Assignment – E11
DS- 203 program

200260018 – Gopal Parwani
22D1628 – Roomani Srivastava
22D1630-Kushal Kelshikar

Data

- Daily averaged values of observations of some parameters at a chemical processing plant
- 240 columns and 1025 rows. Each row corresponds to data for the date given in column c1
- Rest of the columns represent can be grouped into operating and controllable parameters
- Controllable parameters: c26, c27, c28, c29, c30, c31, c32, c33, c39, c139, c142, c143, c155, c156, c157, c158, c160, c161, c162, c163

Objectives

- c 51, c52, c53, c54 represent vibrations: need to be kept in limit
- c241 is specific energy or i.e. energy consumption per unit output: should be as minimum as possible
- All of them are non-controllable parameters i.e. can’t control them directly
- Have to control them using controllable parameters

Our Job

Task 1: Reducing the vibrations

- Task 1.1 :
  - Create an ML model with operating + controllable parameters to predict HIGH and CRITICAL vibrations (c51, c52, c53, c54)
  - This model can be used to raise alerts and alarms
- Task 1.2:
  - Create an ML model with controllable parameters for c51, c52, c53, c54
  - From the model create a list of most important parameters to reduce vibrations

Task 2: Reducing the specific energy

- Task 2.1 :
  - Creating an ML model with operating + controllable parameters to predict specific energy, c241
  - From the mode, create a list of most important parameters to reduce the energy consumption
- Task 2.2:
  - Find the minimum number of independent variables which can predict the energy consumption
  - Create an ML model with those variables

Data Pre-processing

While eliminating features, we take care not to drop the vibration, specific energy & controllable parameter

Eliminating Missing Features

Visualization

Converted the data into dataframe df1 and dropped the columns which have data missing on > 50% of the days by visualization.
We also drop the column c1 which is date.

Eliminating Const. Features

Box Plot and Histograms

Using plotly, created the box plot and found the variables using for which the spread was very less. If the variable was constant examined by count vs value histogram, dropped from df1

Imputing Outliers & Missing Values

Mean

Imputed the outliers and missing values in the columns of df1 using the mean of the available values

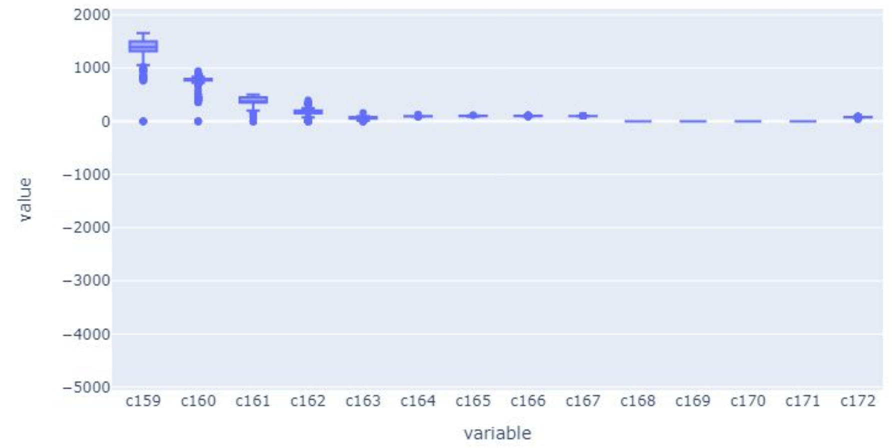
Reducing Multicollinearity

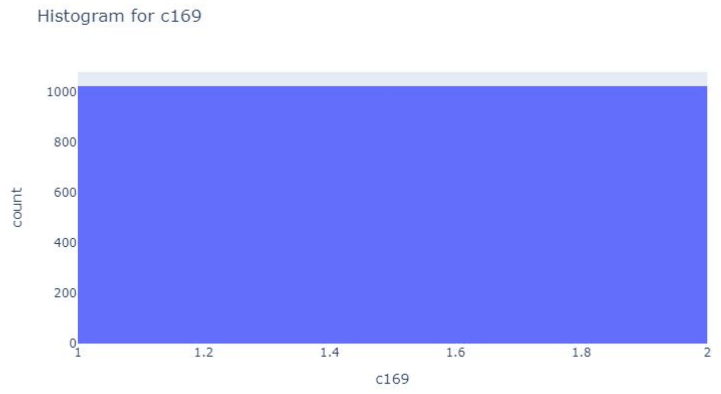
VIF

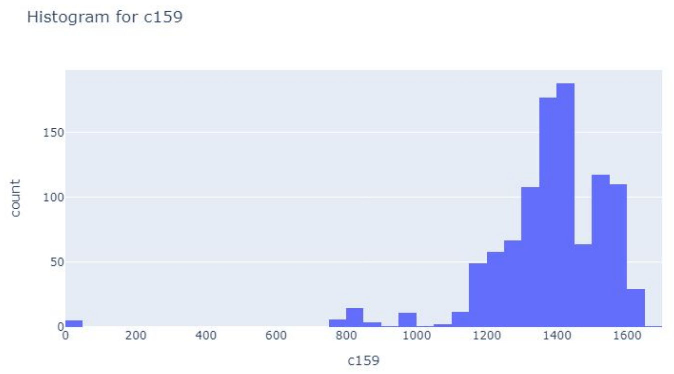
Created a dataframe df2 after dropping the variables which had Variation Inflation Factor, VIF > 10 without changing df1 which has features before reducing multicollinearity

