Classification of Glitches in the Gravitational Wave DataSet

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1 Introduction

The era of Gravitational-Wave (GW) Astronomy started in 2015 with the detection of the GWs emitted in the coalescence of two black holes by the Advanced LIGO detectors. To date, the LIGO-Virgo-KAGRA (LVK) collaboration has reported results from three observing runs, which comprise 90 confident detections.[1]

GW detectors operate in extremely low noise conditions which may be disrupted by the ground motion surrounding the detectors or earthquakes, storms or even anthropogenic sources of noise.With a higher detection rate, non-Gaussian noise transients of instrumental or environmental origin, commonly dubbed "glitches", will become increasingly more of a concern for the LVK detectors.

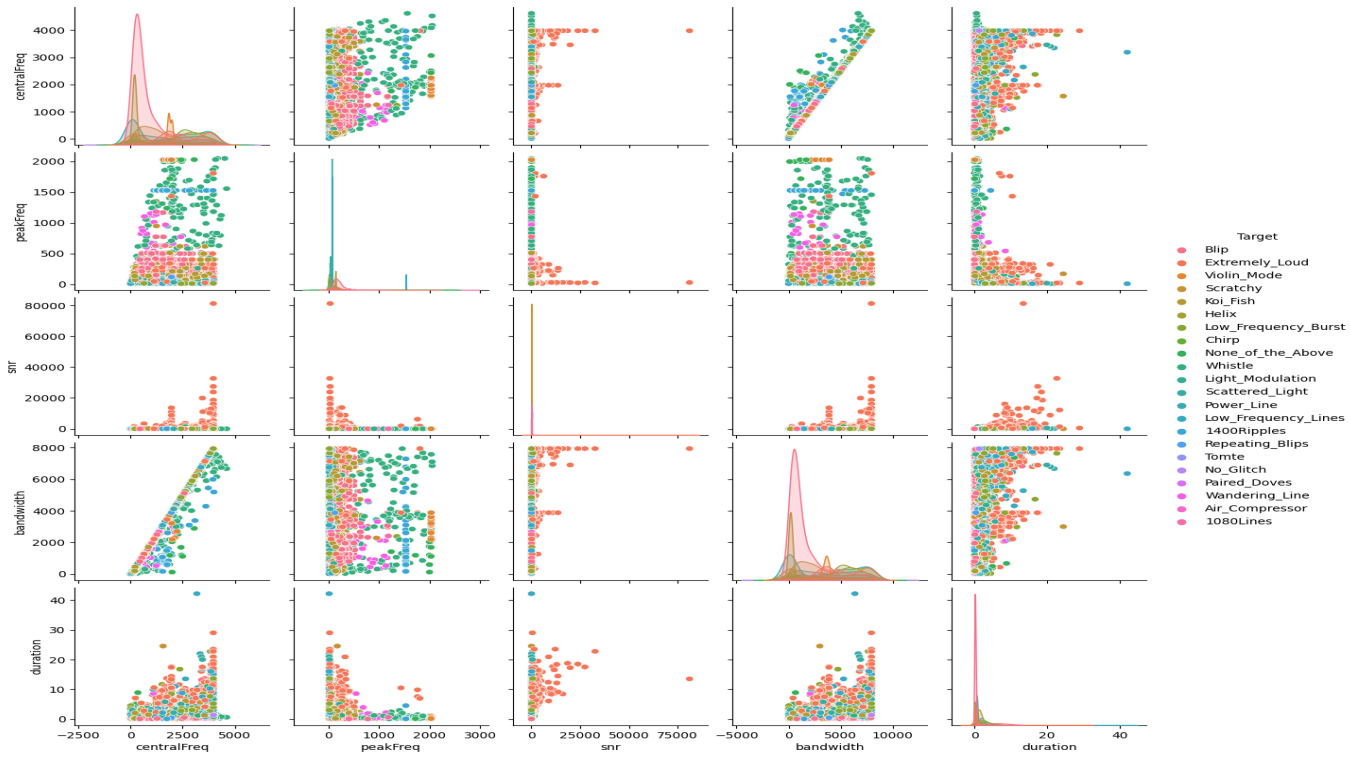


Figure 1: Overview of Data Set using pairplot()

