# Feature Selection Methodology

## Data

|  |  |
| --- | --- |
| Features | 20253 |
| Observation | 128 |

## Methodology

Various Methodologies were applied to the feature selection process. First, we started with a baseline model to understand the predictive capabilities of the data. Based on the results of the baseline model, we employed some feature selection methods.

Feature selection is usually applied with three methods:

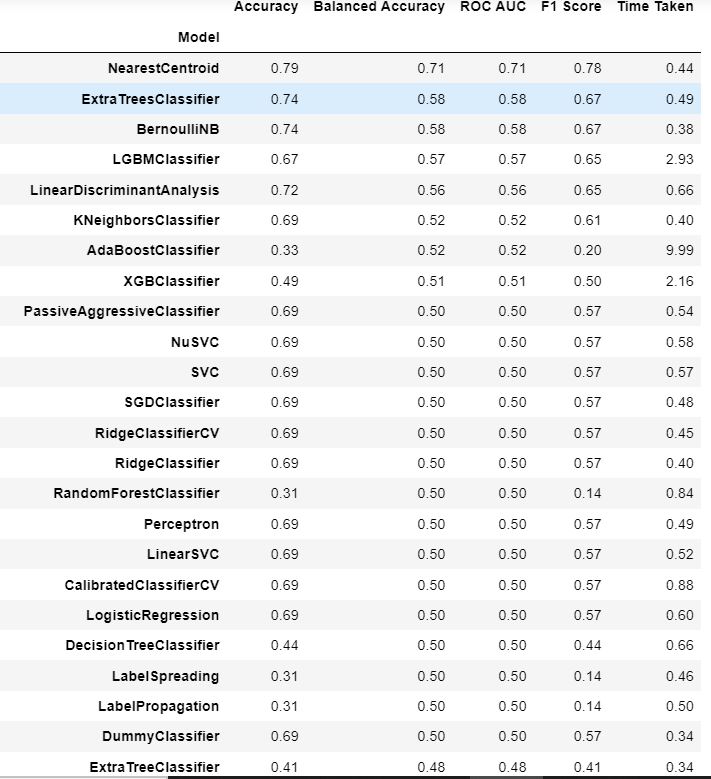
Filter Methods: These are naïve methods that looks at intrinsic properties measured via univariate statistics of the features and filters based on these properties. e.g Filter the top 10 most correlated features to the target. While this method would work best for linear models like logistic regression, selections based on this might severely affect other models that would have produced better results.

Wrapper Methods: Wrappers require some method to search the space of all possible subsets of features, assessing their quality by learning and evaluating a classifier with that feature subset. The feature selection process is based on a specific machine learning algorithm that we are trying to fit on a given dataset.

Embedded Methods: These methods encompass the benefits of both the wrapper and filter methods, by including interactions of features but also maintaining reasonable computational cost. Embedded methods are iterative in the sense that takes care of each iteration of the model training process and carefully extracts those features which contribute the most to the training for a particular iteration.

## Baseline Model

For the baseline model, we use the LazyClassifier method from the Lazy Predict library. This method fits all scikit learn ML models on the data and provides a result like below:



## Feature Selection

The overarching approach is to strategically search the space for all possible subsets of features evaluate with the cross-validation performance using top ranking models (based on baseline results) for each category of ML algorithms. For example, top ranking baseline models for Linear Models, Tree-based models, similarity-base models and ensembles.

**Challenge**: The data has 20532 features and iterating over all possible combinations is computationally expensive.

**Solution**: Adopt a two-step selection approach based on feature importance in step one and cross-validation performance in step two.

**Step One**: For step one, we adopted the recursive feature elimination method to eliminate redundant and non-informative features to a significant degree while maintaining the best possible performance (No performance degradation). The issue with most recursive feature elimination implementations is that it requires a pre-set number of features to either keep or eliminate. In this case, we do not know how many features to eliminate or keep. Instead, we want to eliminate as much possible redundant values without any performance reduction. To achieve this, we implemented a custom version of RFE that eliminates all features below the median important feature for both positive and negative category.

The result of step is the cross validated performance for each elimination iteration.