Data Pre-processing: Eliminating Constant Features

- A section of box plots for all variables



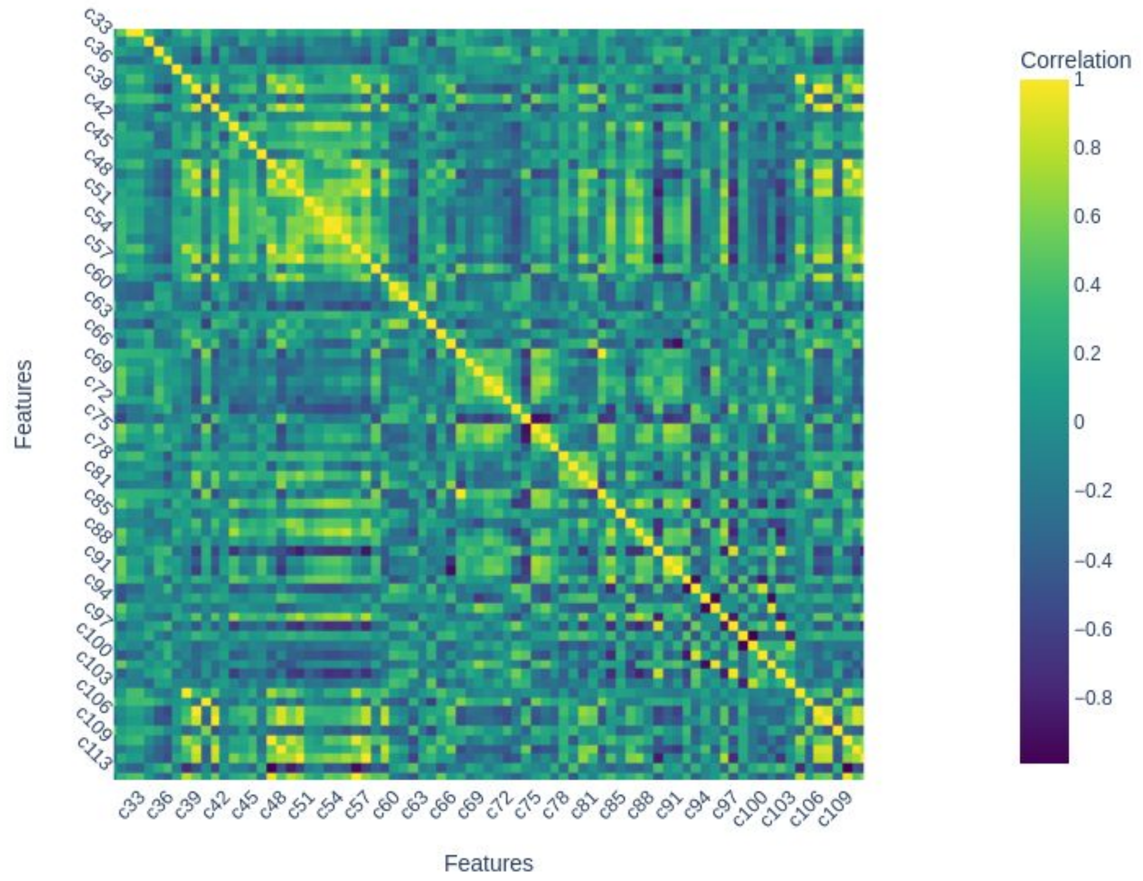




- c168, c169, c170, c171 look constant and on plotting histograms of such variables we find it to be the case and we such variables
- count vs value histogram of non-constant variables like c159 looks like the third figure and we keep such variables

Data Pre-processing: Reducing Multicollinearity

- Visualization using heat maps: In a section of heat map presented below, it can be seen that there is high collinearity between some variables as indicated by bright yellow and dark green squares, off the diagonal.



Data Pre-processing: Reducing Multicollinearity using VIF

VIF

Variance inflation factor of all variables were checked

Determining High VIF features

Features with VIF higher than 10 identified

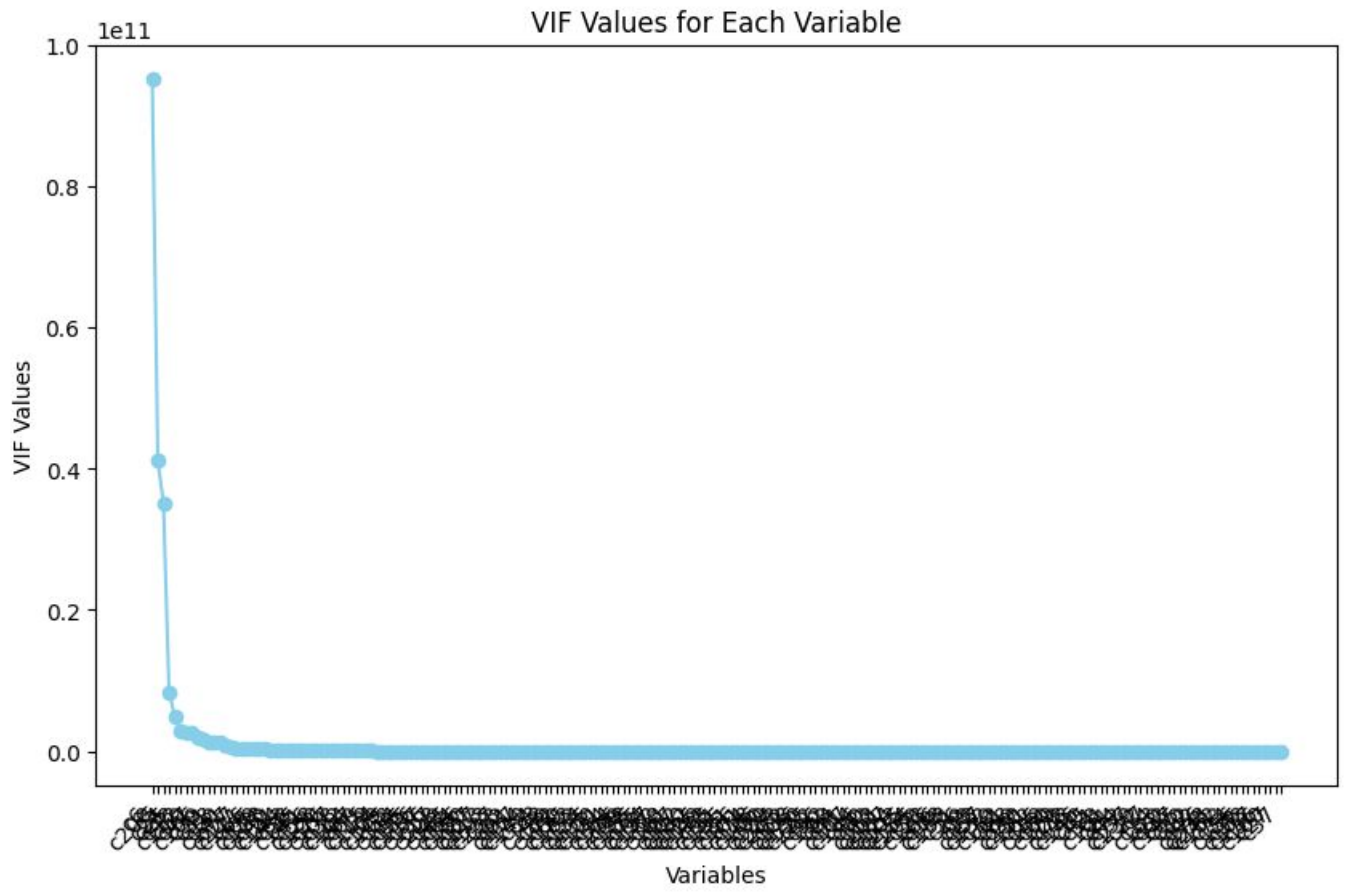
Deleting High features

High VIF features deleted after checking if they were either ‘controllable parameters’ or ‘target variables’ in which case they were retained

Now we create a new df, df2 which has 53 columns after dropping hgh VIF features as opposed to df1 which has 202 columns after dropping redundant variables

KOITA CENTRE FOR DIGITAL HEALTH

Data Pre-processing: Plot showing VIF



Task 1: Reducing the vibrations

Task 1.1: Implementing ML to predict High and Critical Vibration Levels

- Creating model using df1 which contains variables with multicollinearity as well

Feature Transformation

We created a new target variable 'overall risk' using columns c51, c52, c53 & c54.
'overall_risk' takes values CRITICAL, HIGH, MODERATE, SAFE if any of the values from c51, c52, c53, c54 satisfy the criteria with 'CRITICAL>HIGH>MODERATE>SAFE.

Label Encoding

We label encode overall_risk i.e.
CRITICAL = 0
HIGH = 1
MODERATE = 2
SAFE = 3
Interestingly, we don't find any SAFE
Our input features are features in df1 other than c51, c52, c53 & c54 and target is overall_risk

