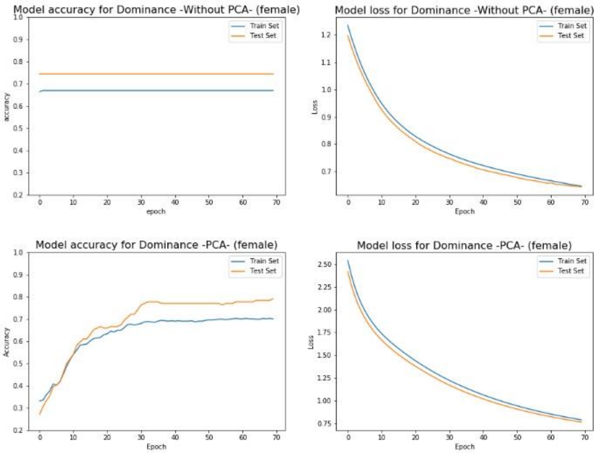


**Figure 124 Model Accuracy and Model Loss (binary Cross Entropy) for Dominance for the MLP-BP Algorithm along with DWT and Approximate Entropy for feature extraction in UC2 (female dataset)**

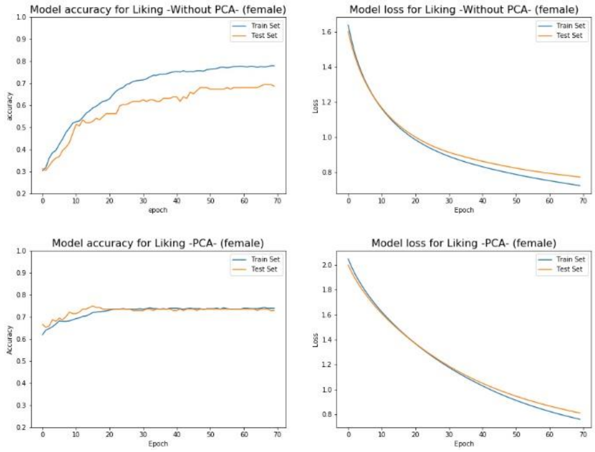


**Figure 125 Model Accuracy and Model Loss (binary Cross Entropy) for Liking using for the MLP-BP Algorithm along with DWT and Approximate Entropy for feature extraction in UC2 (female dataset)**

In order to sum up the results for accuracy and f1 score, we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 14 Feature Extraction Method: DWT with Approximate Entropy in UC2 (female dataset)**

| Feature Extraction Method: DWT with Approximate Entropy | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=18) | | | |
| Algorithm | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| SVM | 65.97 / 53.14 | 66.67 / 54.03 | 75.0 / 64.96 | 72.22 / 60.57 | 68.06 / 58.54 | 72.92 / 66.27 | 75.69 / 66.5 | 75.0 / 66.62 |
| k-NN | 68.06 / 67.32 | 72.92 / 71.71 | 75.69 / 70.77 | 72.22 / 62.91 | 65.28 / 63.65 | 72.92 / 71.71 | 77.08 / 71.78 | 72.92 / 65.26 |
| RF | 66.67 / 60.63 | 70.14 / 65.33 | 74.31 / 67.56 | 73.61 / 66.57 | 67.36 / 61.14 | 68.75 / 66.75 | 75.0 / 68.84 | 72.22 / 63.91 |
| NB | 60.42 / 59.06 | 45.14 / 44.46 | 50.0 / 53.08 | 68.06 / 68.29 | 64.58 / 62.42 | 68.75 / 68.83 | 65.28 / 65.28 | 68.06 / 67.52 |
| MLP-BP | 64.58 / 74.72 | 65.97 / 76.35 | 74.31 / 85.1 | 68.75 / 79.69 | 65.97 / 77.03 | 66.67 / 74.43 | 79.17 / 88.6 | 72.92 / 82.71 |

Moving on***, Figures 126 - 133*** present the accuracy and the f1 score for all the algorithms using the Power Spectral Density Feature Extraction Method along with Standard Deviation (see Chapter 4.2.3)

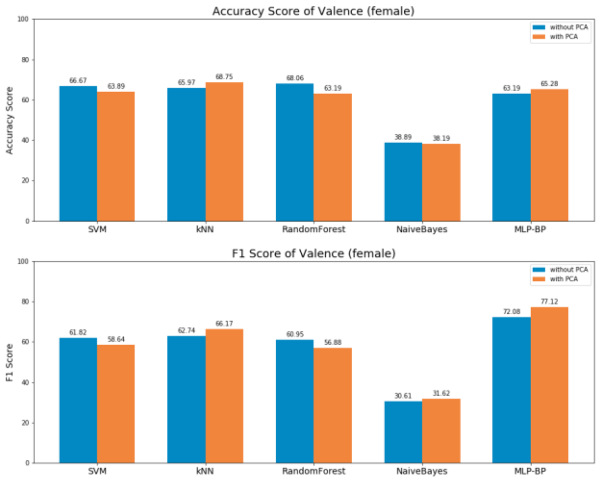


**Figure 126 Accuracy and f1 Score for Valence for all algorithms in UC2 (female dataset) using PSD and Standard Deviation for feature extraction**

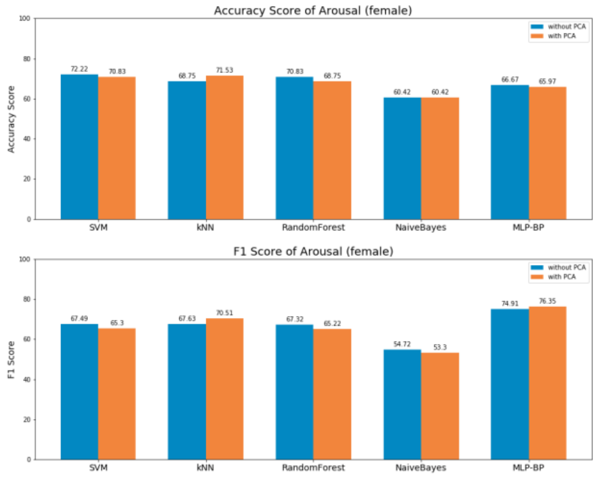


**Figure 128 Accuracy and f1 Score for Arousal for all algorithms in UC2 (female dataset) using PSD and Standard Deviation for feature extraction**

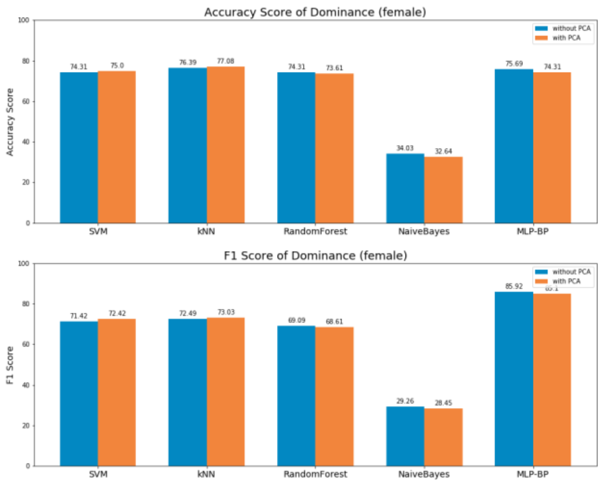


**Figure 127 Accuracy and f1 Score for Dominance for all algorithms in UC2 (female dataset) using PSD and Standard Deviation for feature extraction**

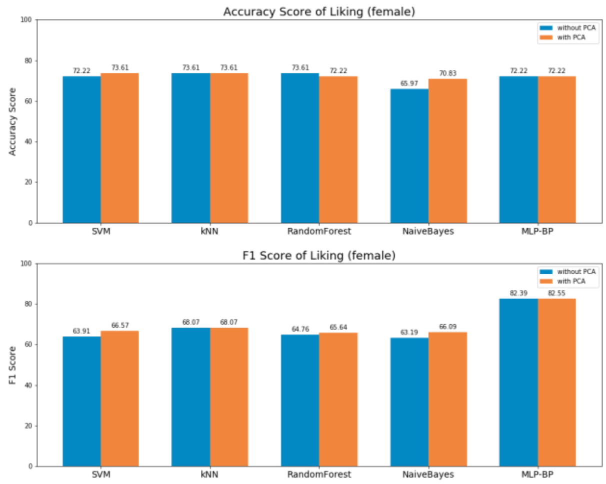


**Figure 129 Accuracy and f1 Score for Liking for all algorithms in UC2 (female dataset) using PSD and Standard Deviation for feature extraction**

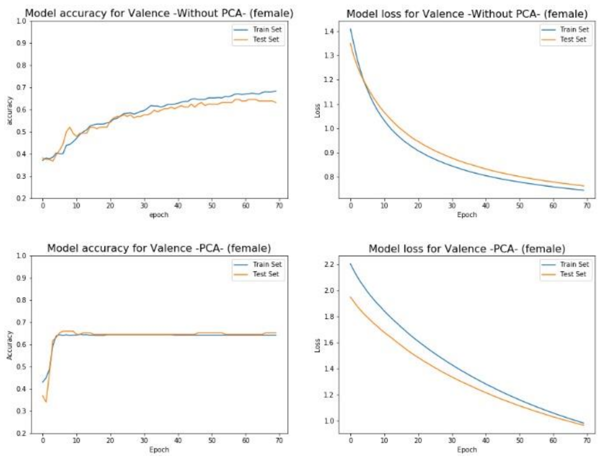


**Figure 130 Model Accuracy and Model Loss (binary Cross Entropy) for Valence for the MLP-BP Algorithm along with PSD and Standard Deviation for feature extraction in UC2 (female dataset)**

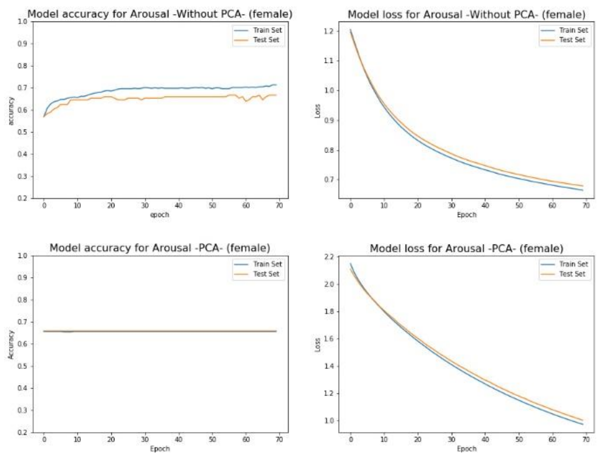


**Figure 131 Model Accuracy and Model Loss (binary Cross Entropy) for Arousal for the MLP-BP Algorithm along with PSD and Standard Deviation for feature extraction in UC2 (female dataset)**

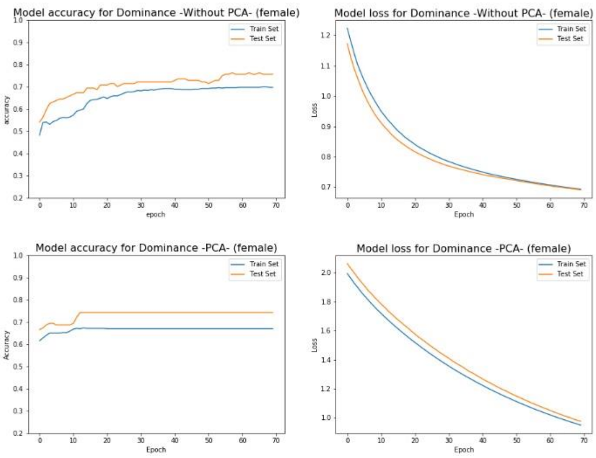


**Figure 132 Model Accuracy and Model Loss (binary Cross Entropy) for Dominance for the MLP-BP Algorithm along with PSD and Standard Deviation for feature extraction in UC2 (female dataset)**

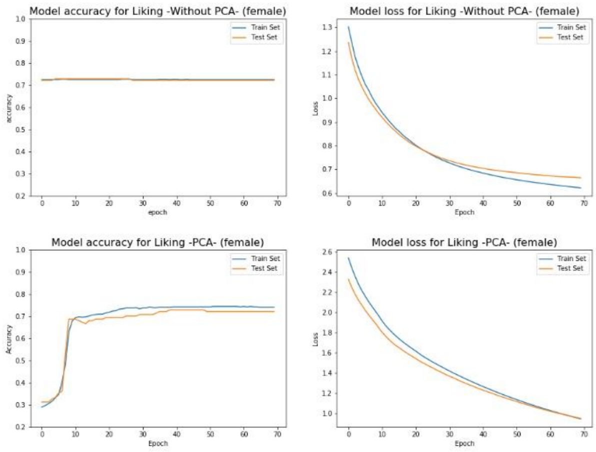


**Figure 133 Model Accuracy and Model Loss (binary Cross Entropy) for Liking using for the MLP-BP Algorithm along with PSD and Standard Deviation for feature extraction in UC2 (female dataset)**

