

Music Moods Classification

Final Year, Major Project

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Information Technology

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The problem

Introduction

Music is an integral part of the human experience.

Advances in storage technology and connectivity has enabled individuals to access million of songs for their use.

Motivation

With million of songs at our fingertips how to find the right music to listen to as per our mood.

How to automate the cataloguing and increase discoverability in ever increasing music repositories.

Problem statement

To develop an Automated Smart System for **classifying a song as either Happy or Sad** by applying ML Techniques.

Challenges deep-dive

Data Acquisition

Labels and Features

Crowdsourcing the labels associated with songs to eliminate subjectivity of one's perception.

Calculating features that represent physical nature of song

Feature Selection

Removing attributes

Finding the right subset of features to solve the problem.

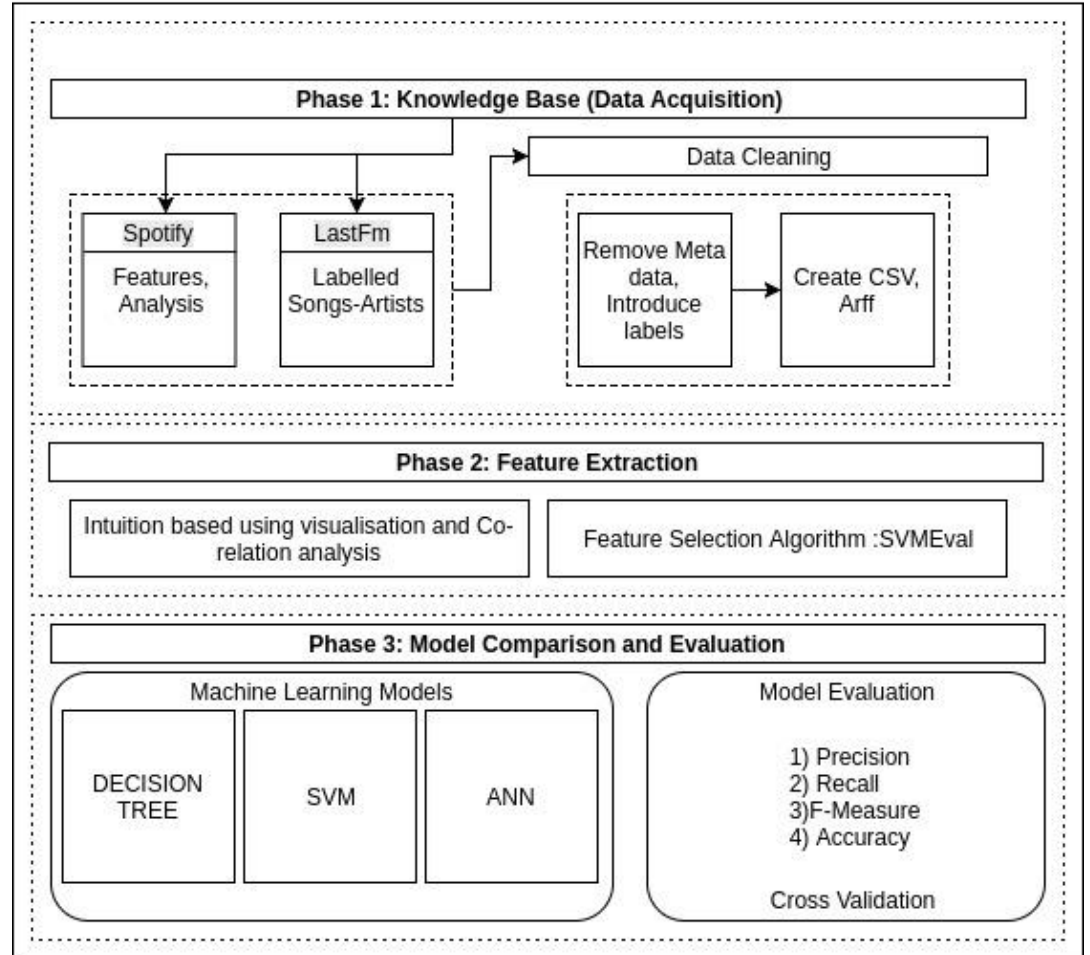
Modeling and Evaluation

Increase accuracy

Finding the right algorithm to solve the problem.

Tuning the hyper-parameters to increase efficiency.