In this project, we would try to classify the glitches using ML by their features like Central frequency, peak frequency, snr(signal and noise ratio), bandwidth, duration. There are eight features,

two of which are categorical. I have ignored 'GPStime', because that does not directly contribute to glitch classification. There are 22 target classes. The highest target class 'blip' has 1587 instances and the lowest class '1080Lines' has only 4 instances. There are total 6000 instances. There is no missing value in the dataset.

2 Methods

The models used in this project are Logistic Regression, Random Forest, Support Vector Machine, K Nearest Neighbour Classifier, Decision Tree Classifier and Adaptive boosting.

Though there is no missing value, some data preprocessing is still needed. To convert the categorical feature to a numerical feature I have used One-Hot Encoding. I have only converted the 'ifo' feature to a numerical feature. I have removed 'id' and 'GPStime' from the dataset. After all of that, I have a total of seven attributes in the dataset. I have also used Pipeline so I don't have to scale the data every time.

Hyperparameters: These are the higher-level parameters that we set manually before starting the training, which are based on properties such as the characteristics of the data and the capacity of the algorithm to learn.[1] In sklearn we can use exhaustive 'GridsearchCV' which explores all the combinations of given hyperparameters. It is efficient but time-consuming. Or we can use 'RandomizedsearchCV' which explore the specific number of iteration(less than the total combinations) and give the hyperparameters based on that iteration combinations only. But there is a trade-off of efficiency occurs. In this project, I have used 'GridSearchCV' only for all the models.[3]

- For Logistic Regression I have tuned the 'C' value, 'penalty type', 'maximum iteration number' and 'class weight'.
- For Random Forest I have tuned 'class weight', 'number of decision trees', 'maximum depth of the decision tree', 'splitting criterion' and 'Number of sample splitting'.
- For SVM I have tuned 'kernel', 'class weight', 'gamma value', and 'probability'.
- For KNN I have tuned the 'number of neighbours', 'distance type' and 'weight of the neighbours'.
- For the Decision Tree I have tuned 'splitting criterion', 'max depth', 'minimum number of sample leaf' and 'class weight'.
- For AdaBoost I have tuned 'number of estimators' and 'learning rate'.

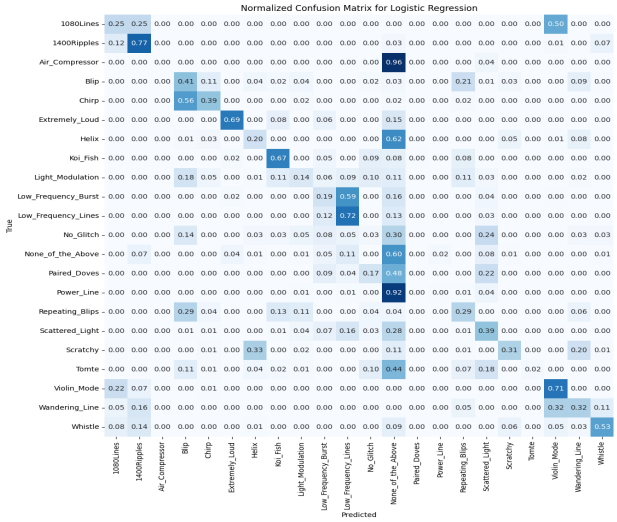
3 Experimental Setup

To evaluate the model I have used macro-averaged precision, recall, f-measuere. I have used Stratified K-fold (k=5) to split the data into training and evaluation sets and then evaluate the test set based on the test set. For this purpose, I have taken the mean value of all the evaluation scores in k folds.

