# Evaluation and Possible Improvements

**Avenues for Further Exploration**

* Tuning hyperparameters for Decision Tree and Random Forest took hours and days. If had access to more computational power, could refine the model even further.
* More feature engineering, PCA etc.
* Try different distance measures for k-NN
* Limitation of having unbalanced classes, sometimes only 1 row in an album in the test set
* Handling of outliers, could be due to Attribute noise: refers to the corruptions in values of one or more attributes due to several causes, such as failures in sensor devices, irregularities in sampling or transcription errors (ref: <https://arxiv.org/pdf/1708.04321.pdf>)
* Combine with NLP to use lyrics for album prediction 🡪 even if songs might not be different in terms of audio attributes, themes explored in the lyrics might be different.
* Use GZTAN data (requires more domain expertise about music) 🡪 choose different features (frequency domain, mel-frequency cepstral coefficients, chroma features, peak centroid, peak smoothness). <https://ijirt.org/master/publishedpaper/IJIRT155461_PAPER.pdf>
* Use a Convolutional Neural Network (<https://ijirt.org/master/publishedpaper/IJIRT155461_PAPER.pdf> )
* Problem with selecting optimal audio features, using Discrete Cosine Transform: <https://ijcert.org/ems/ijcert_papers/V4I206.pdf>
* In favour of polynomial SVM: <https://ijcert.org/ems/ijcert_papers/V4I206.pdf>
* Imbalanced classes: [This](https://towardsdatascience.com/dealing-with-imbalanced-classes-in-machine-learning-d43d6fa19d2#:~:text=A%20simple%20way%20to%20fix,one%20class%20or%20the%20other.) article discusses some of the issues with imbalanced classes, such as diminished recall of the less-represented classes.
* Run K-Means clustering if time.

**k-NN**

An article by Liu and Wu addresses the challenges and limitations of the traditional k-NN classifier in the domain of music genre prediction. The first major obstacle hindering successful music genre classification is the algorithm’s assumption that each feature is equally important, thus ignoring the problem of collinearity or correlation between features. The second limitation is that the similarity between the test samples and ‘neighbors’ across different categories is not considered, only considering the quantity of neighbors in each category. To try to mitigate these challenges, these authors have suggested an improved version of the k-NN algorithm called *Double Weighted k-Nearest Neighbour*, which utilizes a complex notion developed in rough set theory (a branch of set theory dealing with uncertain knowledge) called ‘attribute dependence’, which acts as a metric for quantifying the influence of different features. This assigns weights to *features*, as well as neighbors based on their proximity to the test samples, which helps determine which audio attributes are better predictors of the genre label. Although understanding the concepts of rough set theory and the attribute-dependence calculation would require far more in-depth background reading and learning, it can result in much higher overall accuracy for music classification tasks (Wu & Liu, 2020).