**Step Two**: For this step, we use the forward selection method to test all possible combinations of the significantly reduced feature subset.

The result of step is the cross validated performance for each forward iteration.

**NB: There might be different selected features based on the evaluation metric used in forward selection (step 2)**

Below are the ML algorithms used for each model category.

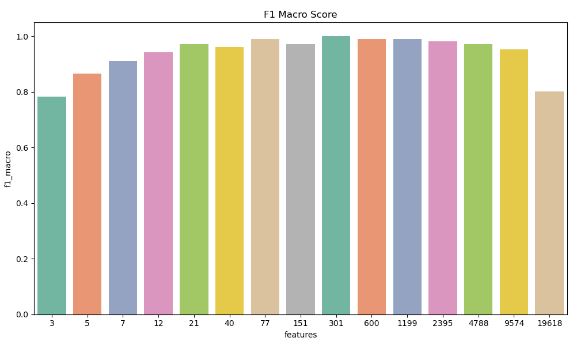
### Linear Models

#### Logistic Regression

For Linear Models, we used the **Logistic Regression** because it performed best in the baseline modelling with an average accuracy of **69%** with **20532** features. For preprocessing, we applied **standard** **scaling** and **removed 914 co-linear features**.

Step One:

At the end of stage one, we were able to maintain a cross validated F1 Macro Score above **90%** with **301** columns as seen below:



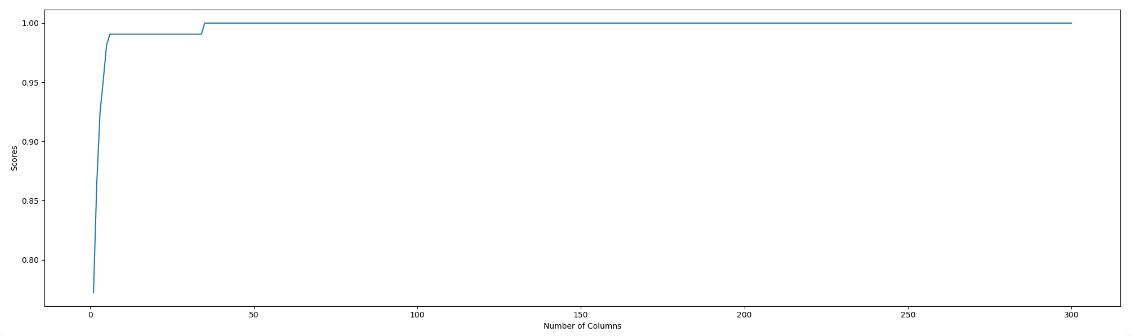
Step Two:

At the end of stage two, we got a cross-validated F1 macro score of **100%** (likely overfitting due to extremely small dataset) at **50** features (which still poses a curse of dimensionality challenge). But from the figure below, we had a steep climb to **98%** from **6** columns and performance remain constant (straight line) till **50** features.

Based on these results, best performing features are:

['LOC101060339', 'LOC90784', 'MGC22265', 'PWP2', 'LOC100133331', 'TMLHE']

to achieve a cross validated f1 macro score of **98%** and ['LOC90784','ENTHD2','CCL4L1','ACCPN','PWP2','PRKY','LINC00965','FOXQ1','RPS26P11','KATNBL1P6'] with a cross validated recall macro score of **98.75%**



### Ensemble Models

#### Extra Trees

Step one:

|  |  |
| --- | --- |
| Peak Performance Score (f1 macro score) | 85% |
| No of Columns | 37 |
| Diagram |  |