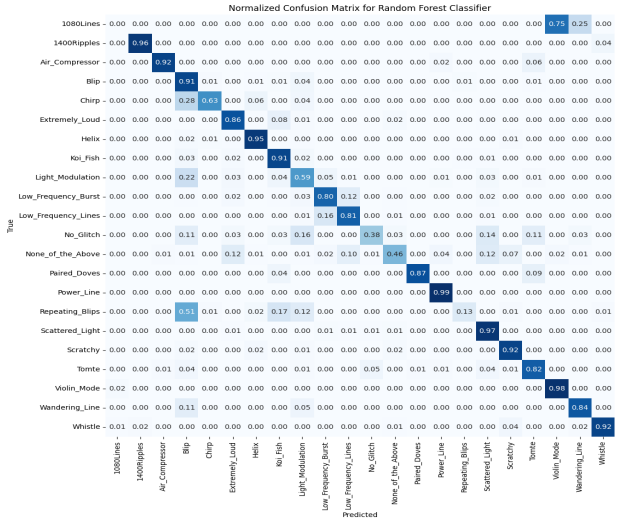
The best hyperparameters for this classification problem are,

- For Logistic Regression C=0.001,class weight='balanced',
- For Random Forest class weight='balanced', max depth=20, max features='log2', number of estimators=200, min samples split=8
- For SVM C=10,class weight='balanced', kernel='linear', probability=True
- For Decision Tree criterion='entropy', max depth=9, min samples split=10
- number of neighbors=4, distance type='Manhattan', weights='distance'
- For AdaBoost base estimator= Decision Tree, criterion= 'entropy', number of estimator=200, learning rate=1

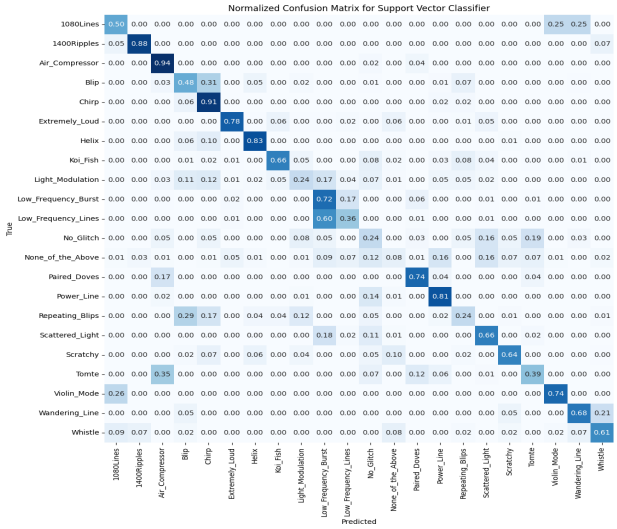
4 Results and Discussion



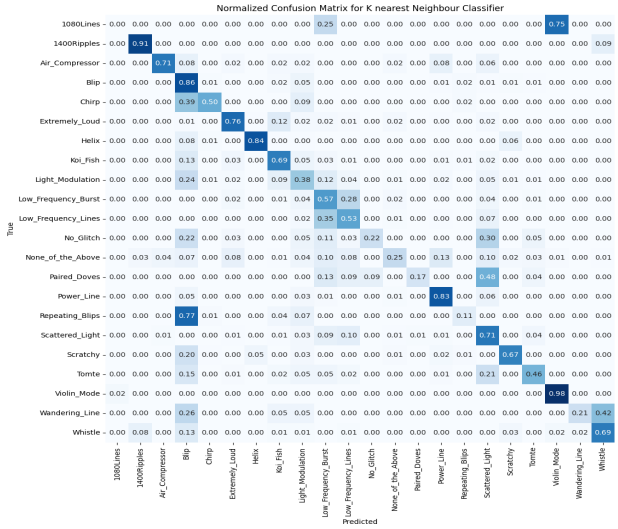
(a) Normalized Confusion Matrix for logistic Regression