Architecture of the system



Data Acquisition

Sources:

- Spotify, to get features
- LastFm, to get labels

Tools:

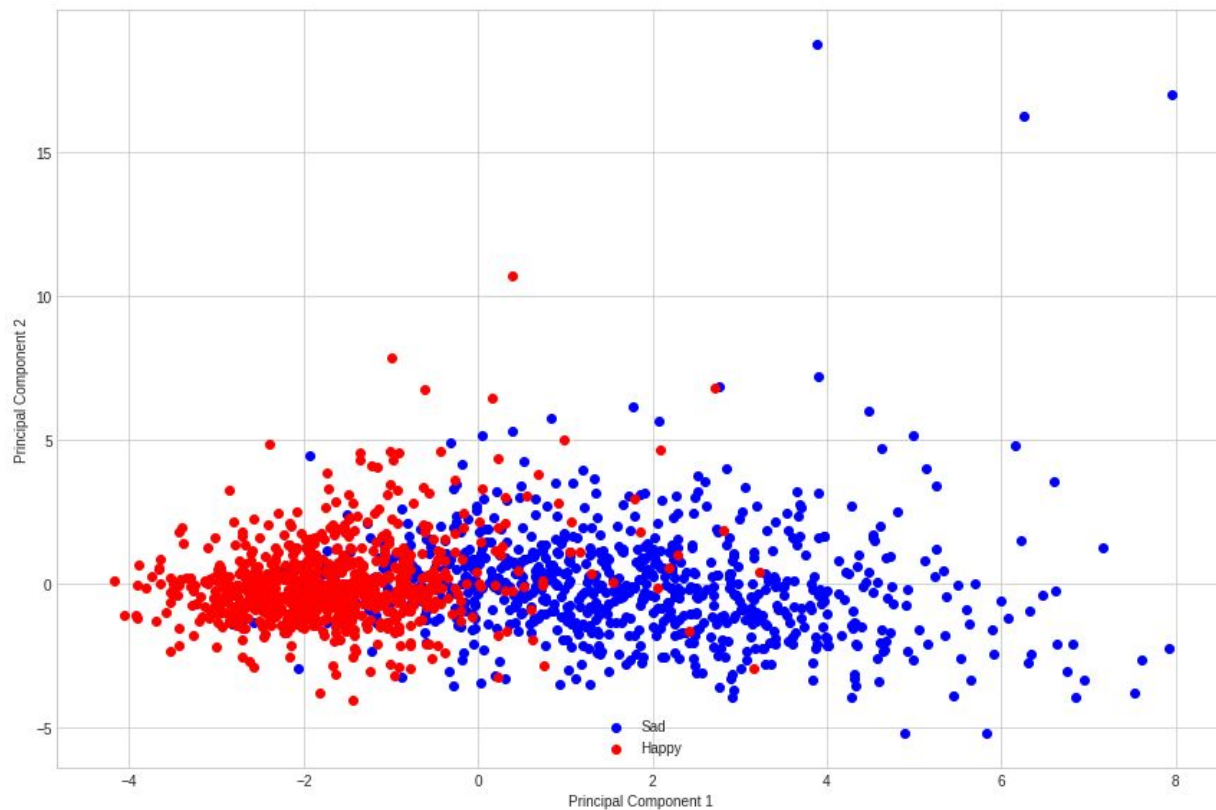
- NodeJS
 - MongoDB
-

Features: 26 in number

- **Time_Signature** - An estimated overall time signature of a track. The time signature(meter) is a notational convention to specify how many beats are in each bar (or measure).
- **Acousticness** - A confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.
- **Speechiness** -Speechiness detects the presence of spoken words in a track. The more exclusively speech-like the recording, the closer to 1.0 the attribute value.

and many more...