Step Two: ![Chart, line chart

Description automatically generated with medium confidence](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEAkACQAAD/4REYRXhpZgAATU0AKgAAAAgABAE7AAIAAAAaAAAISodpAAQAAAABAAAIZJydAAEAAAA0AAAQ3OocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFJhamksIE1hamVlZCAoQ29udHJhY3RvcikAAAWQAwACAAAAFAAAELKQBAACAAAAFAAAEMaSkQACAAAAAzgyAACSkgACAAAAAzgyAADqHAAHAAAIDAAACKYAAAAAHOoAAAAIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA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AKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigArm/E/8AyMPg7/sMSf8ApBd10lc34n/5GHwd/wBhiT/0gu6AOkooooAKKKKACiiigAooooAwPBf/ACA7n/sLaj/6WzVv1geC/wDkB3P/AGFtR/8AS2at+gAooooAKKKKACiiigDEkBufHUIxlLGwZj7NK4A/SJq26xNDxcaxrl8pyr3S26H2iQA/+PlxW3WlTdLsjOnqm+7CiiiszQKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigArm/E/8AyMPg7/sMSf8ApBd10lc34n/5GHwd/wBhiT/0gu6AOkooooAKKKKACiiigAooooAwPBf/ACA7n/sLaj/6WzVv1geC/wDkB3P/AGFtR/8AS2at+gAooooAKKKKACmySLFE8khwqKWY+gFOrI8VzPD4VvhF/rJoxboR2aQiMH82qormkkTKXLFsb4SiZPC9pLJ/rLsNdv7GVjJj8N2PwrZpkEKW9vHDCu2ONQij0AGBT6JS5pNhCPLFIKKKKkoKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigArm/E//ACMPg7/sMSf+kF3XSVzfif8A5GHwd/2GJP8A0gu6AOkooooAKKKKACiiigAooooAwPBf/IDuf+wtqP8A6WzVv1geC/8AkB3P/YW1H/0tmrfoAKKKKACiiigArD8QEz6lodiPuzXvnSD1WJGcf+PhP0rcrFGbjx0SMFLLT8H2aWTP8ov1rSno79jOpqrd2bVFFFZmgUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAVzfif8A5GHwd/2GJP8A0gu66Sub8T/8jD4O/wCwxJ/6QXdAHSUUUUAFFFFABXKa7HqY8TRyWUd8wxatE8Tt5Kqsrm4DKDjcYyAMjklcdMjq6KAOa1GzutR1SWZft1paLpkhJhkYSNNINo2qDjciq3Hq6nqKsaCNTbRbqNneORZmWznvIDudMAhnj3A/eLDGVyADxmt2igDnPAizL4amW6kSSYapqIkeNCis322bJCknA9sn610dYHgv/kB3P/YW1H/0tmrfoAKKKKACiiigArD8P4uL/Wr8fdmvTEh9ViVYz/48HrYuJ0traWeU4SJC7H2AyazPCkBg8LWJk/1k8f2iT/fkJkb9WNaR0g2Zy1ml8zXooorM0CiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACub8T/8jD4O/wCwxJ/6QXddJXN+J/8AkYfB3/YYk/8ASC7oA6SiiigAooooAKKKKACiiigDA8F/8gO5/wCwtqP/AKWzVv1geC/+QHc/9hbUf/S2at+gAooooAKKKKAMbxbI6+F7uKL791stV9vNcR/+zVroixxqiDaqgBQOwrF1z/SNb0KyxlTcvcuP9mOM4P8A32yfjitytJaQS+f9fcZx1m38v1/UKKKKzNAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigAooooAKKKKACiiigArm/E//Iw+Dv8AsMSf+kF3XSVzfif/AJGHwd/2GJP/AEgu6AOkooooAKKKKACiiigAooooAwPBf/IDuf8AsLaj/wCls1b9YHgv/kB3P/YW1H/0tmrfoAKKKKACiiigDL+x3D+LTeuuLaKx8mNsjl2ky/HXoifnWpRRTcmyVFIKKKKRQUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAVzfif8A5GHwd/2GJP8A0gu66Sub8T/8jD4O/wCwxJ/6QXdAHSUUUUAFFFFABRRRQAUUUUAc9p+i63pUU8Flqdh5El3cXKiawdmXzZnl2kiUA4L4zgdKtfZ/Ef8A0E9L/wDBdJ/8frXooAw7hPE0UW6O+0yVtyjaNPkHBYAn/Xdgc/hUv2fxH/0E9L/8F0n/AMfqLxYJ20uBIjeC2a5QXhsN/niHBzsMfzj5tuSvOM4qx4bN83hqwOq+Z9rMI8zzhh/bcP72MZ980AM+z+I/+gnpf/guk/8Aj9H2fxH/ANBPS/8AwXSf/H616KAMj7P4j/6Cel/+C6T/AOP0fZ/Ef/QT0v8A8F0n/wAfrXooAyPs/iP/AKCel/8Aguk/+P0fZ/Ef/QT0v/wXSf8Ax+teigDI+z+I/wDoJ6X/AOC6T/4/R9n8R/8AQT0v/wAF0n/x+teigDI+z+I/+gnpf/guk/8Aj9H2fxH/ANBPS/8AwXSf/H616KAMj7P4j/6Cel/+C6T/AOP0fZ/Ef/QT0v8A8F0n/wAfrXooAyPs/iP/AKCel/8Aguk/+P0fZ/Ef/QT0v/wXSf8Ax+teigDI+z+I/wDoJ6X/AOC6T/4/R9n8R/8AQT0v/wAF0n/x+teigDAuf+EohmtUiutNmWaYpI40+QeUuxm3H99zyoX/AIFVj7P4j/6Cel/+C6T/AOP1l+Lra5bVtIvLOfUHktnJWxthciK4JeM/vHiZUXAUgeblcM2Qa6ugDI+z+I/+gnpf/guk/wDj9H2fxH/0E9L/APBdJ/8AH616KAMj7P4j/wCgnpf/AILpP/j9H2fxH/0E9L/8F0n/AMfrXooAyPs/iP8A6Cel/wDguk/+P0fZ/Ef/AEE9L/8ABdJ/8frXooAyPs/iP/oJ6X/4LpP/AI/R9n8R/wDQT0v/AMF0n/x+teigDI+z+I/+gnpf/guk/wDj9H2fxH/0E9L/APBdJ/8AH616KAMj7P4j/wCgnpf/AILpP/j9H2fxH/0E9L/8F0n/AMfrXooAyPs/iP8A6Cel/wDguk/+P0fZ/Ef/AEE9L/8ABdJ/8frXooAyPs/iP/oJ6X/4LpP/AI/R9n8R/wDQT0v/AMF0n/x+teigDDlTxOk0Cpe6Y6yOVdhp8nyDaTn/AF3qAPxqX7P4j/6Cel/+C6T/AOP1y0zzO+pWpbxELBNXLF447wS7DbAjY2Nxj84NwhwOB9089tpRvDo9mdTCi9MCfaAvQSbRux+OaAKX2fxH/wBBPS//AAXSf/H6Ps/iP/oJ6X/4LpP/AI/WvRQBkfZ/Ef8A0E9L/wDBdJ/8fo+z+I/+gnpf/guk/wDj9a9FAGR9n8R/9BPS/wDwXSf/AB+j7P4j/wCgnpf/AILpP/j9a9FAGR9n8R/9BPS//BdJ/wDH6Ps/iP8A6Cel/wDguk/+P1r0UAZH2fxH/wBBPS//AAXSf/H6Ps/iP/oJ6X/4LpP/AI/WvRQBkfZ/Ef8A0E9L/wDBdJ/8fo+z+I/+gnpf/guk/wDj9a9FAGR9n8R/9BPS/wDwXSf/AB+j7P4j/wCgnpf/AILpP/j9a9FAGR9n8R/9BPS//BdJ/wDH6Ps/iP8A6Cel/wDguk/+P1r1HOFNvIHLhdhyY87sY7Y5z9OaAMgR+JjdNGb7TAgQMJP7PkwSSeP9d7D86k+z+I/+gnpf/guk/wDj9cj5dzOujXNpPr7tZXUsSWU8d/H9oX7Qu1pX3LnEY4Mu5SCcg816LQBkfZ/Ef/QT0v8A8F0n/wAfo+z+I/8AoJ6X/wCC6T/4/WvRQBkfZ/Ef/QT0v/wXSf8Ax+j7P4j/AOgnpf8A4LpP/j9a9FAGR9n8R/8AQT0v/wAF0n/x+j7P4j/6Cel/+C6T/wCP1r0UAZH2fxH/ANBPS/8AwXSf/H6Ps/iP/oJ6X/4LpP8A4/WvRQBkfZ/Ef/QT0v8A8F0n/wAfo+z+I/8AoJ6X/wCC6T/4/WvRQBkfZ/Ef/QT0v/wXSf8Ax+j7P4j/AOgnpf8A4LpP/j9a9FAGR9n8R/8AQT0v/wAF0n/x+j7P4j/6Cel/+C6T/wCP1r0UAZH2fxH/ANBPS/8AwXSf/H6Ps/iP/oJ6X/4LpP8A4/WvWV4nljh8N3bzQahcKFH7rTDILhyWAAUx4cc4yR0GSeM0AVrceKJbi6SS70yJYZQkbnT5D5o2K24fvuOWK/8AAan+z+I/+gnpf/guk/8Aj9cxENZ/tDSzJLqcjpBZi3KLOImJmYXQmDAAkRbcGUA9CvzE131AGR9n8R/9BPS//BdJ/wDH6Ps/iP8A6Cel/wDguk/+P1r0UAZH2fxH/wBBPS//AAXSf/H6Ps/iP/oJ6X/4LpP/AI/WvRQBkfZ/Ef8A0E9L/wDBdJ/8fo+z+I/+gnpf/guk/wDj9a9FAGR9n8R/9BPS/wDwXSf/AB+j7P4j/wCgnpf/AILpP/j9a9FAGR9n8R/9BPS//BdJ/wDH6Ps/iP8A6Cel/wDguk/+P1r0UAZH2fxH/wBBPS//AAXSf/H6Ps/iP/oJ6X/4LpP/AI/WvRQBkfZ/Ef8A0E9L/wDBdJ/8fo+z+I/+gnpf/guk/wDj9a9FAGR9n8R/9BPS/wDwXSf/AB+j7P4j/wCgnpf/AILpP/j9a9c344kZdEjSFNUa4kmCQPp3n/un2nDyeSCxQYyQQQTgY5oAdpzeKry1eS6n020dZ5ohG1hISypIyK/+uHDKoYezd+tW/s/iP/oJ6X/4LpP/AI/WXaW88XxAmuUudRuo7iMCSOZLqOG2URpgrubyGJZeQqbwXbnAIrq6AMj7P4j/AOgnpf8A4LpP/j9H2fxH/wBBPS//AAXSf/H616KAMj7P4j/6Cel/+C6T/wCP0fZ/Ef8A0E9L/wDBdJ/8frXooAyPs/iP/oJ6X/4LpP8A4/R9n8R/9BPS/wDwXSf/AB+teigDI+z+I/8AoJ6X/wCC6T/4/R9n8R/9BPS//BdJ/wDH616KAMj7P4j/AOgnpf8A4LpP/j9H2fxH/wBBPS//AAXSf/H616KAMj7P4j/6Cel/+C6T/wCP0fZ/Ef8A0E9L/wDBdJ/8frXooAyPs/iP/oJ6X/4LpP8A4/R9n8R/9BPS/wDwXSf/AB+teigDI+z+I/8AoJ6X/wCC6T/4/QbfxHj/AJCWl/8Aguk/+P1r1yvjFbo3GmyaU2ofbo7iMqlv9o8p4zIu8Ps/dfdz/rAe+MHmgCzpjeKr3SbS6u7jTbOeeBJJbZ7CQmFioJQnzhkgnHTtVr7P4j/6Cel/+C6T/wCP1keBP7TEMv8Aah1Au1rbvc/bQ/F4d/2gR7/4P9XgJ+7/ALveuuoAyPs/iP8A6Cel/wDguk/+P0fZ/Ef/AEE9L/8ABdJ/8frXooAyPs/iP/oJ6X/4LpP/AI/R9n8R/wDQT0v/AMF0n/x+teigDI+z+I/+gnpf/guk/wDj9H2fxH/0E9L/APBdJ/8AH616KAMj7P4j/wCgnpf/AILpP/j9H2fxH/0E9L/8F0n/AMfrXooAyPs/iP8A6Cel/wDguk/+P0fZ/Ef/AEE9L/8ABdJ/8frXooAyPs/iP/oJ6X/4LpP/AI/R9n8R/wDQT0v/AMF0n/x+teigDI+z+I/+gnpf/guk/wDj9H2fxH/0E9L/APBdJ/8AH616KAMj7P4j/wCgnpf/AILpP/j9QXo8UW1jPPBeaZcSxxsyQrp8gMhAyFB87v0rerh/FcF7N4kgGmXer26yQzQ3r26XTJFGbeTa6AfuywfYfkxJnAB6igDofs/iP/oJ6X/4LpP/AI/R9n8R/wDQT0v/AMF0n/x+ofCEcsOhmGX7S6RzMIpro3HmSqcHcRcM0i8krhj/AA5GAQK3aAMj7P4j/wCgnpf/AILpP/j9H2fxH/0E9L/8F0n/AMfrXooAyPs/iP8A6Cel/wDguk/+P0fZ/Ef/AEE9L/8ABdJ/8frXooAyPs/iP/oJ6X/4LpP/AI/R9n8R/wDQT0v/AMF0n/x+teigDI+z+I/+gnpf/guk/wDj9VZ9E1e+1jR7vUdSsmi0y7a6EcFk6NITBLFjcZWwP3pPTtXQ0UAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUActpfxB0nU5LJPKurV7uNnVZ4xlMSwxqGCk4L/AGiJl7bWySKvSeMNFjkZDczMVfy28u0mcK3nPCASqkAmSNlHqRxnIzVPgHQ/tUNzGk8U8NklkkiSkEIjpIjehYNEnP8AsgHIq1Z+EtNsoXjjM775Y5XaSXczMlw9wCT/ANdJGP04oArw+NtOl8QSacwlSMQW8kdwYpMF5ZZYvLcbf3ZDRY+YjJbGARzJb+OPD94yLaXrzvIyKkcdtKztvV2UhQuSpWKQhunynmg+DdMOrNf77kPIyNJEJsRyFJpJ0yPaSVj+QORUuneFrHTPsq28ly0dm4a2jkl3CICN4wo4yRtkYZOT054oAsXfiDTrHUBZXM0izkKcLBIy5bdtG4KRuO04XOScADkZoWXir7RoGj381hILjV3C29pC2W5VnBJcJjEaFj9MDdxm7c+H7O71iPUZmmLoUYw+YfKdkzsYr6jcefYZztGCXw9Zy6VYWKtNENO2G0mjfEkRVCgIPf5SQcgggkEc0ARXHia0tA0dzFNDdrGX8h4yQDhiqtIu5FLBCQCc8jjkCo4vGGk/2THe3c/kAxl5E2O/llYBOwyF5whzx16DninSeFLGaYSTT3cuVxIrzkrMwDAOw7sN5x24Xj5VxWbwLpLM2WuvLaNo/K887BugEDNj1KKB9RnucgFlvGGiolw8s9xELVHebzLOZCoXbuGCnJ+dTgckEEDFTW3ibS7u7jtYJZmnkLARm1lVl2ttO4Ffl5/vYz1FF94csNQ8/wC0rIftBYvtfH3lRT+iLUc/hewub6G5lMpMNz9rWPcNvm5BDdMjp2IyODkcUAbNFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFABRRRQAUUUUAFFFFAH//Z)