In order to sum up the results for accuracy and f1 score, we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 15 Feature Extraction Method: PSD with Standard Deviation in UC2 (female dataset)**

| Feature Extraction Method: PSD with Standard Deviation | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=18) | | | |
| Algorithm | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| SVM | 66.67 / 61.82 | 72.22 / 67.49 | 74.31 / 71.42 | 72.22 / 63.91 | 63.89 / 58.64 | 70.83 / 65.3 | 75.0 / 72.42 | 73.61 / 66.57 |
| k-NN | 65.97 / 62.74 | 68.75 / 67.63 | 76.39 / 72.49 | 73.61 / 68.07 | 68.75 / 66.17 | 71.53 / 70.51 | 77.08 / 73.03 | 73.61 / 68.07 |
| RF | 68.06 / 60.95 | 70.83 / 67.32 | 74.31 / 69.09 | 73.61 / 64.76 | 63.19 / 56.88 | 68.75 / 65.22 | 73.61 / 68.61 | 72.22 / 65.64 |
| NB | 38.89 / 30.61 | 60.42 / 54.72 | 34.03 / 29.26 | 65.97 / 63.19 | 38.19 / 31.62 | 60.42 / 53.3 | 32.64 / 28.45 | 70.83 / 66.09 |
| MLP-BP | 63.19 / 72.08 | 66.67 / 74.91 | 75.69 / 85.92 | 72.22 / 82.39 | 65.28 / 77.12 | 65.97 / 76.35 | 74.31 / 85.1 | 72.22 / 82.55 |

Moving on, ***Figures 134 - 141*** present the accuracy and the f1 score for all the algorithms using the Power Spectral Density Feature Extraction Method along with Approximate Entropy (see Chapter 4.2.3)

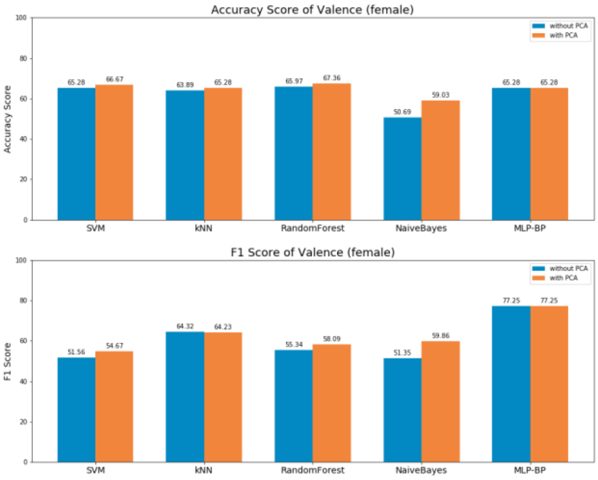


Figure 134 Accuracy and f1 Score for Valence for all algorithms in UC2 (female dataset) using PSD and Approximate Entropy for feature extraction

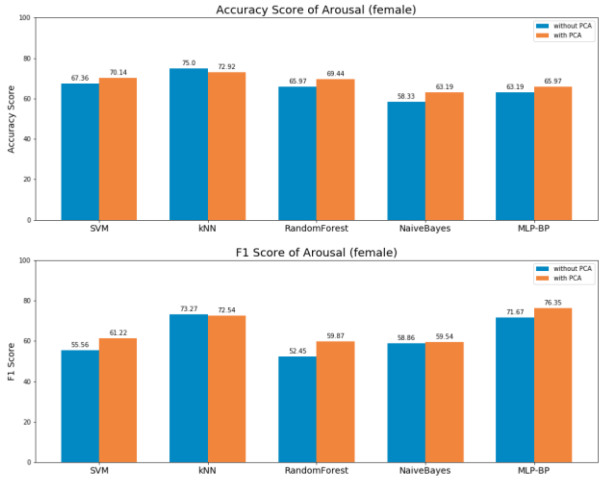


Figure 136 Accuracy and f1 Score for Arousal for all algorithms in UC2 (female dataset) using PSD and Approximate Entropy for feature extraction

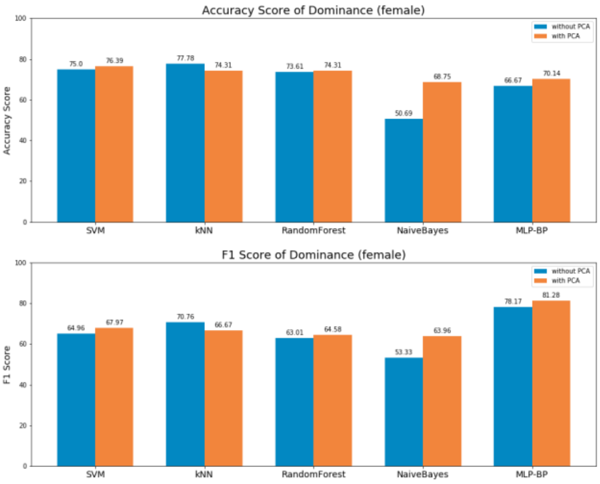


Figure 135 Accuracy and f1 Score for Dominance for all algorithms in UC2 (female dataset) using PSD and Approximate Entropy for feature extraction

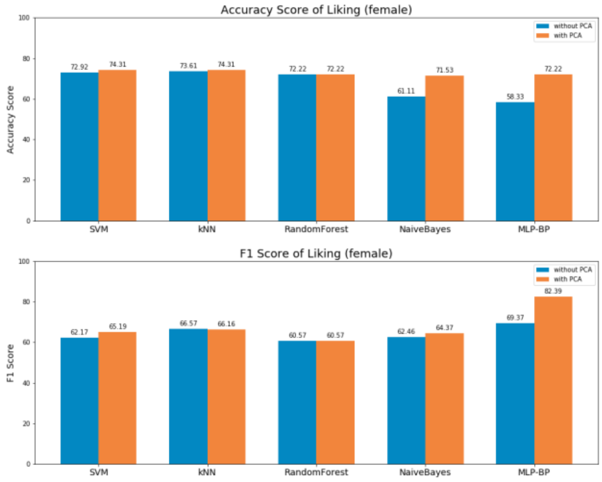


Figure 137 Accuracy and f1 Score for Liking for all algorithms in UC2 (female dataset) using PSD and Approximate Entropy for feature extraction

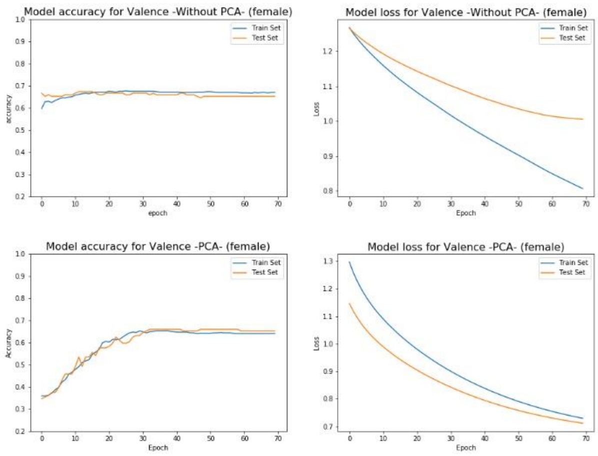


Figure 138 Model Accuracy and Model Loss (binary Cross Entropy) for Valence for the MLP-BP Algorithm along with PSD and Approximate Entropy for feature extraction in UC2 (female dataset)

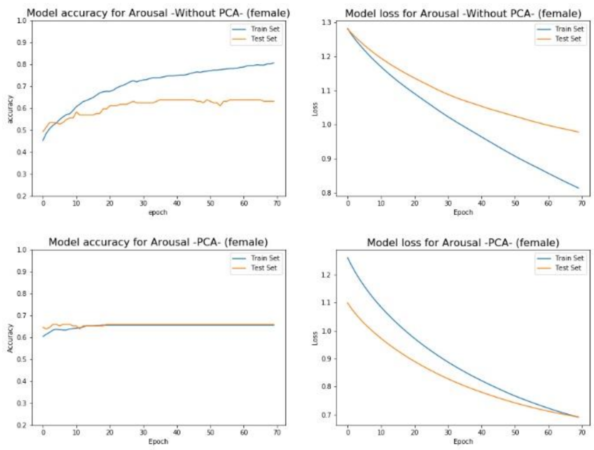


Figure 139 Model Accuracy and Model Loss (binary Cross Entropy) for Arousal for the MLP-BP Algorithm along with PSD and Approximate Entropy for feature extraction in UC2 (female dataset)

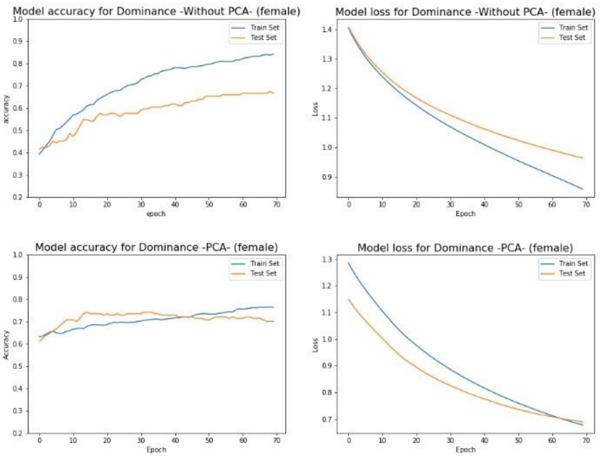


**Figure 140 Model Accuracy and Model Loss (binary Cross Entropy) for Dominance for the MLP-BP Algorithm along with PSD and Approximate Entropy for feature extraction in UC2 (female dataset)**

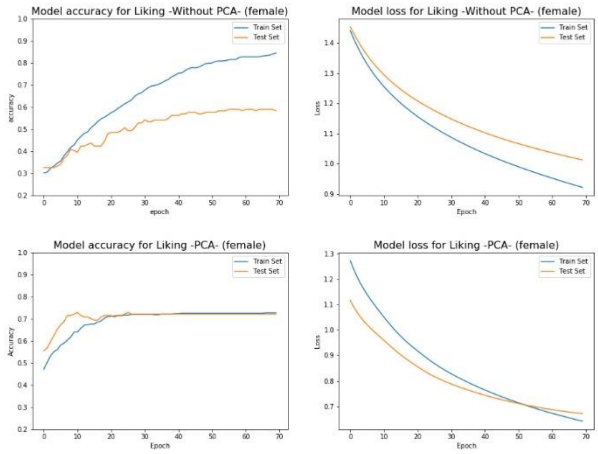


**Figure 141 Model Accuracy and Model Loss (binary Cross Entropy) for Liking using for the MLP-BP Algorithm along with PSD and Approximate Entropy for feature extraction in UC2 (female dataset)**

In order to sum up the results for accuracy and f1 score we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 16 Feature Extraction Method: PSD with Approximate Entropy in UC2 (female dataset)**

| Feature Extraction Method: PSD with Approximate Entropy | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=18) | | | |
| Algorithm | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| SVM | 65.28 / 51.56 | 67.36 / 55.56 | 75.0 / 64.96 | 72.92 / 62.17 | 66.67 / 54.67 | 70.14 / 61.22 | 76.39 / 67.97 | 74.31 / 65.19 |
| k-NN | 63.89 / 64.32 | 75.0 / 73.27 | 77.78 / 70.76 | 73.61 / 66.57 | 65.28 / 64.23 | 72.92 / 72.54 | 74.31 / 66.67 | 74.31 / 66.16 |
| RF | 65.97 / 55.34 | 65.97 / 52.42 | 73.61 / 63.01 | 72.22 / 60.57 | 67.36 / 58.09 | 69.44 / 59.87 | 74.31 / 64.58 | 72.22 / 60.57 |
| NB | 50.69 / 51.35 | 58.33 / 58.86 | 50.69 / 53.33 | 61.11 / 62.46 | 59.03 / 59.86 | 63.19 / 59.54 | 68.75 / 63.96 | 71.53 / 64.37 |
| MLP-BP | 65.28 / 77.25 | 63.19 / 71.67 | 66.67 / 78.17 | 58.33 / 69.37 | 65.28 / 77.25 | 65.97 / 76.35 | 70.14 / 81.28 | 72.22 / 82.39 |

Moving on, ***Figures 142 - 149*** present the accuracy and the f1 score for all the algorithms using the Short Time Fourier Transform Feature Extraction Method along with Standard Deviation (see Chapter 4.2.2)

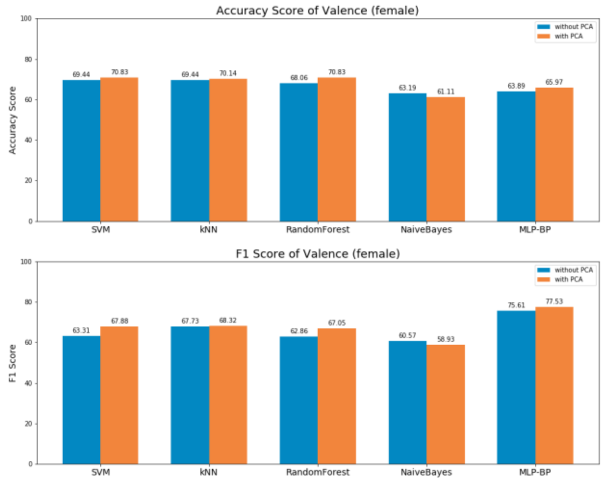


**Figure 142 Accuracy and f1 Score for Valence for all algorithms in UC2 (female dataset) using STFT and Standard Deviation for feature extraction**