Visualization: PCA



Feature Selection

- Intuition Based
- CfsSubsetEval
- SVM-RFE

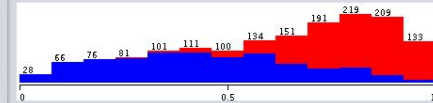
mood



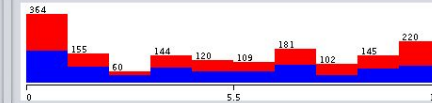
danceability



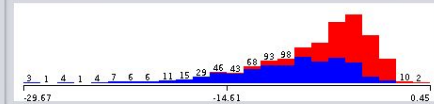
energy



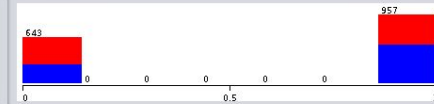
key



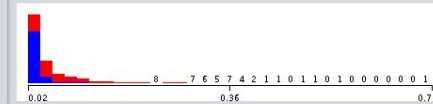
loudness



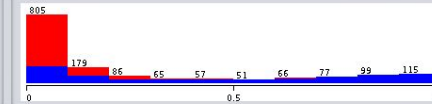
mode



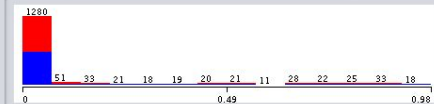
speechiness



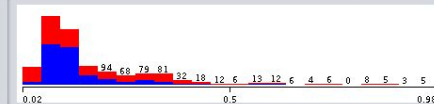
acousticness



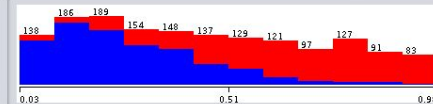
instrumentalness



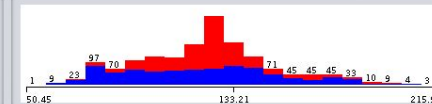
liveness



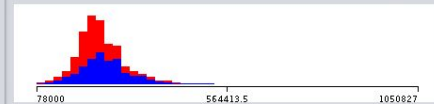
valence



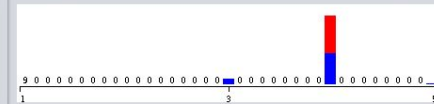
tempo



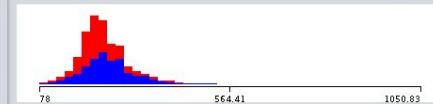
duration_ms



time_signature



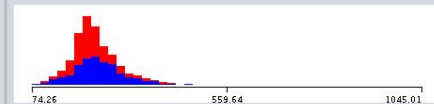
track_duration



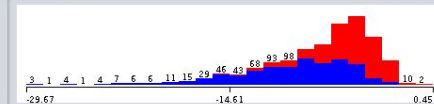
track_end_of_fade_in



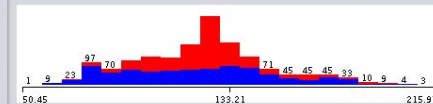
track_start_of_fade_out



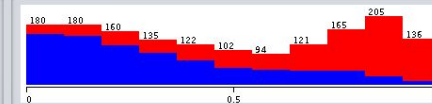
track_loudness



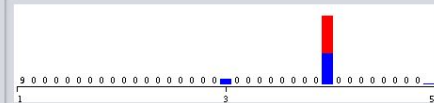
track_tempo



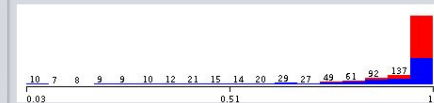
track_tempo_confidence



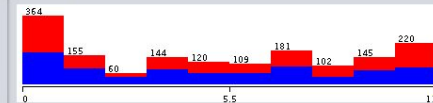
track_time_signature



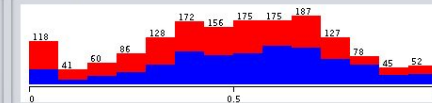
track_time_signature_confidence



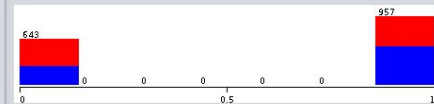
track_key



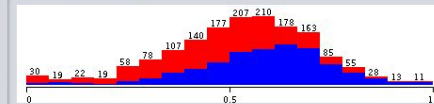
track_key_confidence



track_mode



track_mode_confidence



Intuition Based & CfsSubsetEval

1. Danceability
2. Energy