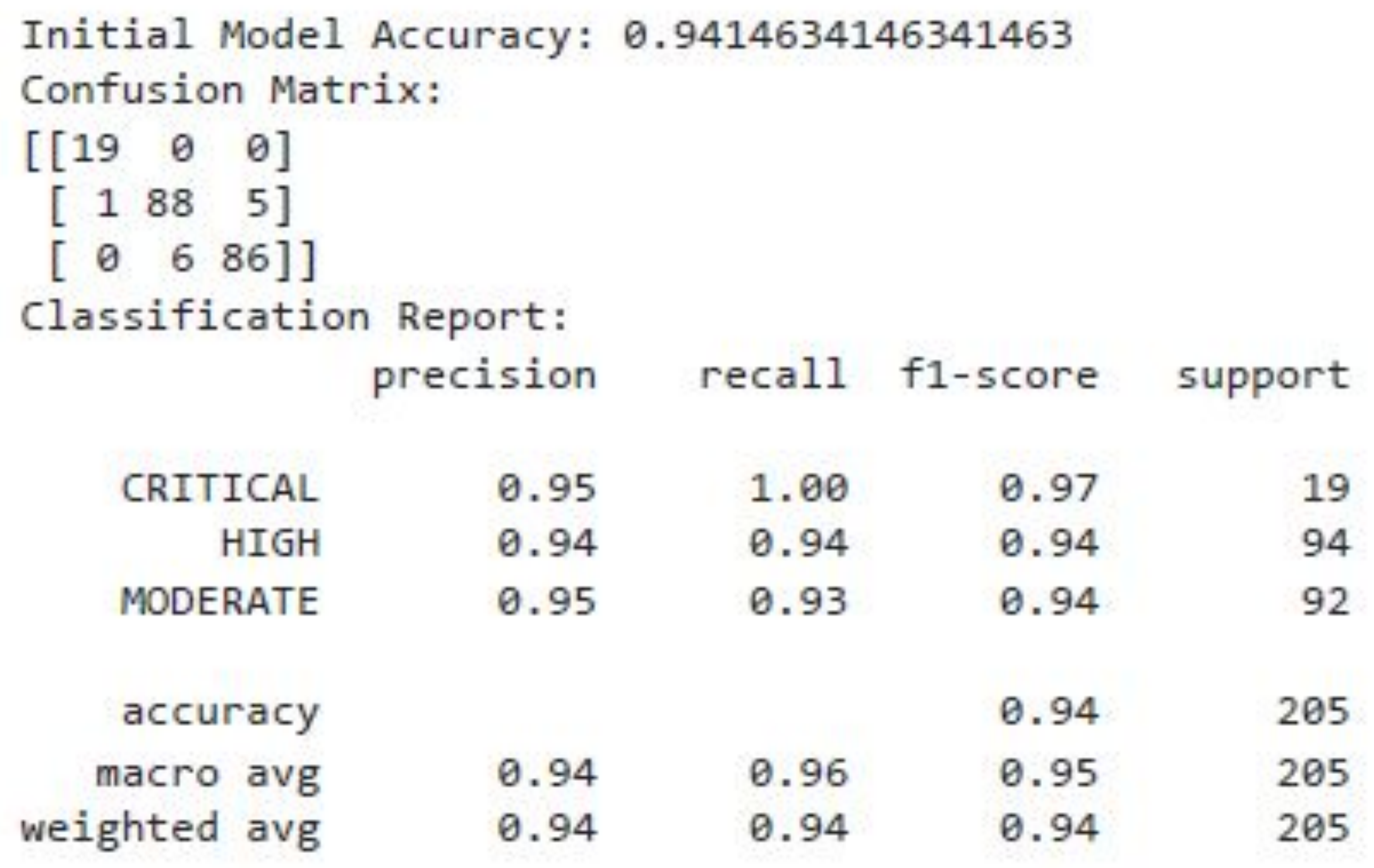
Splitting Data & Normalization

We split the data into train and test with 80:20 ratio and then normalize them separately using min-max scaling. It is necessary to normalize the data after splitting so as to ensure the independence of training and test data.

Creating ML Model

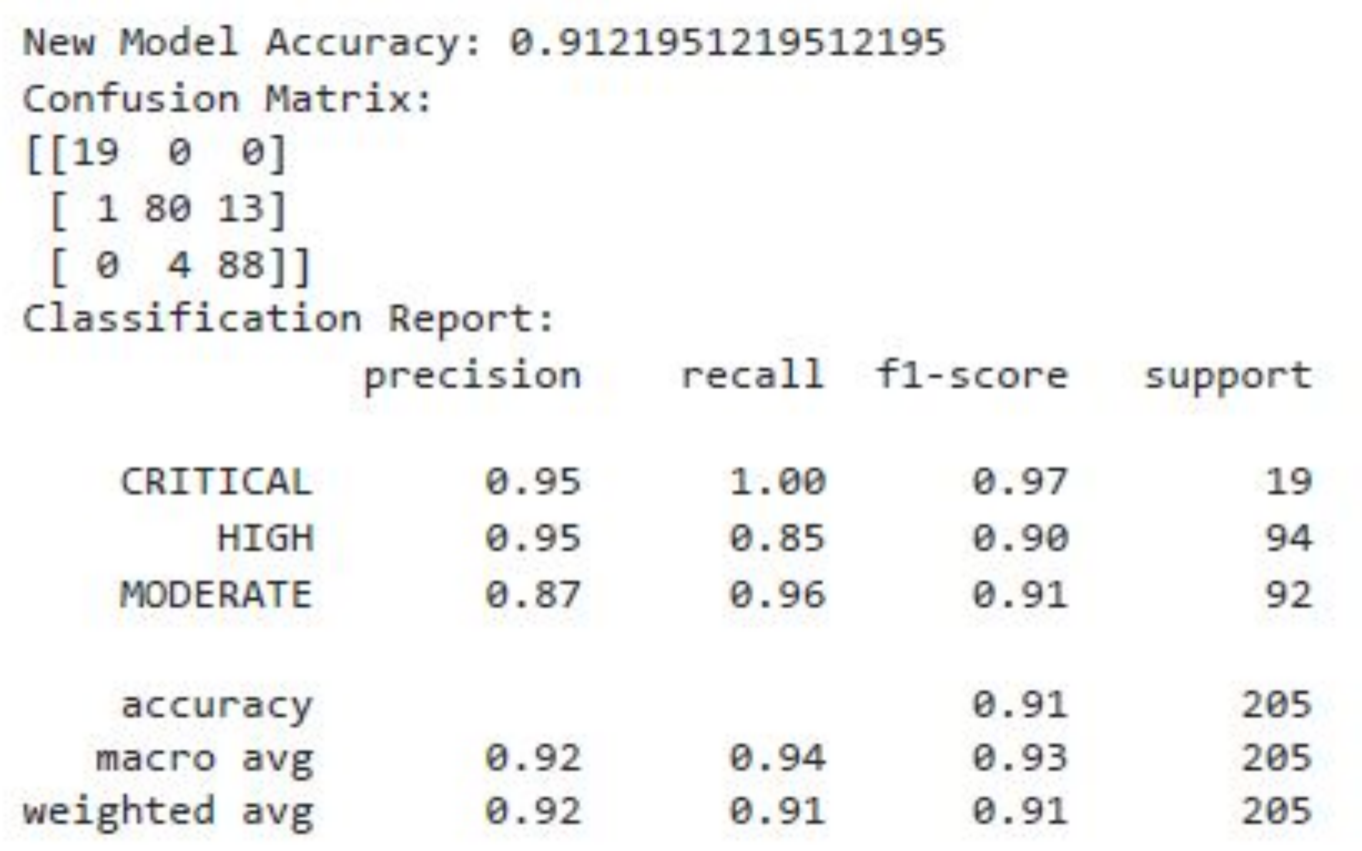
This is a classification problem so we used **Logistic Regression model** as our baseline model which we trained on both dfs with high VIF features and without. We did not see much difference in the outputs. We also used a more sophisticated ML model which is SVM on df1 as models such as SVM automatically take care of multicolinearity

Task 1.1: Implementing ML to predict High and Critical Vibration Levels - Logistic Regression on unfiltered df1



```
Initial Model Accuracy: 0.9414634146341463
Confusion Matrix:
[[19  0  0]
 [ 1 88  5]
 [ 0  6 86]]
Classification Report:
              precision    recall  f1-score   support

    CRITICAL       0.95      1.00      0.97        19
        HIGH       0.94      0.94      0.94        94
    MODERATE       0.95      0.93      0.94        92

    accuracy                           0.94       205
   macro avg       0.94      0.96      0.95       205
weighted avg       0.94      0.94      0.94       205
```

Task 1.1: Implementing ML to predict High and Critical Vibration Levels
Logistic Regression on filtered data that is without features with High VIF