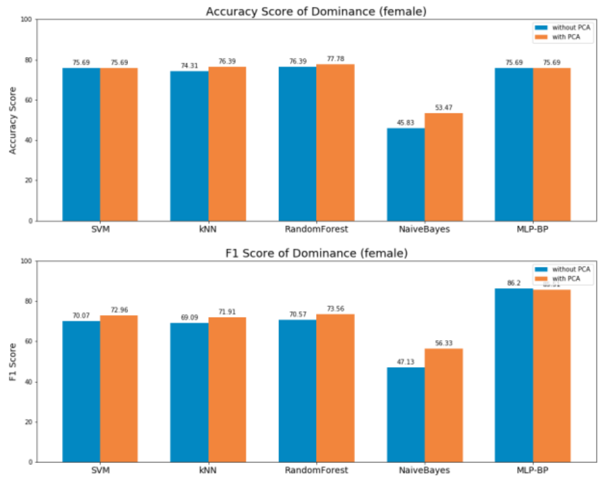


**Figure 143 Accuracy and f1 Score for Dominance for all algorithms in UC2 (female dataset) using STFT and Standard Deviation for feature extraction**

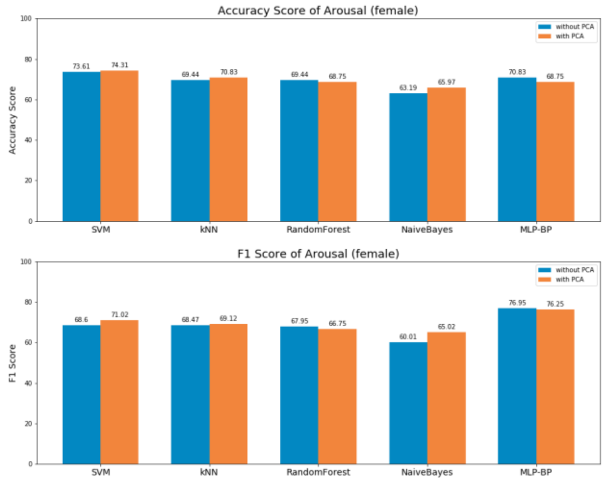


**Figure 144 Accuracy and f1 Score for Arousal for all algorithms in UC2 (female dataset) using STFT and Standard Deviation for feature extraction**

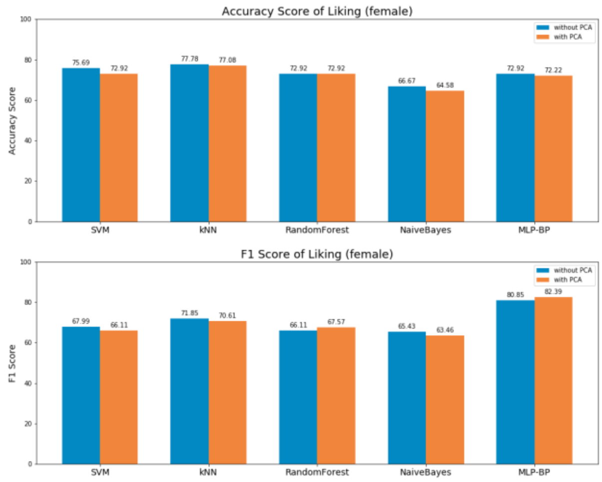


**Figure 145 Accuracy and f1 Score for Liking for all algorithms in UC2 (female dataset) using STFT and Standard Deviation for feature extraction**

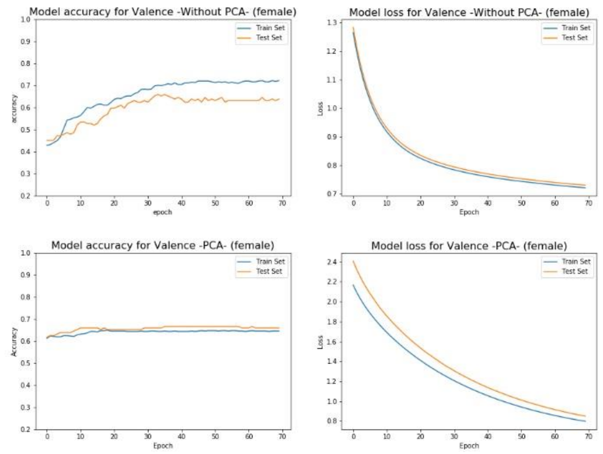


**Figure 146 Model Accuracy and Model Loss (binary Cross Entropy) for Valence for the MLP-BP Algorithm along with STFT and Standard Deviation for feature extraction in UC2 (female dataset)**

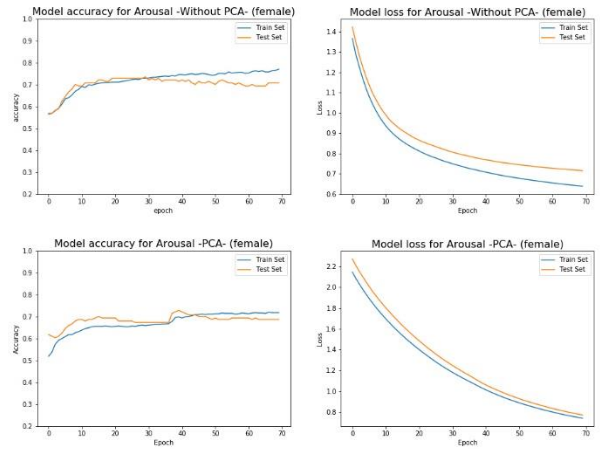


**Figure 147 Model Accuracy and Model Loss (binary Cross Entropy) for Arousal for the MLP-BP Algorithm along with STFT and Standard Deviation for feature extraction in UC2 (female dataset)**

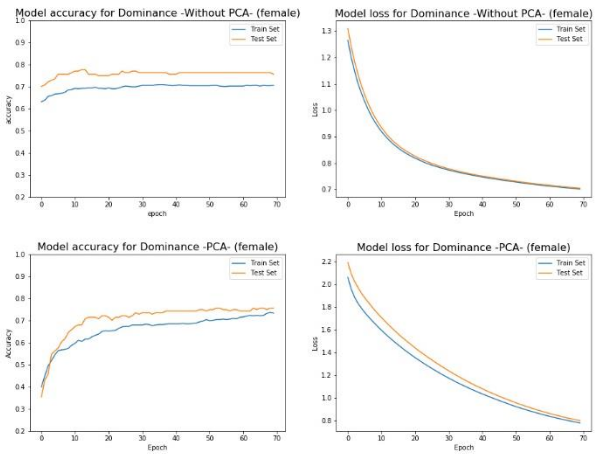


**Figure 148 Model Accuracy and Model Loss (binary Cross Entropy) for Dominance for the MLP-BP Algorithm along with STFT and standard deviation for feature extraction in UC2 (female dataset)**

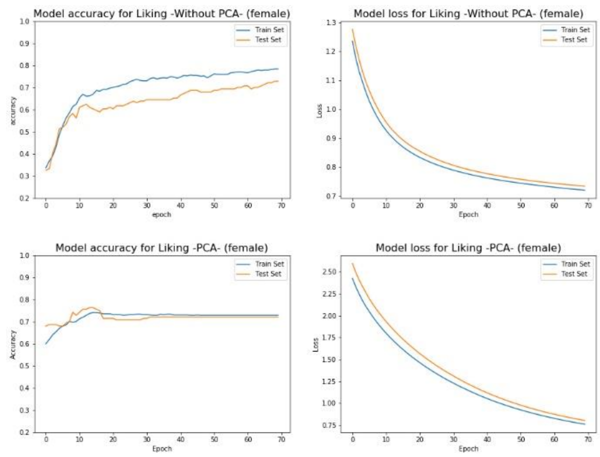


**Figure 149 Model Accuracy and Model Loss (binary Cross Entropy) for Liking using for the MLP-BP Algorithm along with STFT and standard deviation for feature extraction in UC2 (female dataset)**

In order to sum up the results for accuracy and f1 score, we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 17 Feature Extraction Method: STFT with Standard Deviation in UC2 (female dataset)**

| Feature Extraction Method: STFT with Standard Deviation | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=18) | | | |
| **Algorithm** | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| **SVM** | 69.44 / 63.31 | 73.61 / 68.6 | 75.69 / 70.07 | 75.69 / 67.99 | 70.83 / 67.88 | 74.31 / 71.02 | 75.69 / 72.96 | 72.92 / 66.11 |
| **k-NN** | 69.44 / 67.73 | 69.44 / 68.47 | 74.31 / 69.09 | 77.78 / 71.85 | 70.14 / 68.32 | 70.83 / 69.12 | 76.39 / 71.91 | 77.08 / 70.61 |
| **RF** | 68.06 / 62.86 | 69.44 / 67.95 | 76.39 / 70.57 | 72.92 / 66.11 | 70.83 / 67.05 | 68.75 / 66.75 | 77.78 / 73.56 | 72.92 / 67.57 |
| **NB** | 63.19 / 60.57 | 63.19 / 60.01 | 75.83 / 47.13 | 66.67 / 65.43 | 61.11 / 58.93 | 65.97 / 65.02 | 53.47 / 56.33 | 64.58 / 63.46 |
| **MLP-BP** | 63.89 / 75.61 | 70.83 / 76.95 | 75.69 / 86.2 | 72.92 / 80.85 | 65.97 / 77.53 | 68.75 / 76.25 | 75.69 / 85.51 | 72.22 / 82.39 |

Moving on, ***Figures 150 - 157*** present the accuracy and the f1 score for all the algorithms using the Short Time Fourier Transform Feature Extraction Method along with Approximate Entropy (see Chapter 4.2.2)

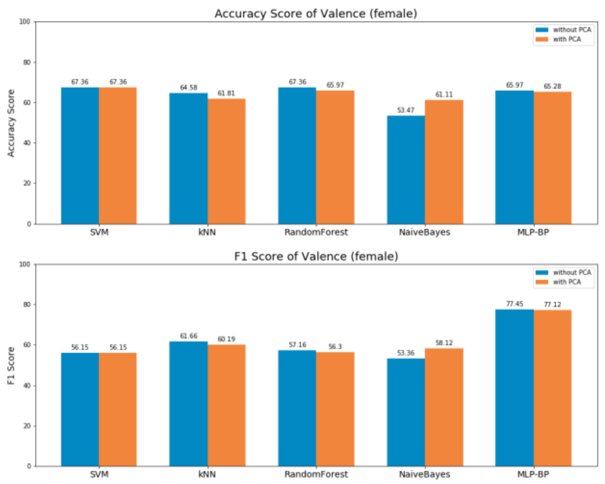


Figure 150 Accuracy and f1 Score for Valence for all algorithms in UC2 (female dataset) using STFT and Approximate Entropy for feature extraction

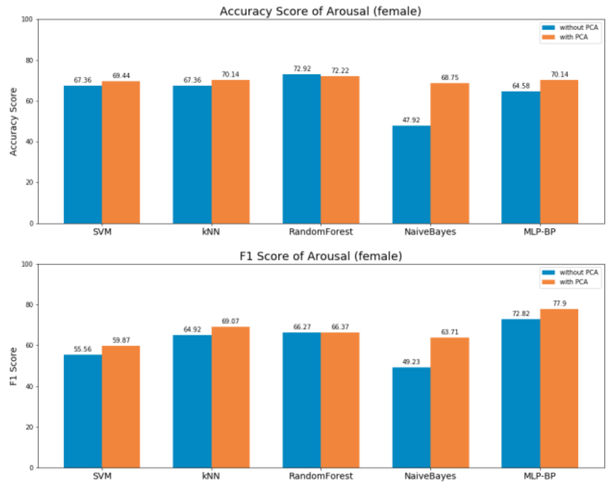


Figure 152 Accuracy and f1 Score for Arousal for all algorithms in UC2 (female dataset) using STFT and Approximate Entropy for feature extraction


Figure 151 Accuracy and f1 Score for Dominance for all algorithms in UC2 (female dataset) using STFT and Approximate Entropy for feature extraction

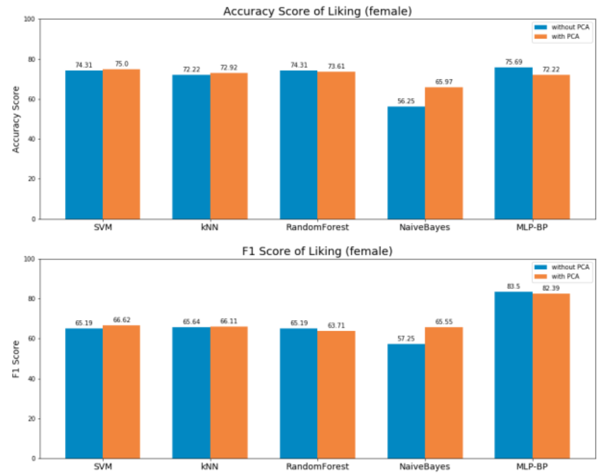


Figure 153 Accuracy and f1 Score for Liking for all algorithms using in UC2 (female dataset) STFT and Approximate Entropy for feature extraction