3. Loudness
4. Speechiness
5. Valence

average merit	average rank	attribute
25 +- 0	1 +- 0	24 energy
24 +- 0	2 +- 0	25 danceability
22.8 +- 0.4	3.2 +- 0.4	20 speechiness
21.9 +- 1.044	4.1 +- 1.04	12 track_duration
20.7 +- 0.458	5.3 +- 0.46	19 acousticness
19.9 +- 0.539	6.1 +- 0.54	16 valence
19 +- 1.095	7 +- 1.1	13 time_signature
18.7 +- 1.187	7.3 +- 1.19	14 duration_ms
16.7 +- 0.9	9.3 +- 0.9	6 track_time_signature
15.4 +- 0.917	10.6 +- 0.92	18 instrumentalness
14.8 +- 0.872	11.2 +- 0.87	10 track_start_of_fade_out
13.4 +- 2.154	12.6 +- 2.15	11 track_end_of_fade_in
13.3 +- 1.345	12.7 +- 1.35	1 track_mode_confidence
12.3 +- 1.418	13.7 +- 1.42	7 track_tempo_confidence
11.1 +- 0.7	14.9 +- 0.7	3 track_key_confidence
10.9 +- 1.375	15.1 +- 1.37	22 loudness
8.6 +- 0.917	17.4 +- 0.92	9 track_loudness
7.8 +- 0.872	18.2 +- 0.87	5 track_time_signature_confidence
7.4 +- 0.917	18.6 +- 0.92	17 liveness
5.8 +- 0.6	20.2 +- 0.6	21 mode
5.1 +- 1.375	20.9 +- 1.37	15 tempo
3.4 +- 1.2	22.6 +- 1.2	23 key
3.1 +- 1.044	22.9 +- 1.04	2 track_mode
2.6 +- 0.663	23.4 +- 0.66	8 track_tempo
1.3 +- 0.64	24.7 +- 0.64	4 track_key

SVM-RFE

1. Energy
2. Danceability
3. Speechiness
4. Track_duration
5. Acousticness
6. Valence
7. Time_signature

Modeling & Evaluation

- ANN
- SVM
- Decision Tree

Experiments

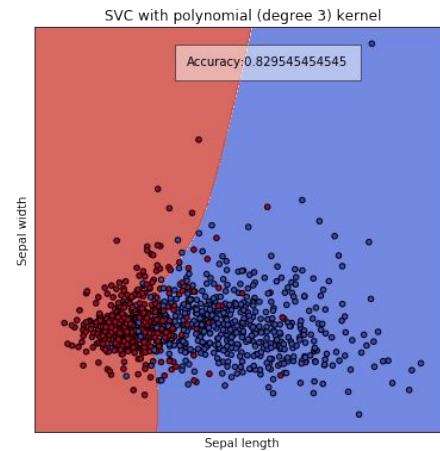
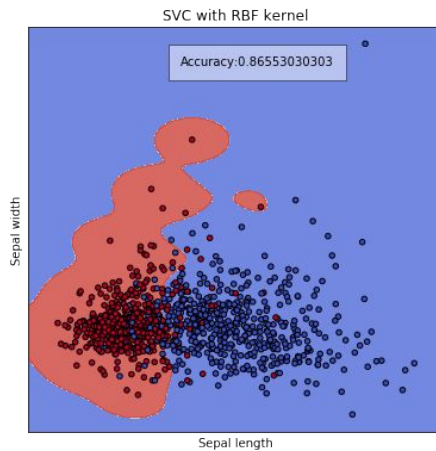
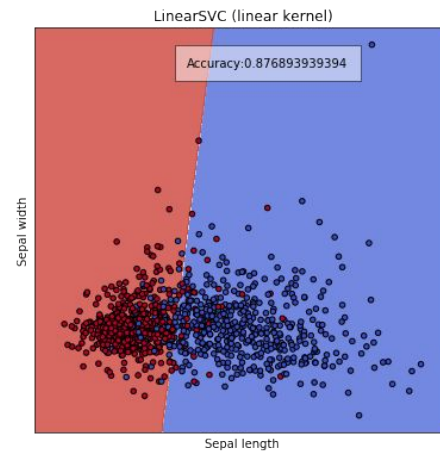
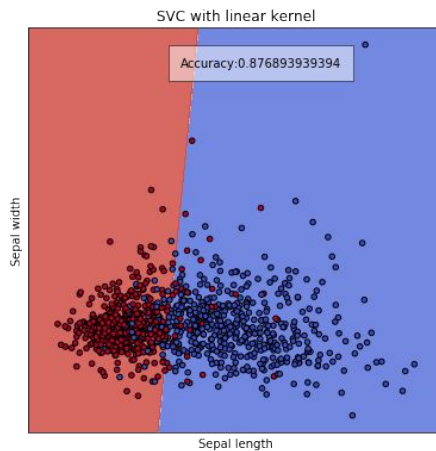
Total 1600 songs

- Train : 800
- Test: 600
- Validation : 200

Tools:

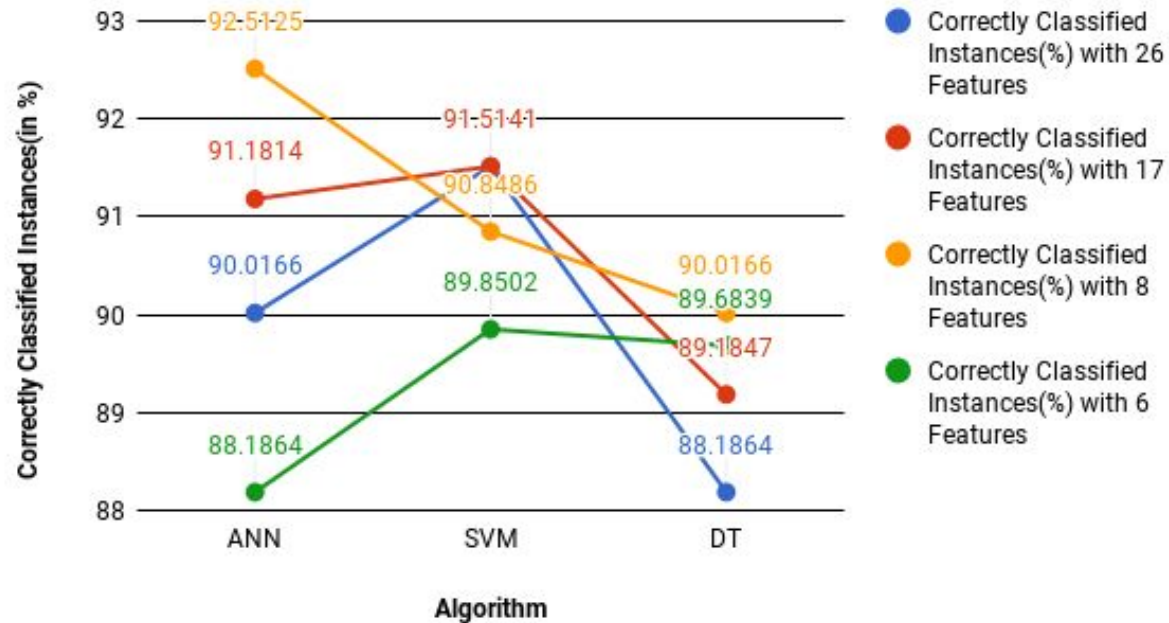
- Weka
- Scikit (Python)

SVM on Principal Components



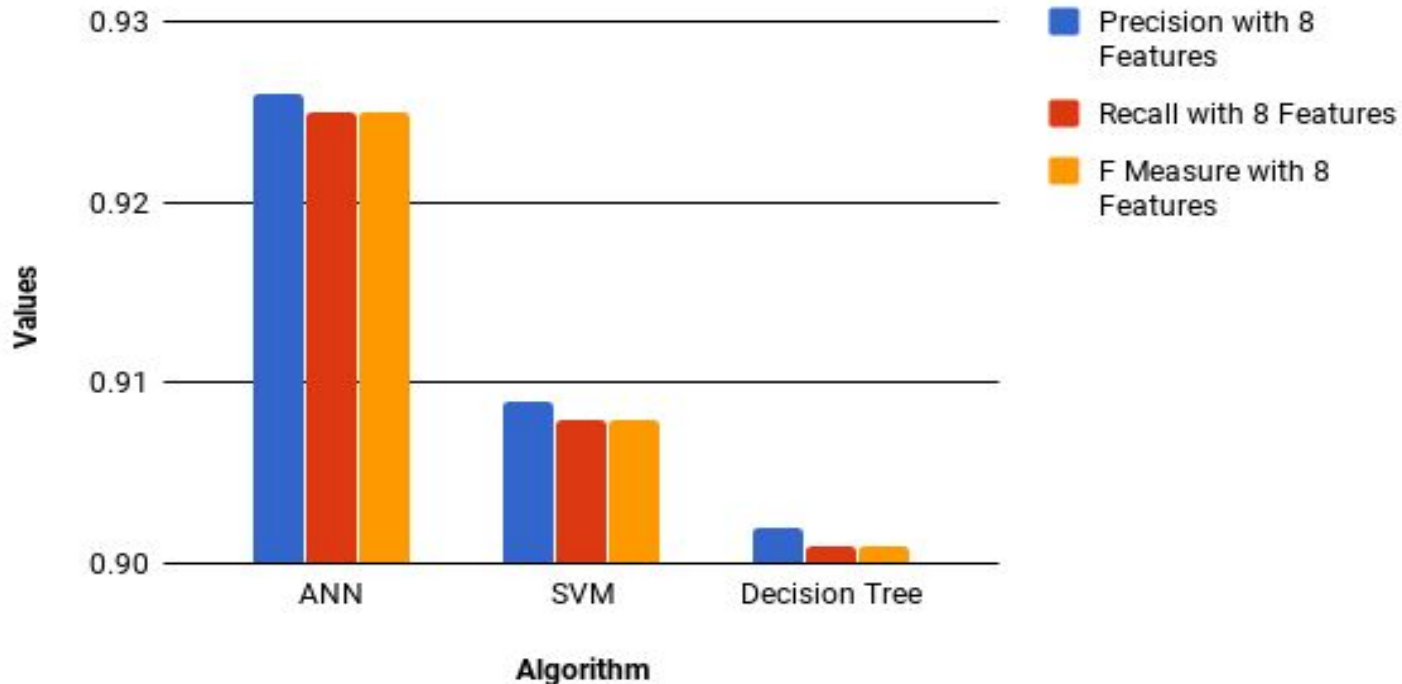
Comparison of Algorithms w.r.t. Feature sets