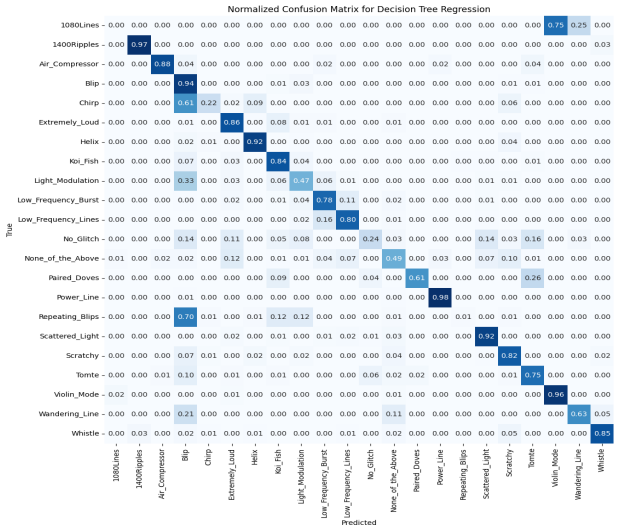
(b) Normalized Confusion Matrix for Random Forest



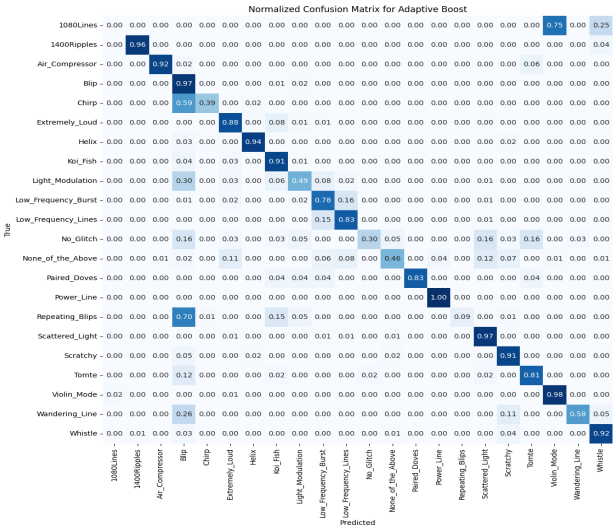
(c) Confusion Matrix for Support Vector Classification



(d) Normalized Confusion Matrix for KNN



(e) Normalized Confusion Matrix for Decision Tree



(f) Normalized Confusion Matrix for Adaptive Boost

Figure 2: Confusion Matrix for all the models

Table 1: Performance Of Different Classifiers

Classifier	Macro-avg Precision	Macro-avg Recall	Macro-avg F-measure
Logistic Regression	0.5251	0.6203	0.5247
Random Forest Classifier	0.7673	0.7515	0.7530
Support Vector Machine	0.5324	0.5935	0.5053
K-Nearest Neighbor	0.6049	0.5591	0.5707
Decision Tree Classifier	0.7149	0.6899	0.6855
Adaptive Boosting	0.81229	0.71466	0.74628

From the Table 1 we can see that Adaptive Boost has a good precision score but worse recall score compared to Random forest. If this was a binary classification problem (like: Non-Glitch or Glitch), then we should have considered Adaptive Boost, because we would have lost some information of GM wave. But this is a multi-class classification problem of glitches. So, we should consider F-measure. F-measure simultaneously tells us how much the prediction has included false instances and excluded true instances.

Logistic Regression and SVM miserably fails in this classification problem.

So for the test set prediction I have used Random Forest with the hyperparameters specified above.

5 Conclusion

From the outcomes we can observe that:

1. Random Forest has the best macro averaged F-measure. And I have considered that for predicting the test data.
2. The low precision and recall score of all the models may be due to minority classes. During cross validation the data set may be split in a biased way.
3. Identification of the glitches is a very important task for GM wave detection and classification or analysis of them can tell us which component of the instrument or which natural affects can cause noise.

References

[1] B. P. Abbott et al. (LIGO Scientific, Virgo), Phys. Rev. Lett. 116, 061102 (2016), 1602.03837.

[2] Tanay Agarwal, Hyperparameter Optimization in Machine Learning.

[3]$https://scikit-learn.org/stable/modules/grid_search.html$