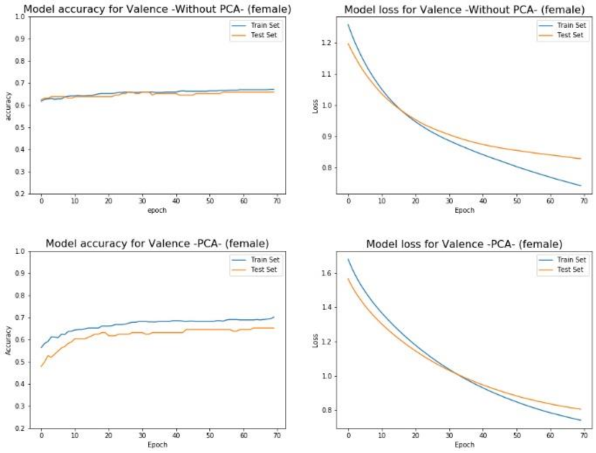


Figure 154 Model Accuracy and Model Loss (binary Cross Entropy) for Valence for the MLP-BP Algorithm along with STFT and Approximate Entropy for feature extraction in UC2 (female dataset)

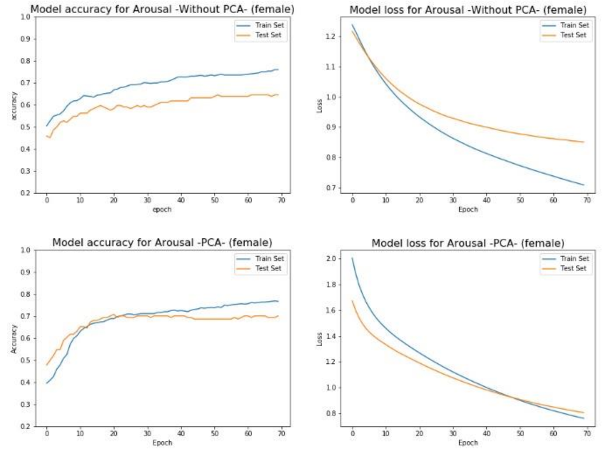


Figure 155 Model Accuracy and Model Loss (binary Cross Entropy) for Arousal for the MLP-BP Algorithm along with STFT and Approximate Entropy for feature extraction in UC2 (female dataset)

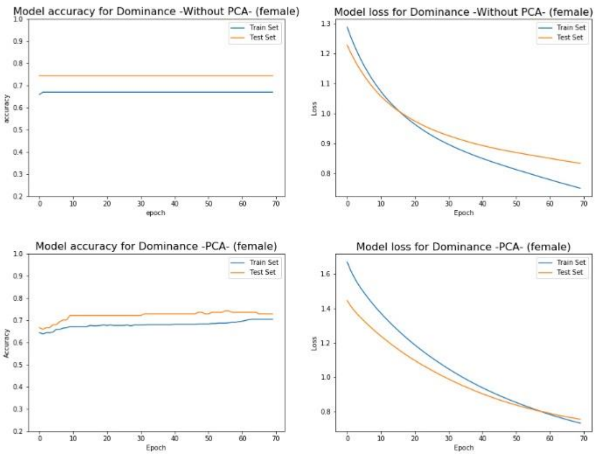


**Figure 156 Model Accuracy and Model Loss (binary Cross Entropy) for Dominance for the MLP-BP Algorithm along with STFT and Approximate Entropy for feature extraction in UC2 (female dataset)**

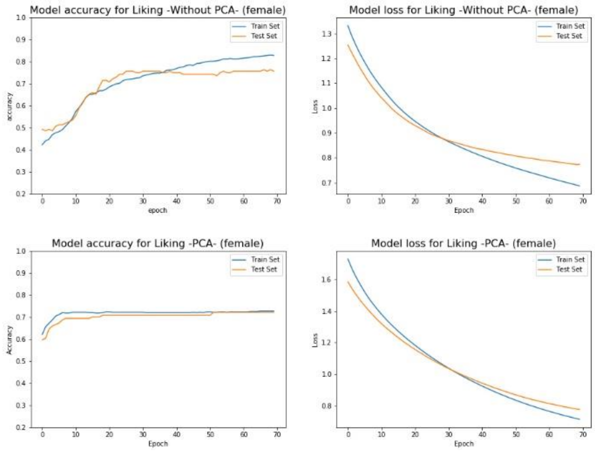


**Figure 157 Model Accuracy and Model Loss (binary Cross Entropy) for Liking using for the MLP-BP Algorithm along with STFT and Approximate Entropy for feature extraction in UC2 (female dataset)**

In order to sum up the results for accuracy and f1 score we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 18 Feature Extraction Method: STFT with Approximate Entropy in UC2 (female dataset)**

| Feature Extraction Method: STFT with Approximate Entropy | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=18) | | | |
| Algorithm | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| SVM | 67.36 / 56.15 | 67.36 / 55.56 | 74.31 / 63.35 | 74.31 / 65.19 | 67.36 / 56.15 | 69.44 / 59.87 | 75.69 / 66.5 | 75.0 / 66.62 |
| k-NN | 64.58 / 61.66 | 67.36 / 64.92 | 71.53 / 64.05 | 72.22 / 65.64 | 61.81 / 60.19 | 70.14 / 69.07 | 73.61 / 67.11 | 72.92 / 66.11 |
| RF | 67.36 / 57.16 | 72.92 / 66.27 | 74.31 / 63.35 | 74.31 / 65.19 | 65.97 / 56.3 | 72.22 / 66.37 | 73.61 / 63.01 | 73.61 / 63.71 |
| NB | 53.47 / 53.36 | 47.92 / 49.23 | 45.83 / 48.92 | 56.25 / 57.25 | 61.11 / 58.12 | 68.75 / 63.71 | 63.19 / 62.28 | 65.97 / 65.55 |
| MLP-BP | 65.97 / 77.45 | 64.58 / 72.82 | 74.31 / 85.1 | 75.69 / 83.5 | 65.28 / 77.12 | 70.14 / 77.9 | 72.92 / 84.21 | 72.22 / 82.39 |

### 5.2.3 Voting Algorithm Results and Recommendation List

In this section, we are going to present the experimentation results for our voting algorithm in UC2 for both the male and the female dataset. As always, the results concern the emotion related labels only, since the voting algorithm with the method of soft voting (see Chapter 4.6) takes into consideration the weights assigned to each of the 5 algorithms in order to predict the emotion related label of each feature vector.

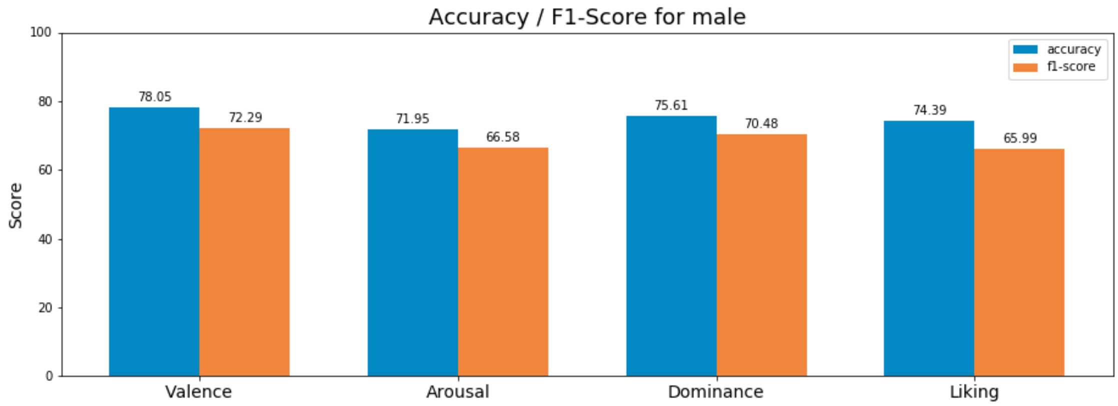


**Figure 158 Accuracy and f1 Score for emotion related labels for the voting algorithm in UC2 (male dataset) using STFT and standard deviation for feature extraction**

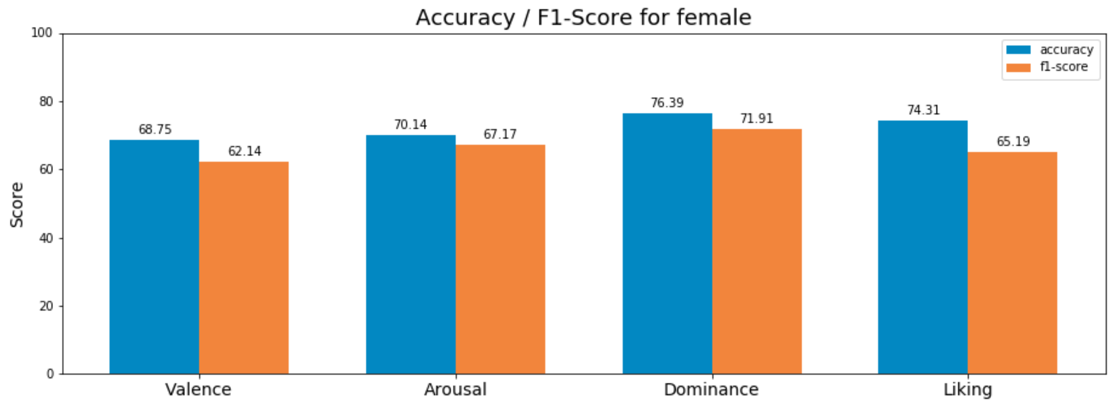


**Figure 159 Accuracy and f1 Score for emotion related labels for the voting algorithm in UC2 (female dataset) using STFT and standard deviation for feature extraction**

Based on the results presented above, we are going to construct the final recommendation list that was extracted from LAST.FM. We are going to use the method presented in Chapter 4.8.

## Recommendation List for Males

**1. The Jacksons , Blame It on the Boogie ,** https://www.last.fm/music/the%2bjacksons/_/blame%2bit%2bon%2bthe%2bboogie
**2. Michael Jackson , Billie Jean ,** https://www.last.fm/music/michael%2bjackson/_/billie%2bjean
**3. The Temptations , My Girl ,** https://www.last.fm/music/the%2btemptations/_/my%2bgirl`
**4. The Supremes , You Can't Hurry Love ,** https://www.last.fm/music/the%2bsupremes/_/you%2bcan%2527t%2bhurry%2blove
**5. Jermaine Jackson , Let's Get Serious ,** https://www.last.fm/music/jermaine%2bjackson/_/let%2527s%2bget%2bserious
**6. Smokey Robinson and The Miracles , The Tracks Of My Tears ,** https://www.last.fm/music/smokey%2brobinson%2band%2bthe%2bmiracles/_/the%2btracks%2bof%2bmy%2btears
**7. The Four Tops , I Can't Help Myself (Sugar Pie, Honey Bunch) ,** https://www.last.fm/music/the%2bfour%2btops/_/i%2bcan%2527t%2bhelp%2bmyself%2b%2528sugar%2bpie%252c%2bhoney%2bbunch%2529
**8. The Miracles , Shop Around ,** https://www.last.fm/music/the%2bmiracles/_/shop%2baround
**9. Commodores , Easy ,** https://www.last.fm/music/commodores/_/easy
**10. Stevie Wonder , Superstition ,** https://www.last.fm/music/stevie%2bwonder/_/superstition
**11. The Spinners , I'll Be Around ,** https://www.last.fm/music/the%2bspinners/_/i%2527ll%2bbe%2baround
**12. The Isley Brothers , It's Your Thing ,** https://www.last.fm/music/the%2bisley%2bbrothers/_/it%2527s%2byour%2bthing
**13. Jr. Walker & The All Stars , Shotgun ,** https://www.last.fm/music/jr.%2bwalker%2b%2526%2bthe%2ball%2bstars/_/shotgun
**14. Marvin Gaye , What's Going On ,** https://www.last.fm/music/marvin%2bgaye/_/what%2527s%2bgoing%2bon
**15. Martha Reeves & The Vandellas , Dancing in the Street ,** https://www.last.fm/music/martha%2breeves%2b%2526%2bthe%2bvandellas/_/dancing%2bin%2bthe%2bstreet
**16. The Marvelettes , Please Mr. Postman ,** https://www.last.fm/music/the%2bmarvelettes/_/please%2bmr.%2bpostman
**17. Benny Benassi , Love Is Gonna Save Us ,** https://www.last.fm/music/benny%2bbenassi/_/love%2bis%2bgonna%2bsave%2bus

**18. Eric Prydz , Call On Me ,** https://www.last.fm/music/eric%2bprydz/_/call%2bon%2bme
**19. Darude , Sandstorm ,** https://www.last.fm/music/darude/_/sandstorm
**20. Benny Benassi , No Matter What You Do ,**
https://www.last.fm/music/benny%2bbenassi/_/no%2bmatter%2bwhat%2byou%2bdo
**21. Avicii , Levels ,** https://www.last.fm/music/avicii/_/levels
**22. Alex Gaudino , Destination Calabria ,** https://www.last.fm/music/alex%2bgaudino/_/destination%2bcalabria
**23. Fedde Le Grand , Put Your Hands Up For Detroit ,**
https://www.last.fm/music/fedde%2ble%2bgrand/_/put%2byour%2bhands%2bup%2bfor%2bdetroit
**24. Zombie Nation , Kernkraft 400 ,** https://www.last.fm/music/zombie%2bnation/_/kernkraft%2b400
**25. Sum 41 , Fat Lip ,** https://www.last.fm/music/sum%2b41/_/fat%2blip
**26. Good Charlotte , The Anthem ,** https://www.last.fm/music/good%2bcharlotte/_/the%2banthem
**27. Sum 41 , Still Waiting ,** https://www.last.fm/music/sum%2b41/_/still%2bwaiting
**28. The Offspring , Want You Bad ,** https://www.last.fm/music/the%2boffspring/_/want%2byou%2bbad
**29. The B-52's , Roam ,** https://www.last.fm/music/the%2bb-52%2527s/_/roam
**30. The B-52's , Rock Lobster ,** https://www.last.fm/music/the%2bb-52%2527s/_/rock%2blobster
**31. Counting Crows , Accidentally in Love ,** https://www.last.fm/music/counting%2bcrows/_/accidentally%2bin%2blove