Correctly Classified Instances(in %) vs Algorithm



The best one: 8 Features using SVM-RFE

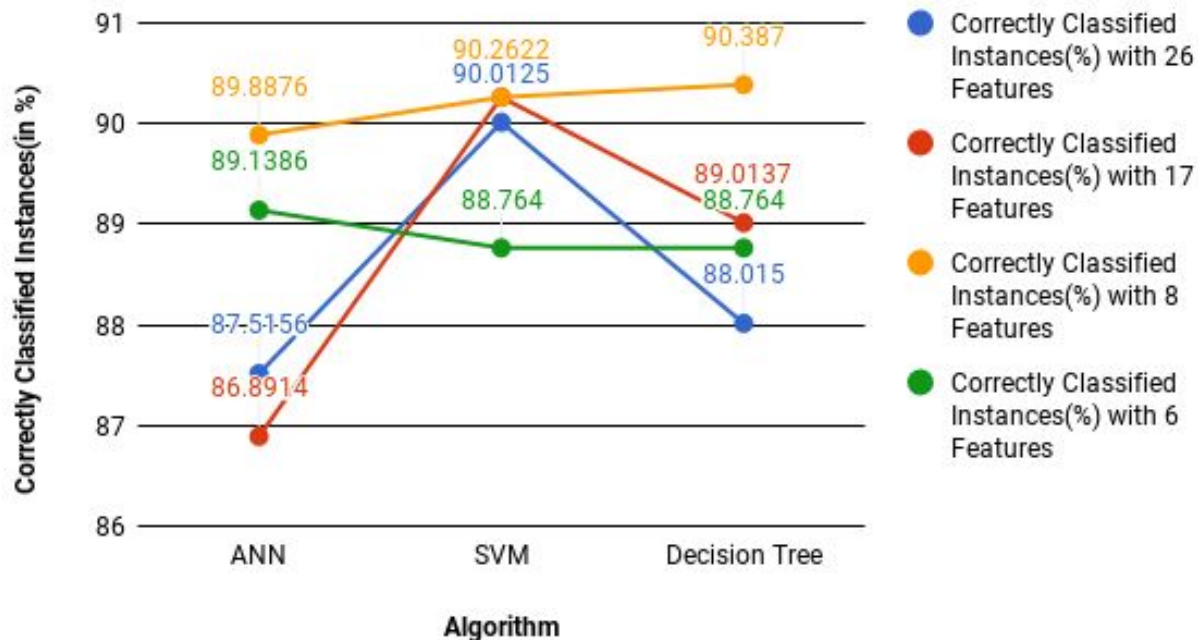
Values of Precision, Recall and F Measure vs Algorithms