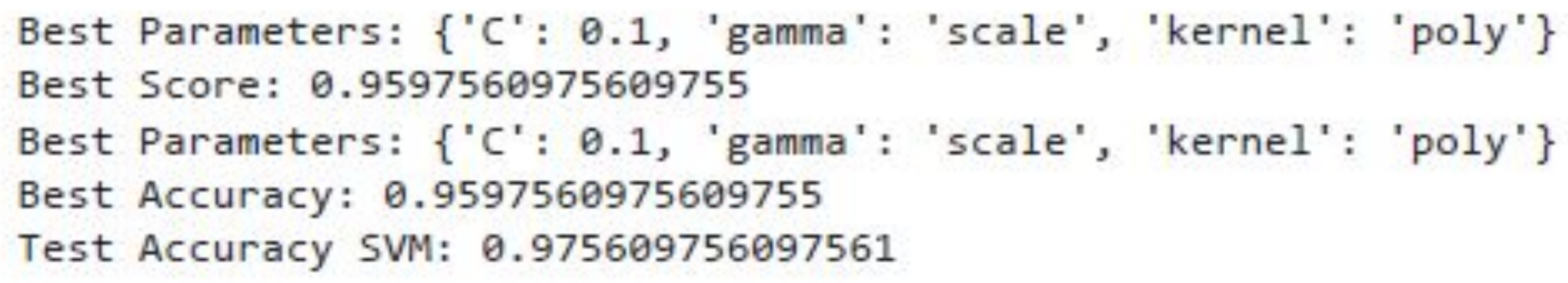
```
New Model Accuracy: 0.9121951219512195
Confusion Matrix:
[[19  0  0]
 [ 1 80 13]
 [ 0  4 88]]
Classification Report:
              precision    recall  f1-score   support

    CRITICAL       0.95      1.00      0.97        19
        HIGH       0.95      0.85      0.90        94
    MODERATE       0.87      0.96      0.91        92

    accuracy                           0.91       205
   macro avg       0.92      0.94      0.93       205
weighted avg       0.92      0.91      0.91       205
```

Alternative ML Model: SVM

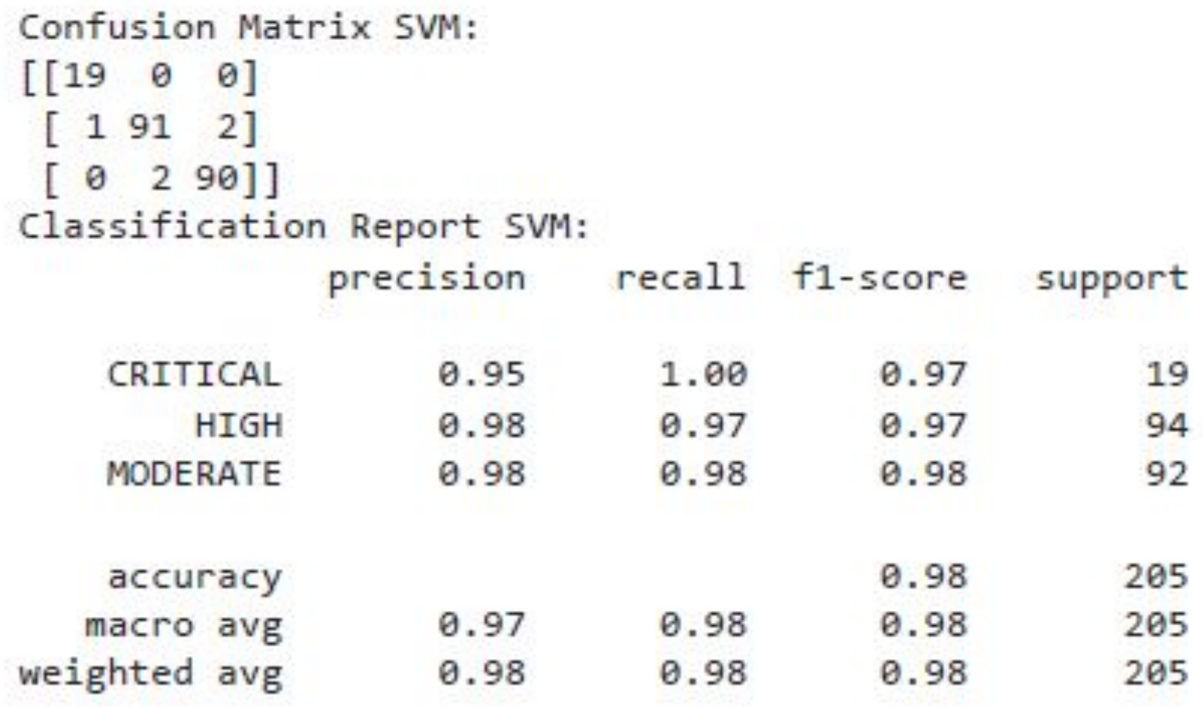
There are some machine learning models which take care of the multicolinearity of the features by using certain methods like regularization and can give good results with the right hyper parameter tuning even without using tools like VIF.

We demonstrate the use of one such ML model which Support Vector Classifier

Results of SVM

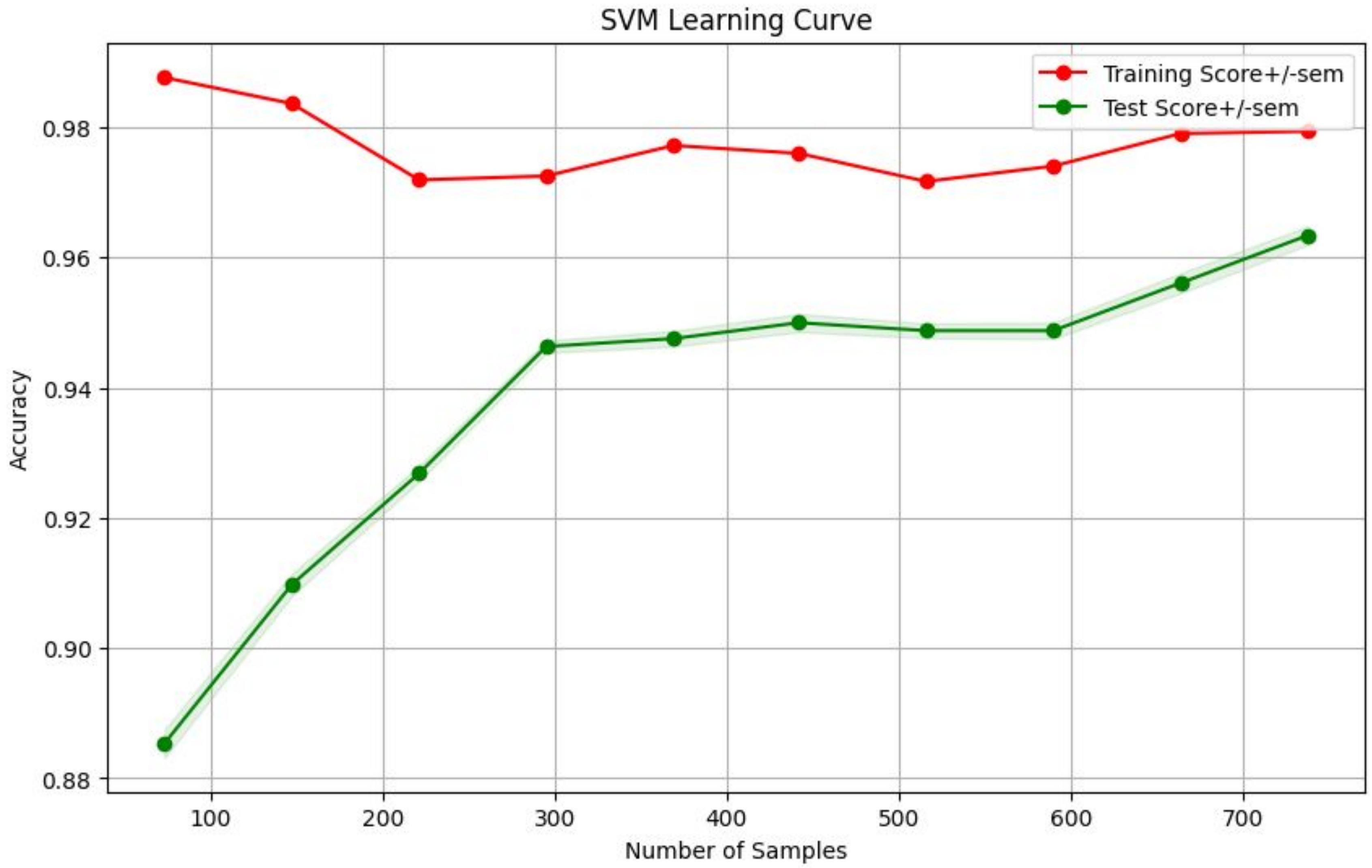


```
Best Parameters: {'C': 0.1, 'gamma': 'scale', 'kernel': 'poly'}
Best Score: 0.9597560975609755
Best Parameters: {'C': 0.1, 'gamma': 'scale', 'kernel': 'poly'}
Best Accuracy: 0.9597560975609755
Test Accuracy SVM: 0.975609756097561
```



```
Confusion Matrix SVM:
[[19  0  0]
 [ 1 91  2]
 [ 0  2 90]]
Classification Report SVM:
              precision    recall  f1-score   support

    CRITICAL       0.95      1.00      0.97        19
        HIGH       0.98      0.97      0.97        94
    MODERATE       0.98      0.98      0.98        92

    accuracy                           0.98       205
   macro avg       0.97      0.98      0.98       205
weighted avg       0.98      0.98      0.98       205
```