## Recommendation List for Females

**1. Benny Benassi , Love Is Gonna Save Us ,**
https://www.last.fm/music/benny%2bbenassi/_/love%2bis%2bgonna%2bsave%2bus
**2. Eric Prydz , Call On Me ,** https://www.last.fm/music/eric%2bprydz/_/call%2bon%2bme
**3. Darude , Sandstorm ,** https://www.last.fm/music/darude/_/sandstorm
**4. Benny Benassi , No Matter What You Do ,**
https://www.last.fm/music/benny%2bbenassi/_/no%2bmatter%2bwhat%2byou%2bdo
**5. Avicii , Levels ,** https://www.last.fm/music/avicii/_/levels
**6. Alex Gaudino , Destination Calabria ,** https://www.last.fm/music/alex%2bgaudino/_/destination%2bcalabria
**7. Fedde Le Grand , Put Your Hands Up For Detroit ,**
https://www.last.fm/music/fedde%2ble%2bgrand/_/put%2byour%2bhands%2bup%2bfor%2bdetroit
**8. Zombie Nation , Kernkraft 400 ,** https://www.last.fm/music/zombie%2bnation/_/kernkraft%2b400
**9. Guru Josh Project , Infinity 2008 ,** https://www.last.fm/music/guru%2bjosh%2bproject/_/infinity%2b2008
**10. David Guetta , Love Is Gone ,** https://www.last.fm/music/david%2bguetta/_/love%2bis%2bgone
**11. Benassi Bros. , Every Single Day ,** https://www.last.fm/music/benassi%2bbros./_/every%2bsingle%2bday
**12. Pakito , Living On Video ,** https://www.last.fm/music/pakito/_/living%2bon%2bvideo
**13. Swedish House Mafia , One ,** https://www.last.fm/music/swedish%2bhouse%2bmafia/_/one
**14. Pakito , You Wanna Rock ,** https://www.last.fm/music/pakito/_/you%2bwanna%2brock
**15. Benassi Bros. , Illusion ,** https://www.last.fm/music/benassi%2bbros./_/illusion
**16. Global Deejays , The Sound of San Francisco ,**
https://www.last.fm/music/global%2bdeejays/_/the%2bsound%2bof%2bsan%2bfrancisco
**17. Dark Funeral , Stigmata ,** https://www.last.fm/music/dark%2bfuneral/_/stigmata
**18. Dark Funeral , In My Dreams ,** https://www.last.fm/music/dark%2bfuneral/_/in%2bmy%2bdreams
**19. Marduk , Serpent Sermon ,** https://www.last.fm/music/marduk/_/serpent%2bsermon
**20. Gorgoroth , Funeral Procession ,** https://www.last.fm/music/gorgoroth/_/funeral%2bprocession
**21. Marduk , Souls for Belial ,** https://www.last.fm/music/marduk/_/souls%2bfor%2bbelial
**22. Gorgoroth , Rebirth ,** https://www.last.fm/music/gorgoroth/_/rebirth
**23. Immortal , All Shall Fall ,** https://www.last.fm/music/immortal/_/all%2bshall%2bfall
**24. 1349 , I Am Abomination ,** https://www.last.fm/music/1349/_/i%2bam%2babomination
**25. Sum 41 , Fat Lip ,** https://www.last.fm/music/sum%2b41/_/fat%2blip
**26. Good Charlotte , The Anthem ,** https://www.last.fm/music/good%2bcharlotte/_/the%2banthem
**27. Sum 41 , Still Waiting ,** https://www.last.fm/music/sum%2b41/_/still%2bwaiting
**28. The Offspring , Want You Bad ,** https://www.last.fm/music/the%2boffspring/_/want%2byou%2bbad
**29. Blur , Beetlebum ,** https://www.last.fm/music/blur/_/beetlebum
**30. Blur , Parklife ,** https://www.last.fm/music/blur/_/parklife
**31. Emilíana Torrini , Big Jumps ,** https://www.last.fm/music/emil%25c3%25adana%2btorrini/_/big%2bjumps

## 5.3 Subject Dependent Experimentation and Results

The presented results in this chapter are about the UC3. The following figures will present the accuracy and the f1 score (see Chapter 2) for all the algorithms used and described in Chapter 4.5. It is really important to notice that in order to present the results we averaged the performance (accuracy/f1) of the algorithms for all the participants.

***Figures 160 - 163*** present the accuracy and the f1 score for all the algorithms using the Discrete Wavelet Transform Feature Extraction Method along with Standard Deviation (see Chapter 4.2.1)

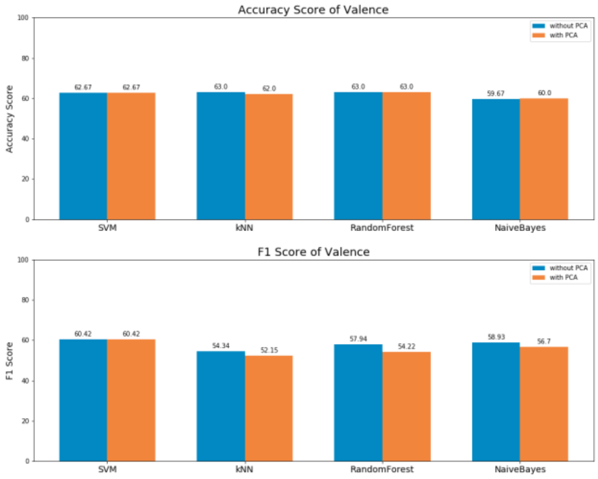


**Figure 160 Accuracy and f1 Score for Valence for all algorithms in UC3 using DWT and Standard Deviation for feature extraction**

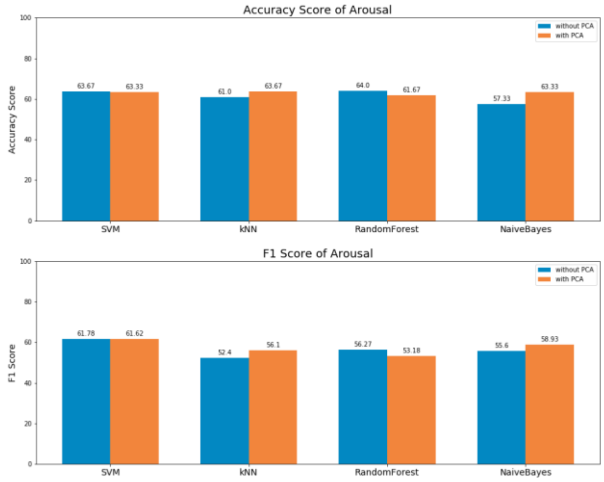


**Figure 161 Accuracy and f1 Score for Arousal for all algorithms in UC3 using DWT and Standard Deviation for feature extraction**


**Figure 162 Accuracy and f1 Score for Dominance for all algorithms in UC3 using DWT and Standard Deviation for feature extraction**

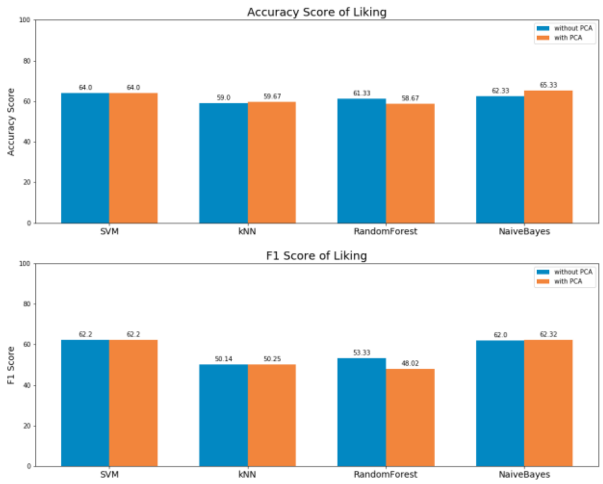


**Figure 163 Accuracy and f1 Score for Liking for all algorithms in UC3 using DWT and Standard Deviation for feature extraction**

In order to sum up the results for accuracy and f1 score we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 19 Feature Extraction Method: DWT with Standard Deviation in UC3**

| Feature Extraction Method: DWT with Standard Deviation | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=40) | | | |
| Algorithm | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| SVM | 62.67 / 60.42 | 63.67 / 61.78 | 64.0 / 62.79 | 64.0 / 62.2 | 62.67 / 60.42 | 63.33 / 61.62 | 64.33 / 59.71 | 64.0 / 62.2 |
| k-NN | 63.0 / 54.34 | 61.0 / 52.4 | 67.33 / 60.61 | 59.0 / 50.14 | 62.0 / 52.15 | 63.67 / 56.1 | 67.33 / 60.61 | 59.67 / 50.25 |
| RF | 63.0 / 57.94 | 64.0 / 56.27 | 66.67 / 61.44 | 61.33 / 53.33 | 63.0 / 54.22 | 61.67 / 53.18 | 63.33 / 56.31 | 58.67 / 48.02 |
| NB | 59.67 / 58.93 | 57.33 / 55.6 | 59.67 / 58.72 | 62.33 / 62.0 | 60.0 / 56.7 | 63.33 / 58.93 | 64.67 / 62.5 | 65.33 / 62.32 |

Moving on, ***Figures 164 - 167*** present the accuracy and the f1 score for all the algorithms using the Discrete Wavelet Transform Feature Extraction Method along with Approximate Entropy (see [Chapter 4.2.1](#))

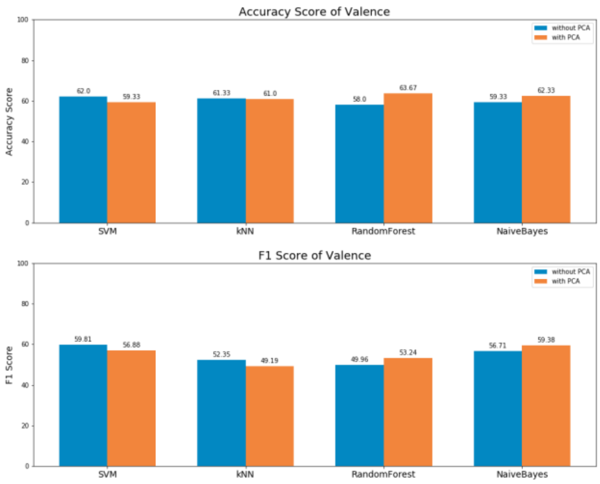


**Figure 164 Accuracy and f1 Score for Valence for all algorithms in UC3 using DWT and Approximate Entropy for feature extraction**


**Figure 165 Accuracy and f1 Score for Arousal for all algorithms in UC3 using DWT and Approximate Entropy for feature extraction**

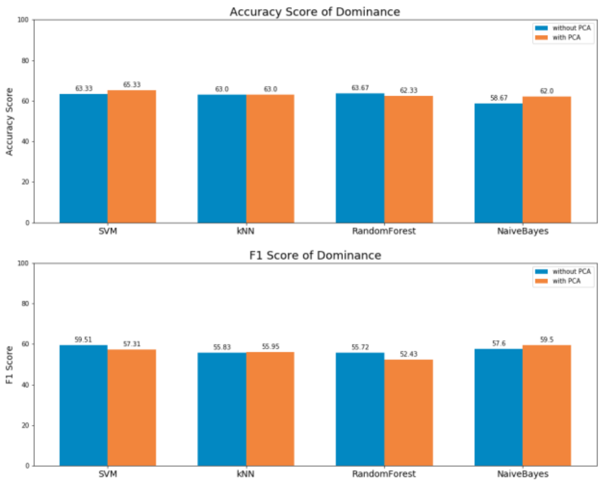


**Figure 166 Accuracy and f1 Score for Dominance for all algorithms in UC3 using DWT and Approximate Entropy for feature extraction**

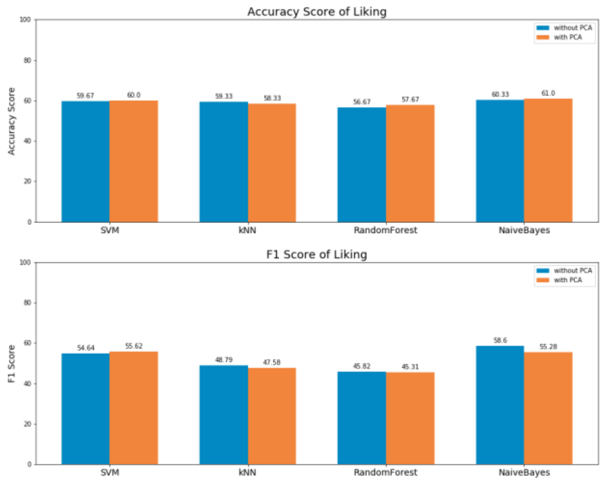


**Figure 167 Accuracy and f1 Score for Liking for all algorithms in UC3 using DWT and Approximate Entropy for feature extraction**