Results:

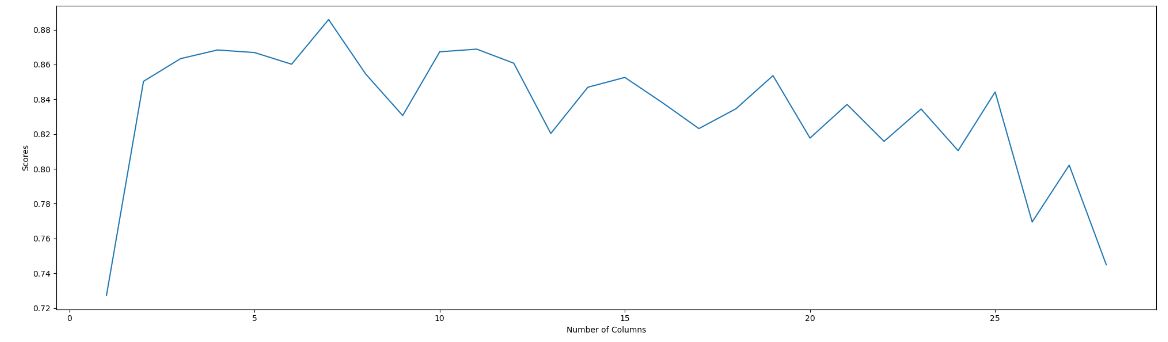
|  |  |
| --- | --- |
| Best Columns based on F1 macro score | ['LOC90784', 'TUBB8', 'CCL3L3', 'GPR173', 'IKBKE', 'ENTHD2', 'PRIMPOL'] |
| Cross validated F1 macro score | 92.6% |
| Best Columns based on Recall macro score | ['LOC90784', 'TUBB8', 'CCL3L3', 'GPR173', 'IKBKE'] |
| Cross validated Recall macro score | 92.1% |