Learning Curves of SVM



Task 1.1: Implementing ML to predict High and Critical Vibration Levels

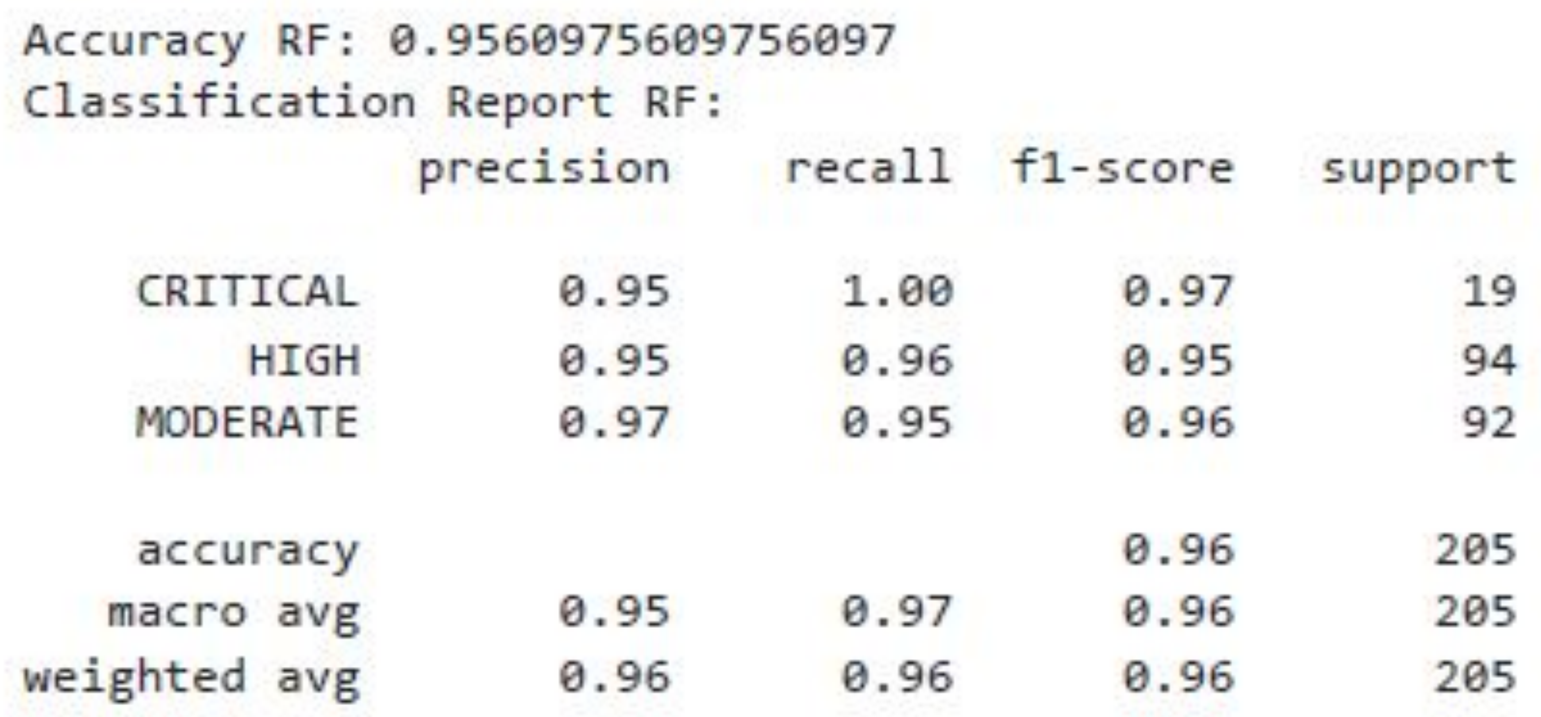
As we can see SVM gave us better results, this could be due to the inherent features of sophisticated ML models such as SVM which take care of factors like multicolinearity.

ML Model for Controllable Parameters only

KOITA CENTRE FOR DIGITAL HEALTH

Task 1.2: Implementing ML to find Important Controllable Parameters

- We take the controllable parameters as x variables and ‘overall_risk’ as the y variable
- We then split the x variables into train and test data 80:20 and normalize using min-max scaling
- We train our model using Random Forest Classifier which has built-in feature importance function
- On fitting we find our performance of the model as follows:



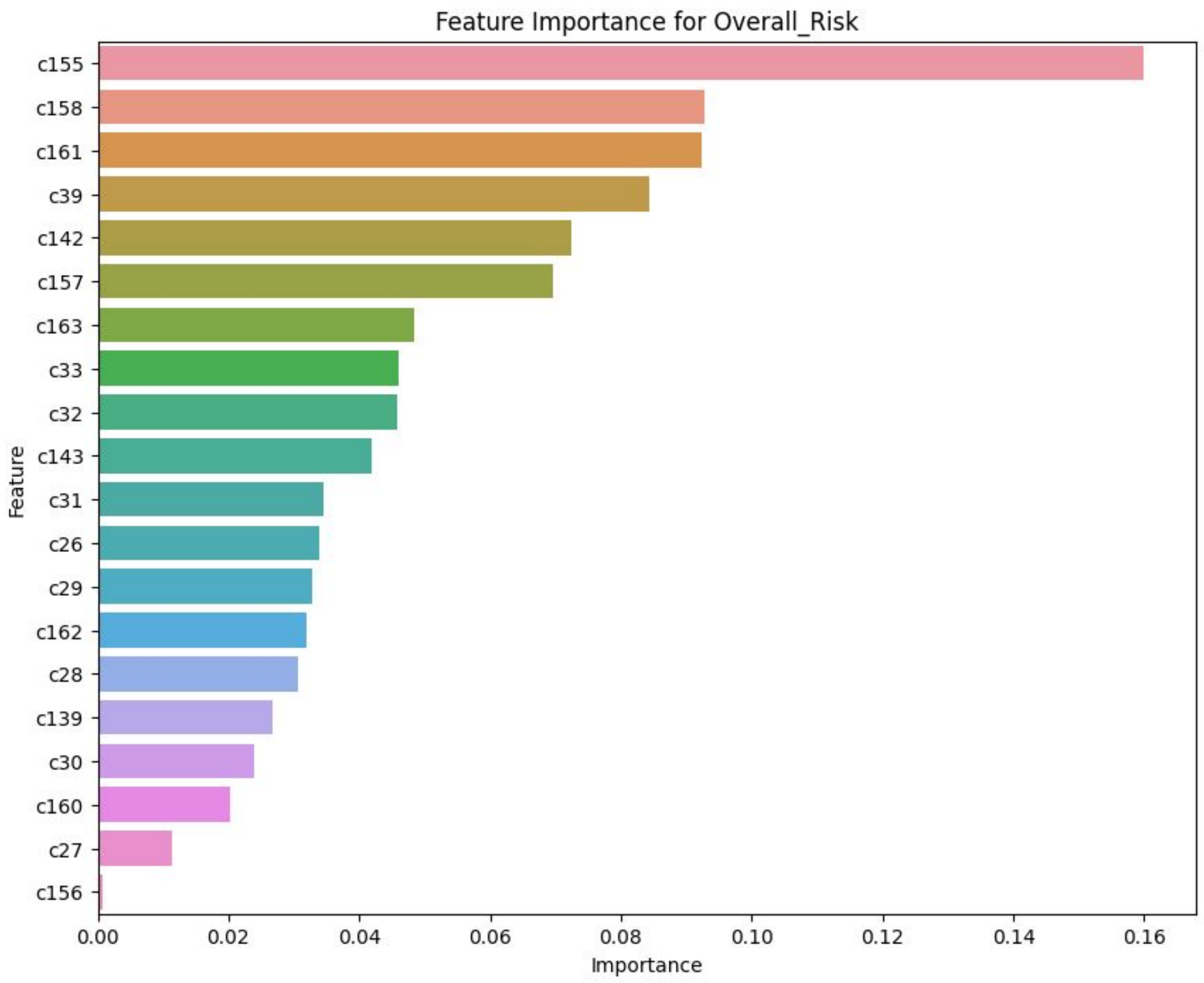
```
Accuracy RF: 0.9560975609756097
Classification Report RF:
             precision    recall  f1-score   support

    CRITICAL       0.95      1.00      0.97        19
        HIGH       0.95      0.96      0.95        94
    MODERATE       0.97      0.95      0.96        92

    accuracy                           0.96       205
   macro avg       0.95      0.97      0.96       205
weighted avg       0.96      0.96      0.96       205
```

Task: List Important Features

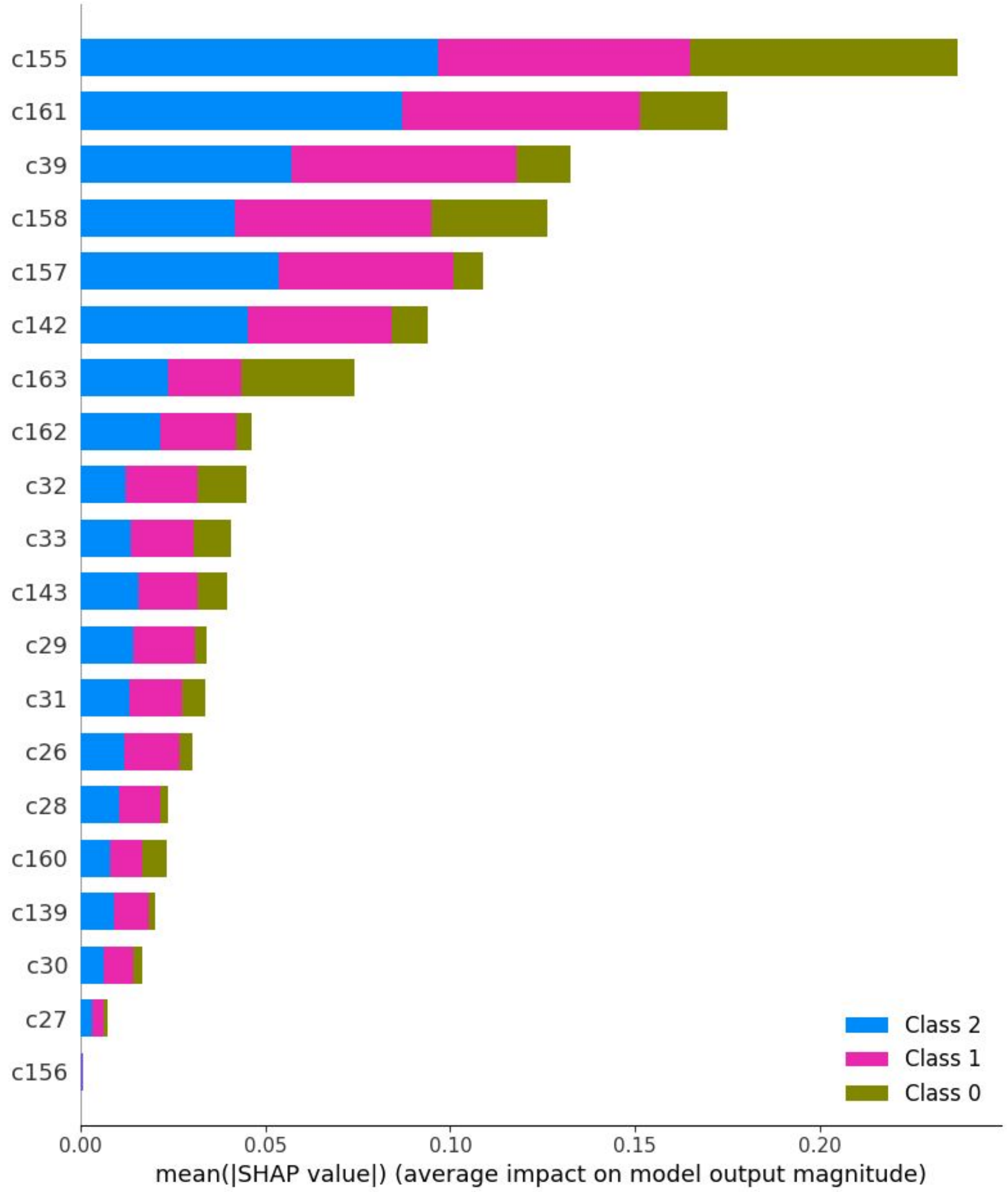
Two Approaches

- Inherent Feature Importance of Random Forest Classifier
- Model Agnostic feature Importance Method Such as SHapeley Additive exPlanations

Feature importance using Random Forest Classifier



Class wise Feature Importance using SHAP



Task 1.2: Important Features

Note that the important features remain the same, but SHAP gives us added information of class wise feature importance.

KOITA CENTRE FOR DIGITAL HEALTH

Task 2: Reducing Specific Energy

Task 2.1: Implementing ML to Find Significant Features for Specific Energy Prediction

- We create a model using df2 which has no feature with high VIF
- Our target is c241 and the independent variables are all features in df2 other than c241

Splitting Data & Normalization

We split the data into train and test with 80:20 ratio and then normalize them separately using min-max scaling. It is necessary to normalize the data after splitting so as to ensure the independence of training and test data.