In order to sum up the results for accuracy and f1 score we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 20 Feature Extraction Method: DWT with Approximate Entropy in UC3**

| Feature Extraction Method: DWT with Approximate Entropy | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=40) | | | |
| Algorithm | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| SVM | 62.0 / 59.81 | 64.0 / 60.51 | 63.33 / 59.51 | 59.67 / 54.64 | 59.33 / 56.88 | 66.0 / 62.27 | 65.33 / 57.31 | 60.0 / 55.62 |
| k-NN | 61.33 / 52.35 | 61.67 / 52.66 | 63.0 / 55.83 | 59.33 / 48.79 | 61.0 / 49.19 | 60.67 / 49.85 | 63.0 / 55.95 | 58.33 / 47.58 |
| RF | 58.0 / 49.96 | 65.33 / 57.08 | 63.67 / 55.72 | 56.67 / 45.82 | 63.67 / 53.24 | 62.33 / 52.11 | 62.33 / 52.43 | 57.67 / 45.31 |
| NB | 59.33 / 56.71 | 61.33 / 57.36 | 58.67 / 57.6 | 60.33 / 58.6 | 62.33 / 59.38 | 63.0 / 56.94 | 62.0 / 59.5 | 61.0 / 55.28 |

Moving on**, *Figures 168 - 171*** present the accuracy and the f1 score for all the algorithms using the Power Spectral Density Feature Extraction Method along with Standard Deviation (see Chapter 4.2.3)

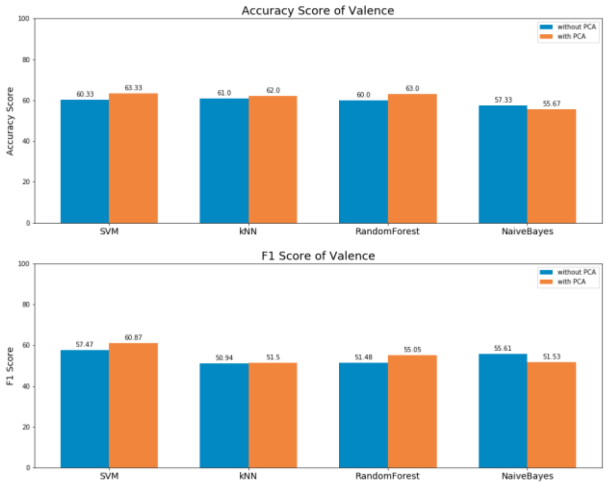


Figure 168 Accuracy and f1 Score for Valence for all algorithms in UC3 using PSD and Standard Deviation for feature extraction

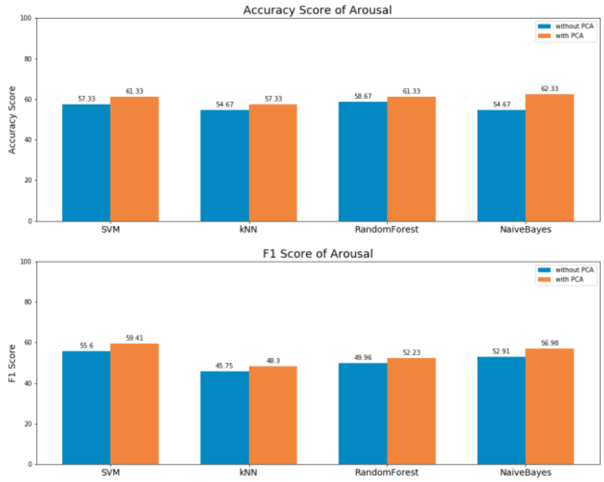


Figure 170 Accuracy and f1 Score for Arousal for all algorithms in UC3 using PSD and Standard Deviation for feature extraction

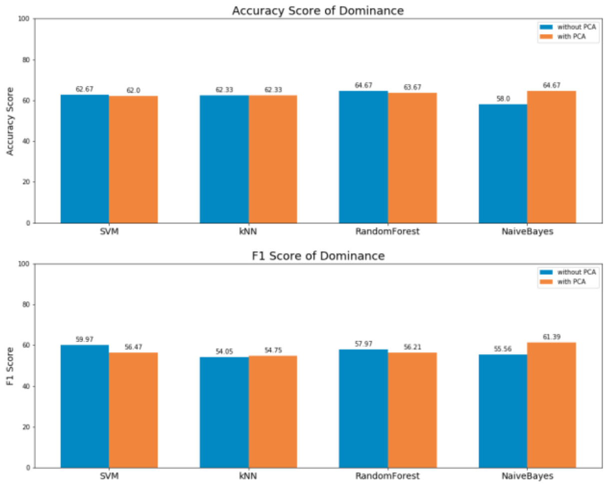


Figure 169 Accuracy and f1 Score for Dominance for all algorithms in UC3 using PSD and Standard Deviation for feature extraction

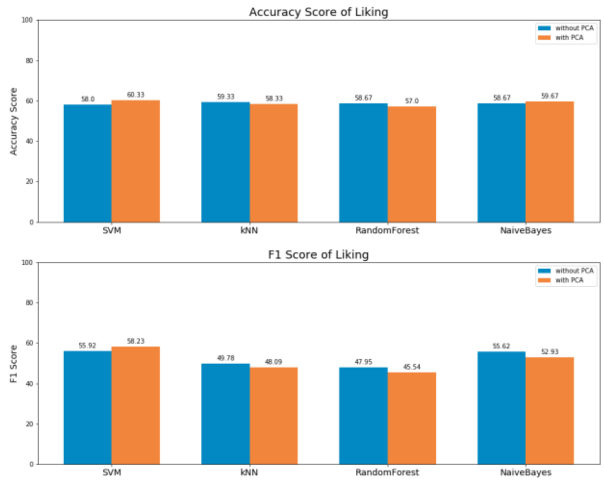


Figure 171 Accuracy and f1 Score for Liking for all algorithms in UC3 using PSD and Standard Deviation for feature extraction

In order to sum up the results for accuracy and f1 score we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 21 Feature Extraction Method: PSD with Standard Deviation in UC3**

| Feature Extraction Method: PSD with Standard Deviation | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=40) | | | |
| Algorithm | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| SVM | 60.33 / 57.47 | 57.33 / 55.6 | 62.67 / 59.97 | 58.0 / 55.92 | 63.33 / 60.87 | 61.33 / 59.41 | 62.0 / 56.47 | 60.33 / 58.23 |
| k-NN | 61.0 / | 54.67 / | 62.33 / | 59.33 / | 62.0 / | 57.33 / | 62.33 / | 58.33 / |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 50.94 | 45.75 | 54.05 | 49.78 | 51.5 | 48.3 | 54.75 | 48.09 |
| **RF** | 60.0 / 51.48 | 58.67 / 49.96 | 64.67 / 57.97 | 58.67 / 45.95 | 63.0 / 55.05 | 61.33 / 52.23 | 63.67 / 56.21 | 57.0 / 45.54 |
| **NB** | 57.33 / 55.61 | 54.67 / 52.91 | 58.0 / 55.56 | 58.67 / 55.62 | 55.67 / 51.53 | 62.33 / 56.98 | 64.67 / 61.39 | 59.67 / 52.93 |

Moving on, ***Figures 37 - 44*** present the accuracy and the f1 score for all the algorithms using the Power Spectral Density Feature Extraction Method along with Approximate Entropy (see Chapter 4.2.3)

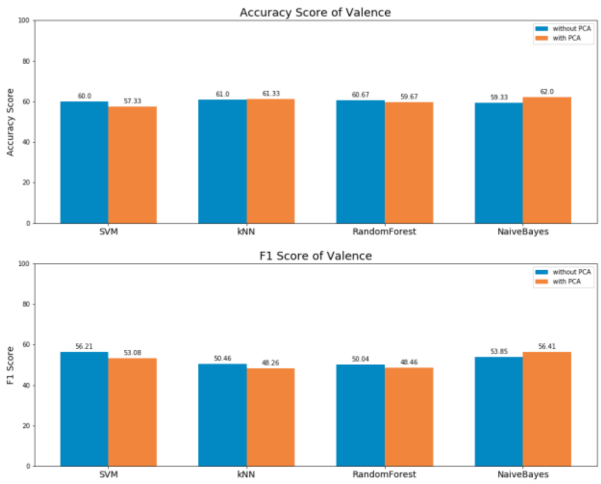


**Figure 172 Accuracy and f1 Score for Valence for all algorithms in UC1 using PSD and Approximate Entropy for feature extraction**

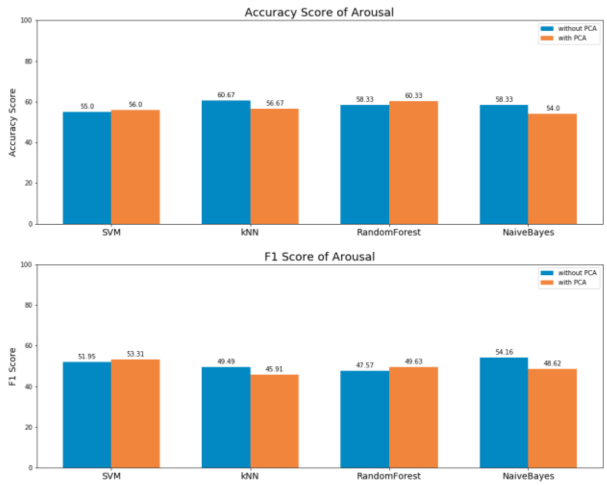


**Figure 174 Accuracy and f1 Score for Arousal for all algorithms in UC1 using PSD and Approximate Entropy for feature extraction**

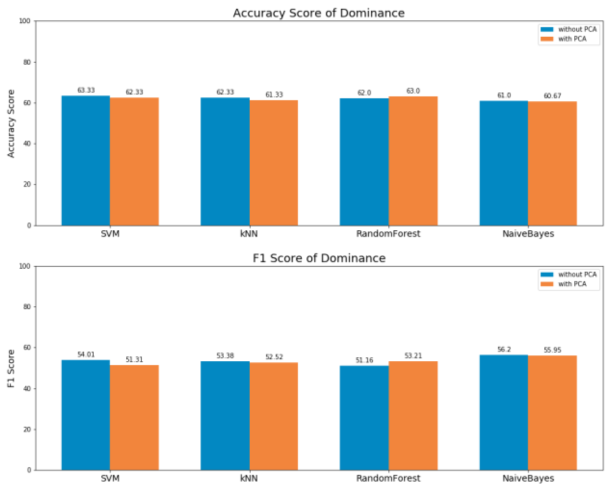


**Figure 173 Accuracy and f1 Score for Dominance for all algorithms in UC1 using PSD and Approximate Entropy for feature extraction**

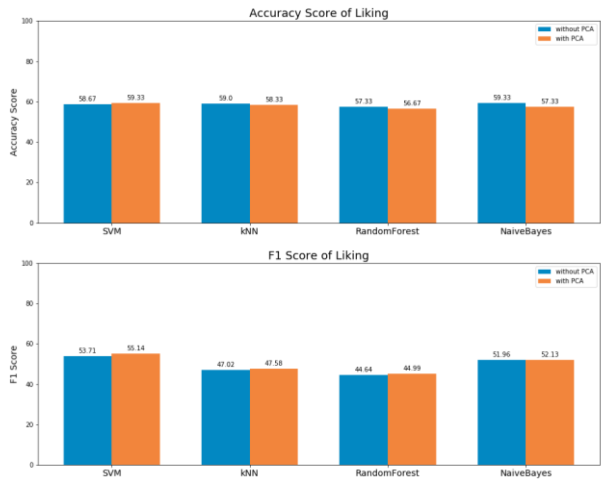


**Figure 175 Accuracy and f1 Score for Liking for all algorithms in UC1 using PSD and Approximate Entropy for feature extraction**

In order to sum up the results for accuracy and f1 score, we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 22 Feature Extraction Method: PSD with Approximate Entropy in UC3**

| Feature Extraction Method: PSD with Approximate Entropy | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=40) | | | |
| Algorithm | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| SVM | 60.0 / 56.21 | 55.0 / 51.95 | 63.33 / 54.01 | 58.67 / 53.71 | 57.33 / 53.08 | 56.0 / 53.31 | 62.33 / 51.31 | 59.33 / 55.14 |
| k-NN | 61.0 / 50.46 | 60.67 / 49.49 | 62.33 / 53.38 | 59.0 / 47.02 | 61.33 / 48.26 | 56.67 / 45.91 | 61.33 / 52.52 | 58.33 / 47.58 |
| RF | 60.67 / 50.04 | 58.33 / 47.57 | 62.0 / 51.16 | 57.33 / 44.64 | 59.67 / 48.46 | 60.33 / 49.63 | 63.0 / 53.21 | 56.67 / 44.99 |
| NB | 59.33 / 53.85 | 58.33 / 54.16 | 61.0 / 56.2 | 59.33 / 51.96 | 62.0 / 56.41 | 54.0 / 48.62 | 60.67 / 55.95 | 57.33 / 52.13 |