#### RandomForest Classifier

Step One:

|  |  |
| --- | --- |
| Peak Performance Score (f1 macro score) | 78% |
| No of Columns | 29 |
| Diagram |  |

Step Two:



Results:

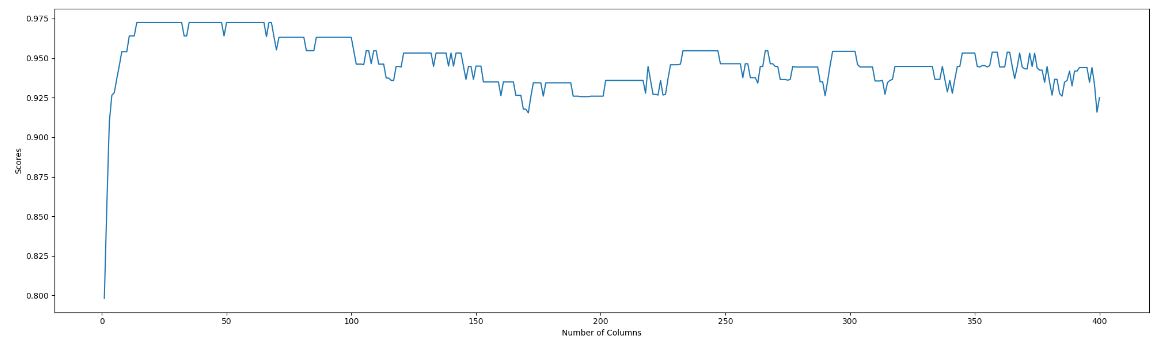
|  |  |
| --- | --- |
| Best Columns based on F1 macro score | ['LOC101060339','MGC22265','CHD1','FAM207A','C2ORF71','AMACR','CCDC154'] |
| Cross validated F1 macro score | 88.58% |
| Best Columns based on Recall macro score | ['LOC101060339', 'MGC22265', 'CHD1', 'ZNF816', 'ZC3H12A', 'MINK1'] |
| Cross validated Recall macro score | 87.24% |

#### LGBMClassifier

Step One:

|  |  |
| --- | --- |
| Peak Performance Score (f1 macro score) | 85.1% |
| No of Columns | 401 |
| Diagram |  |

Step Two:



Results:

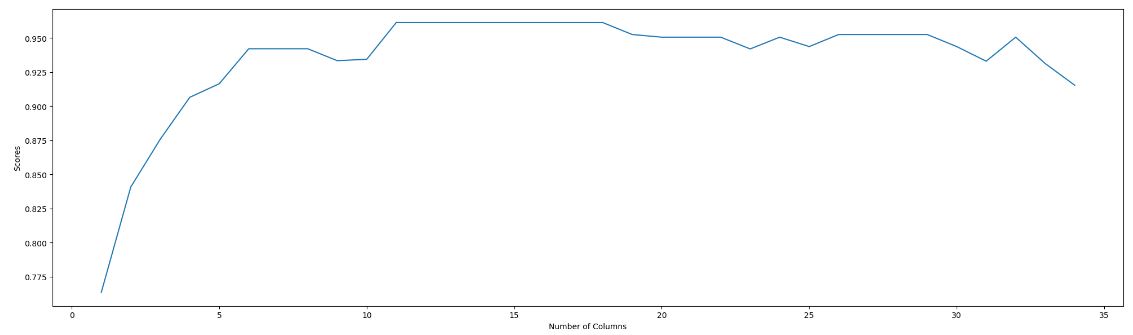
|  |  |
| --- | --- |
| Best Columns based on F1 macro score | ['LOC101060339','LOC100133331','TTC30B','MGC14226',  'COL6A5','SCN7A','FLJ41941','AP5M1','GALNT1','TFRC','NAP1L4','PEG3-AS1','LOC115451','HOXA11-AS'] |
| Cross validated F1 macro score | 97.2% |
| Best Columns based on Recall macro score | ['LOC101060339','LOC100133331','TTC30B','MGC14226','COL6A5',  'SCN7A','LOC96800','GSG2','PLSCR3'] |
| Cross validated Recall macro score | 95.74% |

#### Adaboost

Step One:

|  |  |
| --- | --- |
| Peak Performance Score (f1 macro score) | 81.1% |
| No of Columns | 35 |
| Diagram |  |

Step Two:



Results:

|  |  |
| --- | --- |
| Best Columns based on F1 macro score | ['LOC101060339','CMT2B1','MAP7D1','LOC90784','MGC23947',  'OGFOD2','DKFZP434N231','MPI','LIMK1','DHX40P','MGC22265'] |
| Cross validated F1 macro score | 96.13% |
| Best Columns based on Recall macro score | ['LOC101060339', 'LOC90784', 'PWP2', 'MGC22265', 'TYSND1'] |
| Cross validated Recall macro score | 95.68% |

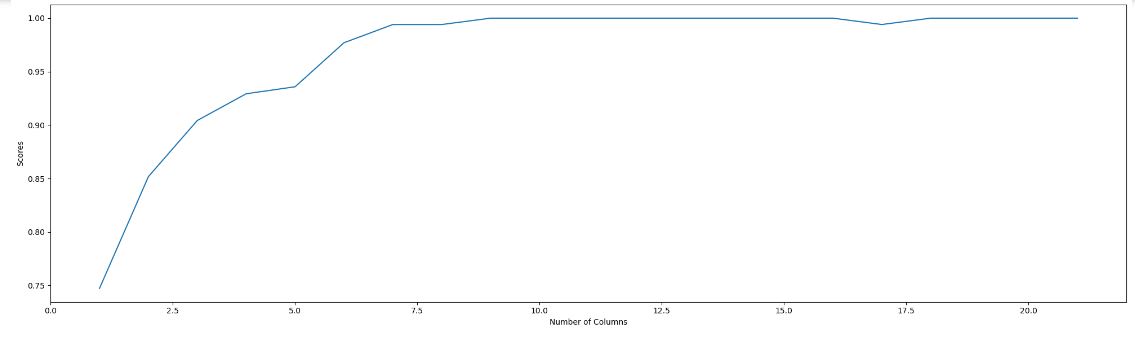
### Non-Linear Model

#### SVM

Step One:

|  |  |
| --- | --- |
| Peak Performance Score (f1 macro score) | 98.86% |
| No of Columns | 22 |
| Diagram |  |

Step Two:



Results:

|  |  |
| --- | --- |
| Best Columns based on F1 macro score | ['LOC90784','PIF1','LOC101060247','KBF2','STON1GTF2A1L','CYP4V2',  'KCNE3','STYXL1','KIAA1324L','DKFZp434E1822','RPS26P11',  'ZNF702P','LOC101060339'] |
| Cross validated F1 macro score | 99.15% |
| Best Columns based on Recall macro score | ['LOC90784','KBF2','DDX51','ADGRF2','LOC101060247','RPS26P11',  'CCL4L1','LOC101060339','DKFZp434E1822'] |
| Cross validated Recall macro score | 99.4% |

### Overall Results:

From this analysis, Logistic Regression produced the best performing model.