Addition of Const. Column

We add the column of constant which we took as 1, to the features

Creating ML Model

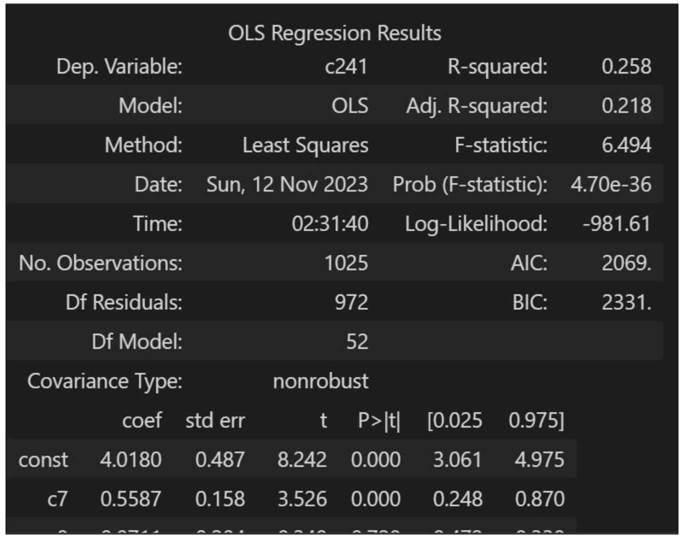
This is a regression problem and we apply Ordinary Least Square (OLS) available in statsmodel.api
It gives p-value for coefficient of each variable in it's summary dataframe

Important Features

The important features are those which have p-value less than 0.05.

Task 2.1: Implementing ML to Find Significant Features for Specific Energy Prediction

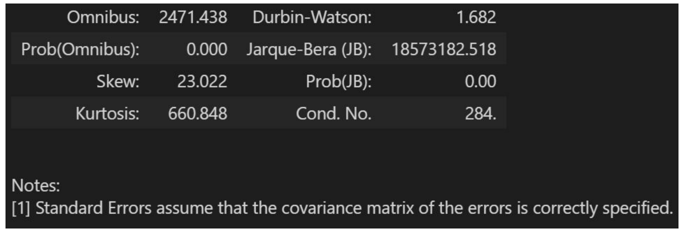
- Truncated OLS results



OLS Regression Results

Dep. Variable:	c241	R-squared:	0.258
Model:	OLS	Adj. R-squared:	0.218
Method:	Least Squares	F-statistic:	6.494
Date:	Sun, 12 Nov 2023	Prob (F-statistic):	4.70e-36
Time:	02:31:40	Log-Likelihood:	-981.61
No. Observations:	1025	AIC:	2069.
Df Residuals:	972	BIC:	2331.
Df Model:	52		
Covariance Type:	nonrobust		

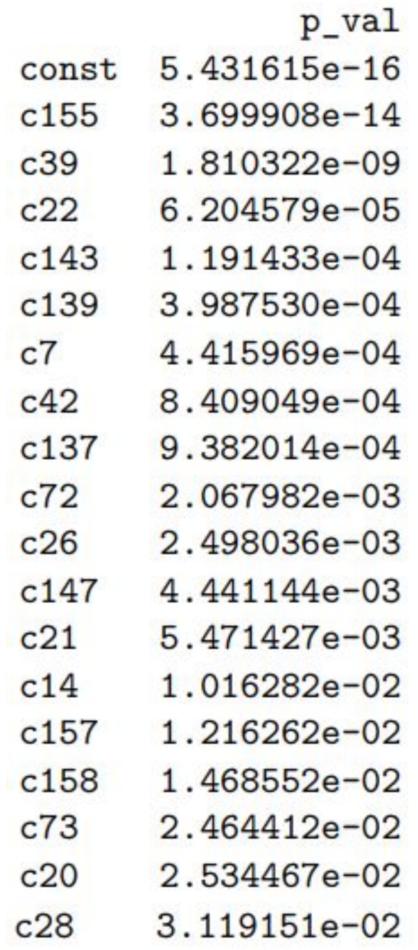
	coef	std err	t	P>|t|	[0.025	0.975]
const	4.0180	0.487	8.242	0.000	3.061	4.975
c7	0.5587	0.158	3.526	0.000	0.248	0.870



Omnibus:	2471.438	Durbin-Watson:	1.682
Prob(Omnibus):	0.000	Jarque-Bera (JB):	18573182.518
Skew:	23.022	Prob(JB):	0.00
Kurtosis:	660.848	Cond. No.	284.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

- 19 Significant Features



```
               p_val
const   5.431615e-16
c155    3.699908e-14
c39     1.810322e-09
c22     6.204579e-05
c143    1.191433e-04
c139    3.987530e-04
c7      4.415969e-04
c42     8.409049e-04
c137    9.382014e-04
c72     2.067982e-03
c26     2.498036e-03
c147    4.441144e-03
c21     5.471427e-03
c14     1.016282e-02
c157    1.216262e-02
c158    1.468552e-02
c73     2.464412e-02
c20     2.534467e-02
c28     3.119151e-02
```

Task 2.2: Determining 'minimum set' of 'independent feature' utilized to only 'predict not control' c241

- Here our approach will be to use PCA with the original data set with all features (even ones with high VIF). The reasoning for this as follows:
  - PCA will help us identify those minimum number of components which explain the maximum variance in the dataset.
  - PCA makes us loose feature importance, so we know the principal components but we don't know which features contributed to these principal components.
  - However, since our purpose is to only 'predict' and 'not control' the target, we can afford to loose explainability in lieu of better predictions.
  - Use of original df even with high VIF features is justified and PCA itself takes multicolinearity of the data set into consideration.

Task 2.2: Determining 'minimum set' of 'independent feature' utilized to only 'predict not control' c241

- Our approach:

Splitting Data & Normalization

We split the data into train and test with 80:20 ratio and then normalize them separately using min-max scaling. It is necessary to normalize the data after splitting so as to ensure the independence of training and test data.

Performing PCA

We implement PCA such that number of components are enough to explain at least 90% of the variance of the dataset.