Moving on, ***Figures 176 - 179*** present the accuracy and the f1 score for all the algorithms using the Short Time Fourier Transform Feature Extraction Method along with Standard Deviation (see Chapter 4.2.2)

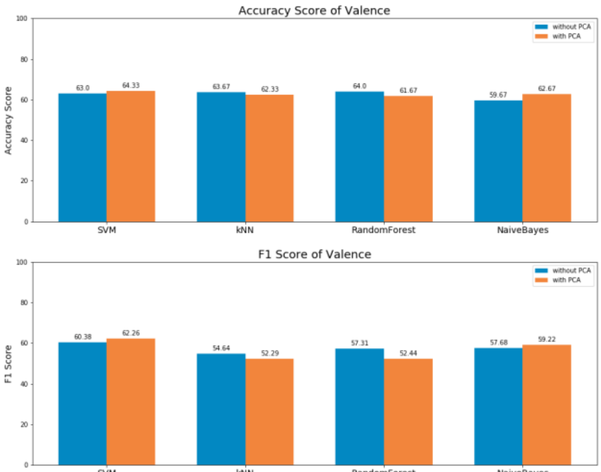


**Figure 176 Accuracy and f1 Score for Valence for all algorithms in UC3 using STFT and Standard Deviation for feature extraction**

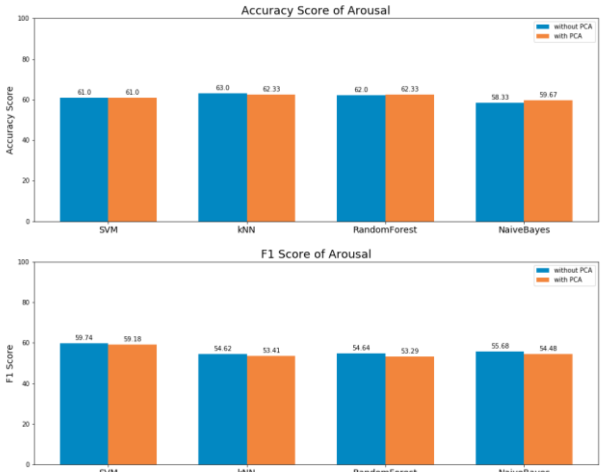


**Figure 177 Accuracy and f1 Score for Arousal for all algorithms in UC3 using STFT and Standard Deviation for feature extraction**

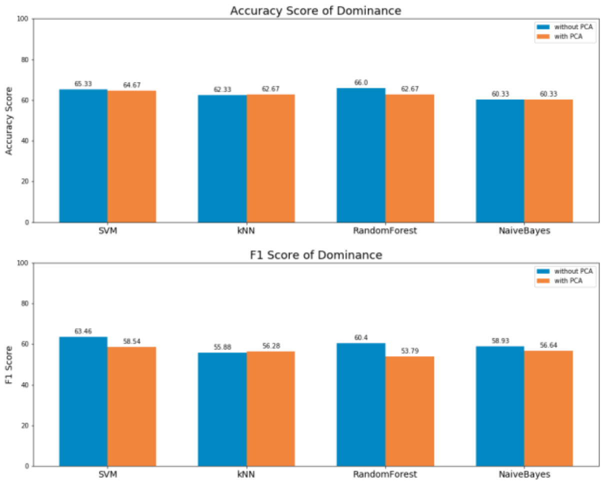


**Figure 178 Accuracy and f1 Score for Dominance for all algorithms in UC3 using STFT and Standard Deviation for feature extraction**

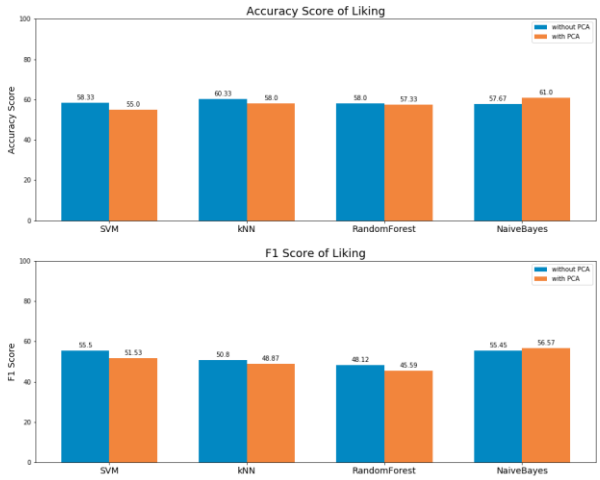


**Figure 179 Accuracy and f1 Score for Liking for all algorithms in UC3 using STFT and Standard Deviation for feature extraction**

In order to sum up the results for accuracy and f1 score, we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 23 Feature Extraction Method: STFT with Standard Deviation in UC3**

| Feature Extraction Method: STFT with Standard Deviation | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=40) | | | |
| **Algorithm** | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| **SVM** | 63.0 / 60.38 | 61.0 / 59.74 | 65.33 / 63.46 | 58.33 / 55.5 | 64.33 / 62.26 | 61.0 / 59.18 | 64.67 / 58.54 | 55.0 / 51.53 |
| **k-NN** | 63.67 / 54.64 | 63.0 / 54.62 | 62.33 / 55.88 | 60.33 / 50.8 | 62.33 / 52.29 | 62.33 / 53.41 | 62.67 / 56.28 | 58.0 / 48.87 |
| **RF** | 64.0 / 57.31 | 62.0 / 54.64 | 66.0 / 60.4 | 58.0 / 48.12 | 61.67 / 52.44 | 62.33 / 53.29 | 62.67 / 53.79 | 57.33 / 45.59 |
| **NB** | 59.67 / 57.68 | 58.33 / 55.68 | 60.33 / 58.93 | 57.67 / 55.45 | 62.67 / 59.22 | 59.67 / 54.48 | 60.33 / 56.64 | 61.0 / 56.57 |

Moving on, ***Figures 180 - 183*** present the accuracy and the f1 score for all the algorithms using the Short Time Fourier Transform Feature Extraction Method along with Approximate Entropy (see Chapter 4.2.2)

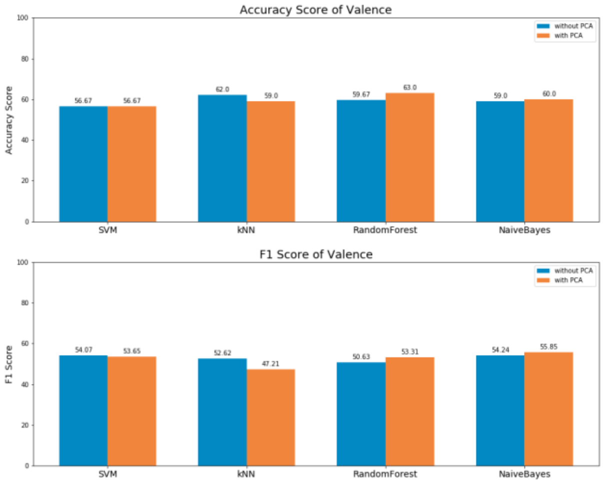


**Figure 180 Accuracy and f1 Score for Valence for all algorithms in UC3 using STFT and Approximate Entropy for feature extraction**

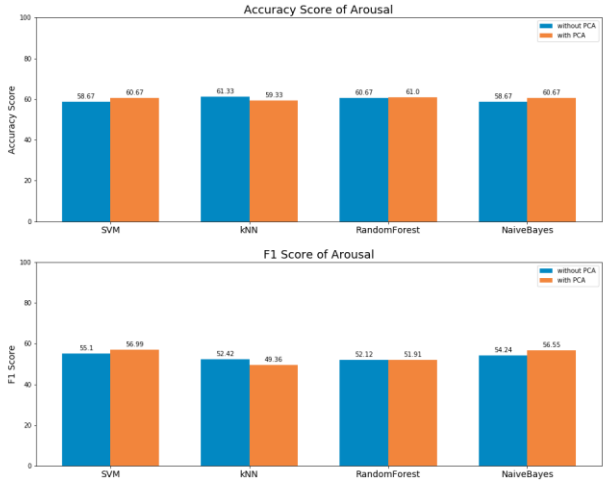


**Figure 182 Accuracy and f1 Score for Arousal for all algorithms in UC3 using STFT and Approximate Entropy for feature extraction**

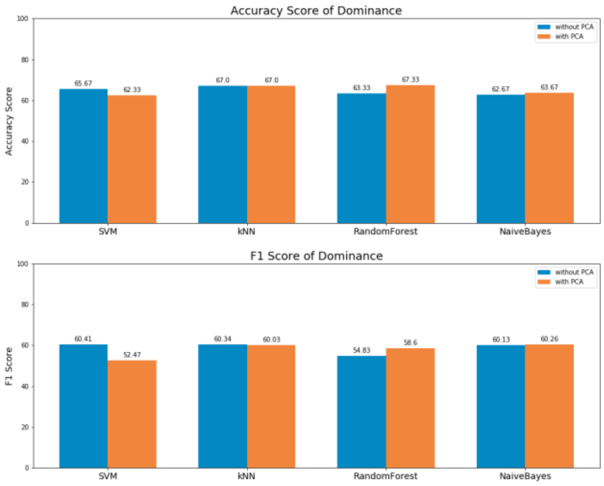


**Figure 181 Accuracy and f1 Score for Dominance for all algorithms in UC3 using STFT and Approximate Entropy for feature extraction**

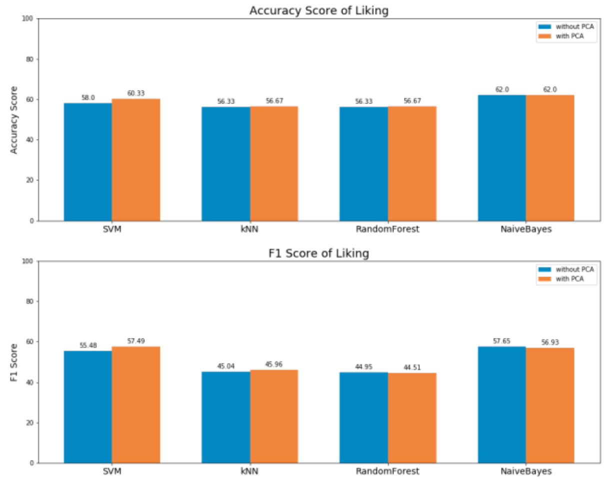


**Figure 183 Accuracy and f1 Score for Liking for all algorithms using in UC3 STFT and Approximate Entropy for feature extraction**

In order to sum up the results for accuracy and f1 score we constructed the table seen below:

Valence: **V**, Arousal: **A**, Dominance: **D**, Liking: **L,** Accuracy: **Acc,** f1 Score: **f1**

**Table 24 Feature Extraction Method: STFT with Approximate Entropy in UC3**

| Feature Extraction Method: STFT with Approximate Entropy | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No PCA | | | | With PCA (Components=40) | | | |
| Algorithm | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % | V Acc / f1 % | A Acc / f1 % | D Acc / f1 % | L Acc / f1 % |
| SVM | 56.67 / 54.07 | 58.67 / 55.1 | 65.67 / 60.41 | 58.0 / 55.48 | 56.67 / 53.65 | 60.67 / 56.99 | 62.33 / 52.47 | 60.33 / 57.49 |
| k-NN | 62.0 / | 61.33 / | 67.0 / | 56.33 / | 59.0 / | 59.33 / | 67.0 / | 56.67 / |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 52.62 | 52.42 | 60.34 | 45.04 | 47.21 | 49.36 | 60.03 | 45.96 |
| **RF** | 59.67 / 50.63 | 60.67 / 52.12 | 63.33 / 54.83 | 56.33 / 44.95 | 63.0 / 53.31 | 61.0 / 51.91 | 67.33 / 58.6 | 56.67 / 44.51 |
| **NB** | 59.0 / 54.24 | 58.67 / 54.24 | 62.67 / 60.13 | 62.0 / 57.65 | 60.0 / 55.85 | 60.67 / 56.55 | 63.67 / 60.26 | 62.0 / 56.93 |

### 5.3.1 Voting Algorithm Results and Recommendation List

In this section, we are going to present the experimentation results for our voting algorithm in UC3. As always, the results concern the emotion related labels only, since the voting algorithm with the method of soft voting (see Chapter 4.6) takes into consideration the weights assigned to each of the 5 algorithms in order to predict the emotion related label of each feature vector. It is really important to notice that in order to present the results we averaged the performance of the voting algorithms for all the participants.