Validation

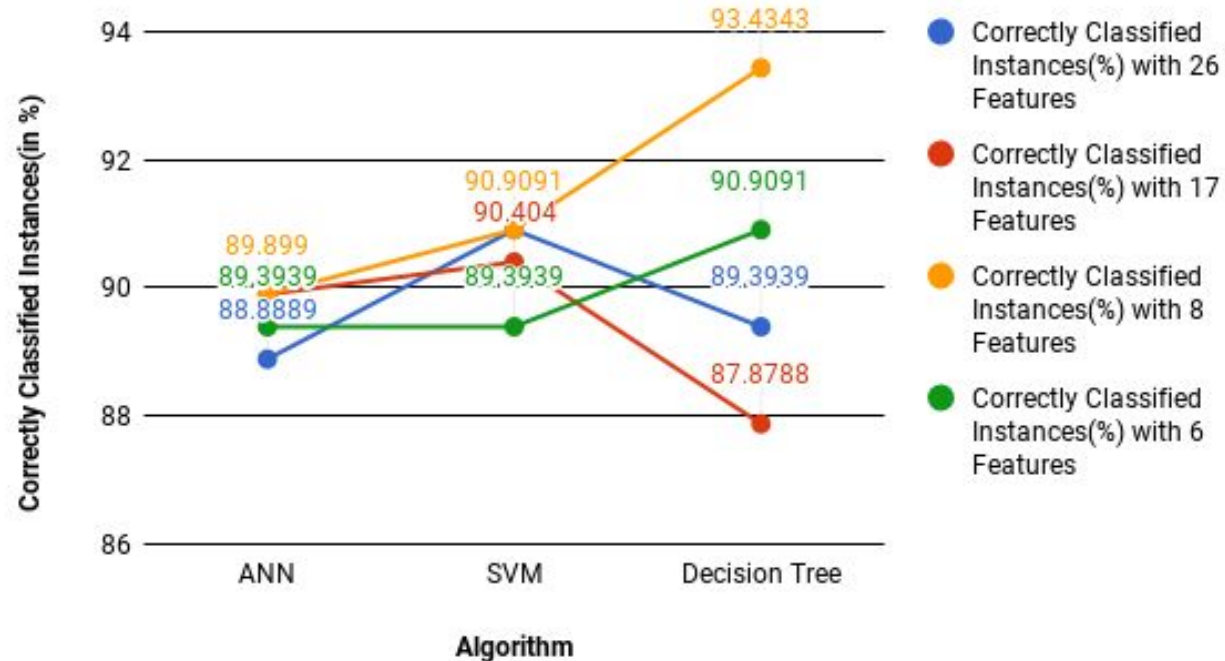
10-fold Cross Validation

Correctly Classified Instances(in %) vs Algorithm



Validation Set

Correctly Classified Instances(in %) vs Algorithm

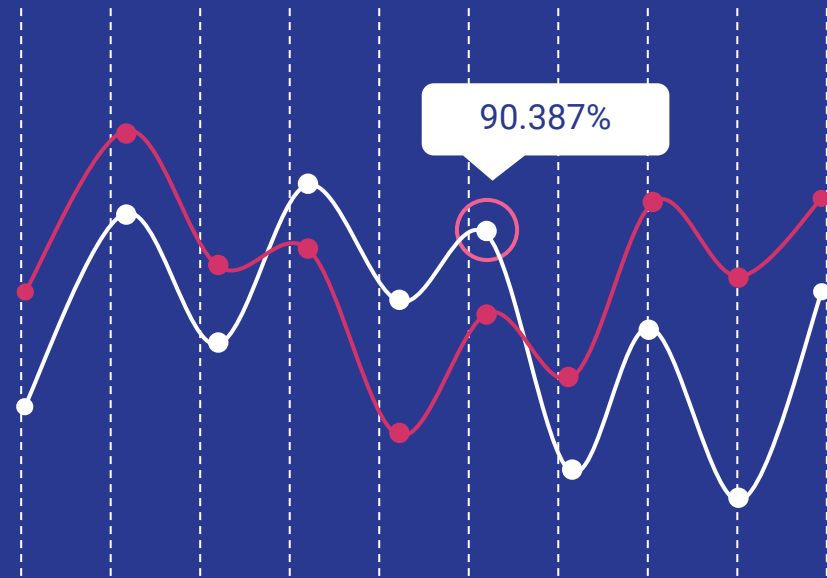




Results and Conclusion

Accuracy

90.387% using Decision Tree



Future Work

- Handling Multiple classes of moods.
- Adding additional crowdsourced labelling platforms.
- Probable Application : playlist generator using proposed algorithms.



Thank You!!