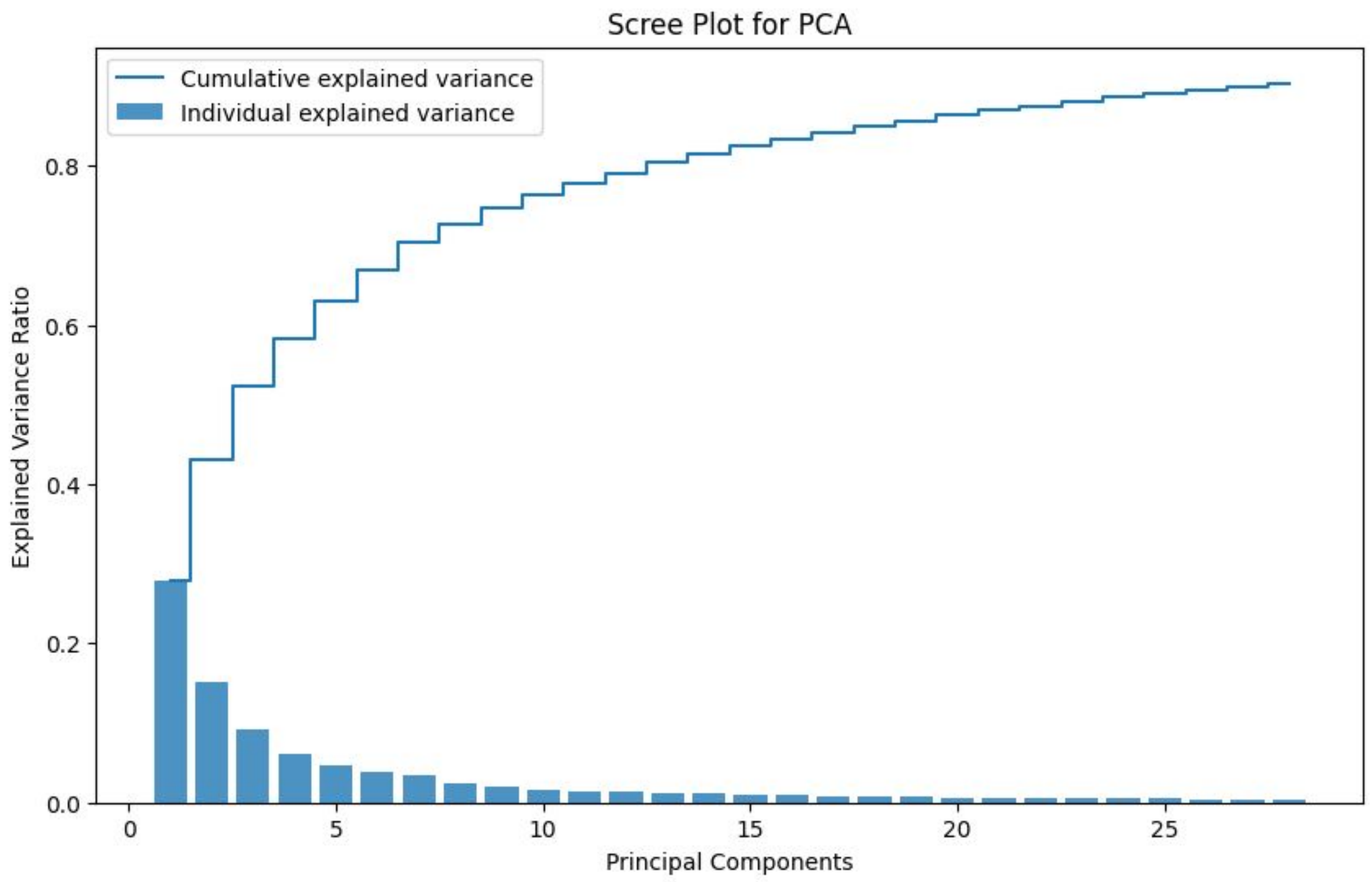
We plot the Scree plot and a scatter plot to visualise this output

Creating ML Model

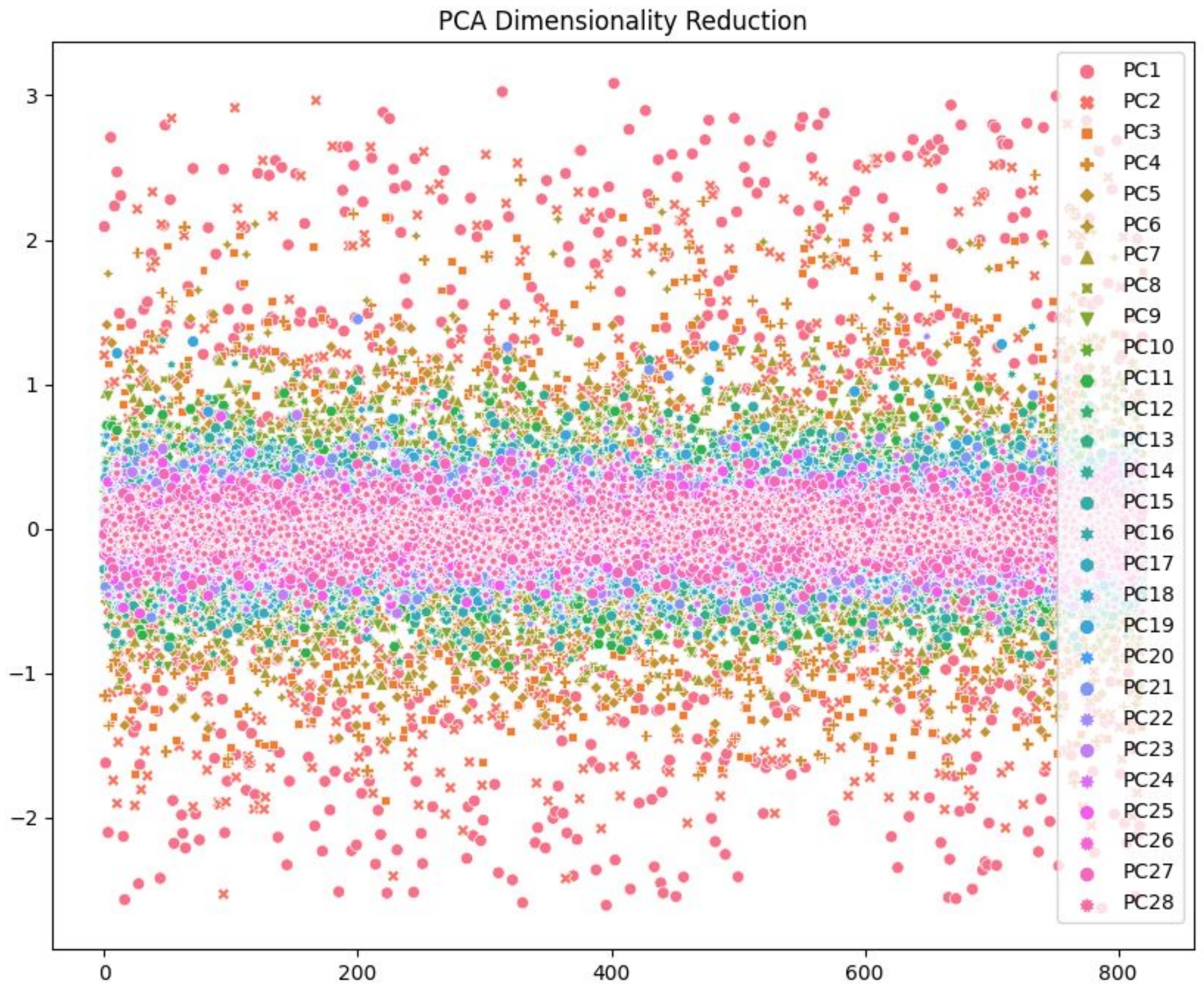
We use the Principal components in the ML model (we used random forest regressor, we tried others too but rf gave the best results).

We used the functions fit_transform for training set and only transform for test set.

Scree plot for PCA



Scatter Plot of PCA components



Results of Random Forest Model using PCA

Training MSE PCA RF: 0.093
Training R2 PCA RF: 0.861

Testing MSE PCA RF: 0.002
Testing R2 PCA RF: 0.847

Key Achievements

- We employed multiple methods of data pre processing for different problems in the data set.
  - Feature binning: For largely missing/ constant variables
  - Data imputation
  - Identifying outliers using IQR
  - Imputing outliers
  - Identifying multicolinearity in the data set and filtering the data set accordingly
- We were successfully able to build machine learning models for the various tasks while taking care of the problems in the dataset.
- For task 1 we created a single ML model and not multiple for c51, c52, c53, c54, by creating a new variable which depended on these four. We could do this as the purpose was to raise an alert if ‘any’ of these were *off.*
- For the feature importance task from among the controllable parameters we used ‘SHAP’ which goes a step ahead and gives us class wise feature importance, thus determining which features contribute heavily to predicting ‘CRITICAL’ level.

Challenges

- Deciding which machine learning algorithm is the best to use can be a challenge, we had to try multiple ones in our effort and then report the one with best results.
- Data being noisy was a challenge, which we tackled with a series of pre processing steps.

Recommendations

- Machine learning models thus created can be deployed to raise alerts/ alarms when levels reach HIgh/ Critical accordingly.
- Important controllable features identified can be monitored more closely for better outcomes
- In task 2.1 we identified ‘significant features’ responsible for the outcome ‘energy consumption’ these features can be adjusted when a rise in energy consumption is seen
- Finally a simple model created using only principal components can help predict/identify changes in energy consumption with even slight change in input variable.

Thank You