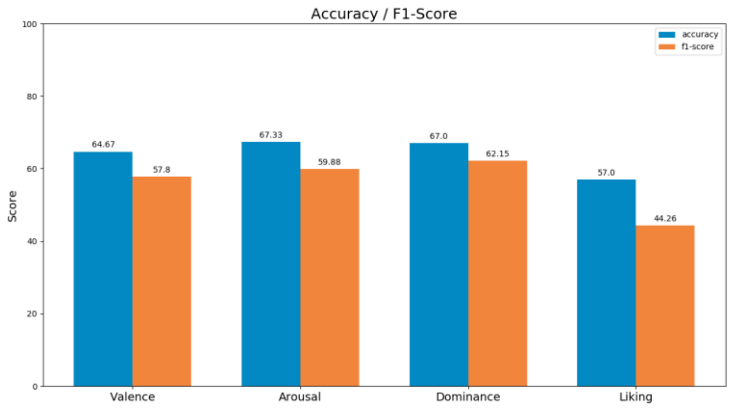


**Figure 184 Accuracy and f1 Score for emotion related labels for the voting algorithm in UC3 using STFT and standard deviation for feature extraction**

Based on the results presented above, we are going to construct the final recommendation lists, one for every participant, that was extracted from LAST.FM. We are going to use the method presented in Chapter 4.8. The list presented below concerns only participant 1. The rest of the participants have their lists created using the already described methods.

**<u>Recommendation List for Participant 1</u>**

**1. Dead To Fall , You've Already Died ,** https://www.last.fm/music/dead%2bto%2bfall/_/you%2527ve%2balready%2bdied
**2. Dead To Fall , Stand Your Ground ,** https://www.last.fm/music/dead%2bto%2bfall/_/stand%2byour%2bground
**3. Martyr AD , American Hollow** , https://www.last.fm/music/martyr%2bad/_/american%2bhollow
**4. A Life Once Lost , Vulture** , https://www.last.fm/music/a%2blife%2bonce%2blost/_/vulture
**5. Darkest Hour , With A Thousand Words To Say But One ,** https://www.last.fm/music/darkest%2bhour/_/with%2ba%2bthousand%2bwords%2bto%2bsay%2bbut%2bone
**6. Darkest Hour , The Sadist Nation ,** https://www.last.fm/music/darkest%2bhour/_/the%2bsadist%2bnation
**7. Himsa , A Girl in Glass ,** https://www.last.fm/music/himsa/_/a%2bgirl%2bin%2bglass
**8. Poison the Well , Nerdy ,** https://www.last.fm/music/poison%2bthe%2bwell/_/nerdy
**9. Himsa , Wolfchild ,** https://www.last.fm/music/himsa/_/wolfchild
**10. Zao , Five Year Winter ,** https://www.last.fm/music/zao/_/five%2byear%2bwinter
**11. Sanction , Radial Lacerations ,** https://www.last.fm/music/sanction/_/radial%2blacerations
**12. Unearth , The Great Dividers ,** https://www.last.fm/music/unearth/_/the%2bgreat%2bdividers
**13. Burnt By The Sun , Dracula With Glasses ,** https://www.last.fm/music/burnt%2bby%2bthe%2bsun/_/dracula%2bwith%2bglasses
**14. The Agony Scene , Scapegoat ,** https://www.last.fm/music/the%2bagony%2bscene/_/scapegoat

**15. Sanction , Paralysis ,** https://www.last.fm/music/sanction/_/paralysis
**16. Remembering Never , "From My Cold Dead Hands" ,** https://www.last.fm/music/remembering%2bnever/_/%2522from%2bmy%2bcold%2bdead%2bhands%2522
**17. Jason Mraz , Butterfly ,** https://www.last.fm/music/jason%2bmraz/_/butterfly
**18. Jason Mraz , Make It Mine ,** https://www.last.fm/music/jason%2bmraz/_/make%2bit%2bmine
**19. Train , Hey, Soul Sister ,** https://www.last.fm/music/train/_/hey%252c%2bsoul%2bsister
**20. Passenger , Let Her Go ,** https://www.last.fm/music/passenger/_/let%2bher%2bgo
**21. Colbie Caillat , Bubbly ,** https://www.last.fm/music/colbie%2bcaillat/_/bubbly
**22. Jack Johnson , Better Together ,** https://www.last.fm/music/jack%2bjohnson/_/better%2btogether
**23. Plain White T's , Hey There Delilah ,** https://www.last.fm/music/plain%2bwhite%2bt%2527s/_/hey%2bthere%2bdelilah
**24. Jack Johnson , Banana Pancakes ,** https://www.last.fm/music/jack%2bjohnson/_/banana%2bpancakes
**25. The Jacksons , Blame It on the Boogie ,** https://www.last.fm/music/the%2bjacksons/_/blame%2bit%2bon%2bthe%2bboogie
**26. Michael Jackson , Billie Jean ,** https://www.last.fm/music/michael%2bjackson/_/billie%2bjean
**27. The Temptations , My Girl ,** https://www.last.fm/music/the%2btemptations/_/my%2bgirl
**28. The Supremes , You Can't Hurry Love ,** https://www.last.fm/music/the%2bsupremes/_/you%2bcan%2527t%2bhurry%2blove
**29. Soulfly , Jumpdafuckup ,** https://www.last.fm/music/soulfly/_/jumpdafuckup
**30. Cavalera Conspiracy , Inflikted ,** https://www.last.fm/music/cavalera%2bconspiracy/_/inflikted
**31. Gorgoroth , Wound Upon Wound ,** https://www.last.fm/music/gorgoroth/_/wound%2bupon%2bwound

# 6. CONCLUSIONS

In the current master thesis, we addressed the problem of EEG sentiment analysis targeting in implementing a music recommendation system based on the predicted emotions. One of the main contributions of our work is to express this task as a combinatorial optimization problem, and to propose methods to solve it using Machine Learning Techniques.

Different feature extraction methods and Machine Learning Classifiers have been presented. Our contribution here is twofold. First an experimental comparison related to the performance of each algorithm has been carried out, and second a Voting Classifier, which performed a soft voting between all the Machine Learning Classifiers that were optimized during the experimental period, was developed and validated.

The main focus of our master thesis was on the optimization itself. Three Use Cases were examined and for each UC we chose the algorithms that best solve the problem. The experimentation phase included 3 types of Feature Extraction methods and 5 Algorithms for Classification. More specifically the DWT, STFT and PSD (with standard deviation and approximate entropy applied to their output) were selected as feature extraction methods and SVM, kNN, Naïve Bayes, Random Forest and MLP as ML Classifiers. In addition, in order to increase the diversity of input data available for training models (without actually collecting new data) and conclude in more accurate results, a Data Augmentation of the feature vectors was performed. Last but not least, we applied a dimensionality reduction method and more precisely the PCA so as to perform a linear mapping of the data to a lower-dimensional space in such a way that the variance of the data in the low-dimensional representation is maximized. By implementing dimensionality reduction we achieve not only lower computational cost but also better performance for the learning algorithm.

From an experimental point of view, our contribution lies in the comparison of the performance of the Machine Learning algorithms for each one of the 3 UCs after selecting the features that most describe the initial data and result in a better outcome. After a long experimental phase, we made several conclusions.

First of all, the Use Case which outperforms the rest of the Use Cases is the Gender Dependent, which achieves accuracy up to 81.25% and f1-score 79.14% using the DWT as a feature extraction method. After an extensive analysis we have concluded that males and females share more similar EEG patterns among them when emotions are evoked in comparison with Individual EEG patterns or Subject Independent EEG patterns. On the other hand, the worst Use Case is the User Dependent, which resulted in a lower performance compared to the other two Use Cases. The final results of the User Dependent Use Case are relevant to the size of the initial data considering that we have only 48 samples (after applying data augmentation) for each one of the participants. As a result, the lack of a larger data set for each participant of the experiment led to inaccurate results.

Additionally, the feature extraction methods that result (in most of the cases) in higher metric values and more accurate emotion predictions are the DWT and STFT after applying Standard Deviation. As for the Machine Learning Classifiers SVM, Random Forest and MLP achieve in most of the experiments the highest accuracy and f1 score while Naïve Bayes result in the worst experimentation results. Moreover, PCA, as expected, led to significantly better output by achieving up to 30% better metric values.

Many different adaptations, tests, and experiments have been left for the future due to lack of time. Future work concerns deeper analysis of particular mechanisms, new proposals to try different methods. There are some ideas that we would like to try in the future such as other types of Deep Learning Methods and more precisely Recurrent Neural Networks (e.g Long short-term memory) which best fit time series problems.

# ABBREVIATIONS - ACRONYMS

| | |
|---|---|
| EEG | Electroencephalography |
| DEAP | Database for Emotion Analysis using Physiological Signals |
| STFT | Short Time Fourier Transform |
| DWT | Discrete Wavelet Transform |
| PSD | Power Spectral Density |
| SVM | Support Vector Machines |
| k-NN | k - Nearest Neighbors |
| MLP-BP | Multilayer Perceptron Back-Propagation |
| NB | Naïve Bayes |
| RF | Random Forest |
| PCA | Principal Component Analysis |
| UC | Use Case |
| ML | Machine Learning |

# ANNEX I

**Standard Deviation:**

In statistics, the **standard deviation** is a measure of the amount of variation or dispersion of a set of values. A low standard deviation indicates that the values tend to be close to the mean of the set, while a high standard deviation indicates that the values are spread out over a wider range.

The standard deviation of a random variable, statistical population, data set, or probability distribution is the square root of its variance. A useful property of the standard deviation is that, unlike the variance, it is expressed in the same units as the data.

**Approximate Entropy:**

In statistics, an approximate entropy is a technique used to quantify the amount of regularity and the unpredictability of fluctuations over time-series data.

# REFERENCES.

[1] S. Koelstra, C. Muehl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, I. Patras, DEAP: A Database for Emotion Analysis using Physiological Signals, IEEE Transaction on Affective Computing, Special Issue on Naturalistic Affect Resources for System Building and Evaluation, in press.

[2] Rafael Ramirez and Zacharias Vamvakousis, Detecting Emotion from EEG Signals Using the Emotive Epoc Device, Department of Information and Communication Technologies Universitat Pompeu Fabra.

[3] Vangelis P. Oikonomou, Georgios Liaros, Kostantinos Georgiadis, Elisavet Chatzilari, Katerina Adam, Spiros Nikolopoulos and Ioannis Kompatsiaris, Comparative evaluation of state-of-the-art algorithms for SSVEP-based BCIs, technical report - arxiv.org January 2016.

[4] Pallavi Pandey and K. R. Seeja, Subject-Independent Emotion Detection from EEG Signals Using Deep Neural Network, International Conference on Innovative Computing and Communications, Indira Gandhi Delhi Technical University for Woman.

[5] Fang Wang, Sheng-hua Zhong Jianfeng Peng, Jianmin Jiang, and Yan Liu, Data Augmentation for EEG-Based Emotion Recognition with Deep Convolutional Neural Networks, College of Computer Science and Software Engineering, Shenzhen University, Shenzhen 518000, People's Republic of China, Department of Computing, The Hong Kong Polytechnic University, Kowloon, Hong Kong.

[6] Danny Oude Bos, EEG-based Emotion Recognition. The Influence of Visual and Auditory Stimuli, Department of Computer Science, University of Twente P.O. Box 217, 7500 AE, Enschede, The Netherlands.

[7] Tegan Grace Harrison, The Emotiv mind: Investigating the accuracy of the Emotiv EPOC in identifying emotions and its use in Intelligent Tutoring System, Department of Computer Science and Software Engineering.

[8] Salma Alhagry, Aly Aly Fahmy, Reda A. El-Khoribi, Emotion Recognition based on EEG using LSTM Recurrent Neural Network, IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 8, No. 10, 2017.

[9] Prommy Sultana Ferdawoos Hossain, Istiaque Mannafee Shaikat, Fabian Parsia George, Emotion Recognition using Brian Signals based on Time-Frequency Analysis and Supervised Learning Algorithm, A thesis submitted to the faculty of BRAC University in partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science and Engineering, April, 2018.

[10] Soraia M. Alarcao, and Manuel J. Fonseca, Senior Member, IEEE, Emotions Recognition Using EEG Signals: A Survey, IEEE TRANSACTIONS ON AFFECTIVE COMPUTING

[11] J. Preethi, M. Sreeshakthy, A.Dhilipan, A Survey on EEG Based Emotion Analysis using various Feature Extraction Techniques, International Journal of Science, Engineering and Technology Research (IJSETR), Volume 3, Issue 11, November 2014.

[12] Nisha Vishnupant Kimmatkar, Dr. Vijaya B. Babu, Human Emotion Classification from Brain EEG Signal Using Multimodal Approach of Classifier, Department of CSE, K L University, Vaddeshwaram, Guntur.

[13] Priyanka A. Abhang, Bharti w. Gawali, Suresh C. Mehrotra, Introduction to eeg- and speech-based emotion recognition, Department of Computer Science and Information Technology.

[14] Roberto Munoz , Rodrigo Olivares ,Carla Taramasco ,Rodolfo Villarroel , Ricardo Soto , Thiago S. Barcelos , Erick Merino, María Francisca Alonso-Sánchez, Using Black Hole Algorithm to Improve EEG-Based Emotion Recognition, Computational Intelligence and Neuroscience Volume 2018,

[15] Russell, J.A.: A circumplex model of affect. Journal of Personality and Social Psychology, Vol 39(6), Dec 1980, 1161-1178

[16] William Forde Thompson and Lena Quinto, Music and Emotion: Psychological Considerations, Article, January 2012

[17] Wikipedia - https://en.wikipedia.org/wiki/Standard_deviation

[18] Wikipedia - https://en.wikipedia.org/wiki/Approximate_entropy

[19] Towards Data Science - https://towardsdatascience.com/