ANOMALY DETECTION IN LONG TERM EVOLUTION (LTE) NETWORK

INTRODUCTION

Long-Term Evolution (LTE) cellular networks are the central component to one of the most essential and in-demand fields globally, telecommunications. However, these LTE networks simultaneously drain expensive and scarce radio resources, primarily electrical power and frequency spectrum. This project thus seeks to develop two supervised classification Machine Learning (ML) models capable of being utilized in a dynamic Radio Resource Management (RRM) system for LTE networks. The ML models will be predicting if a cell exhibits (a) normal behaviour where no redistribution of radio resources is required or (b) anomalous behaviour that requires reconfiguration.

METHODOLOGY

DATASET

1. Telemetry data was obtained from a 4G LTE deployment spanning two weeks
2. 14 total features, consisting ofthe dependent or outcome feature "Beha viour" along with 13 other predictor features
3. Gathered from a set of 10 base stations, in total spanning 33 cells, every 15 minutes.
4. Total sample size of 36904, dataset being imbalanced with the large majority of cell behaviour being normal (72.4%) rather than anomalous (27.6%).

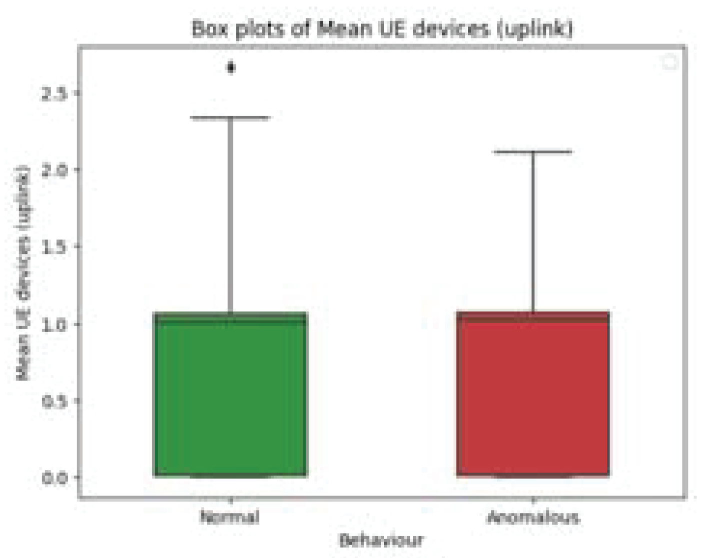
EXPERIMENTAL SETUP

1. All data manipulation and model training was done in Python 3.11.4.
2. The dataset was shuffled and splitinto training (80%) and testing (20%) datasets.

EXPLORATORY DATA ANALYSIS

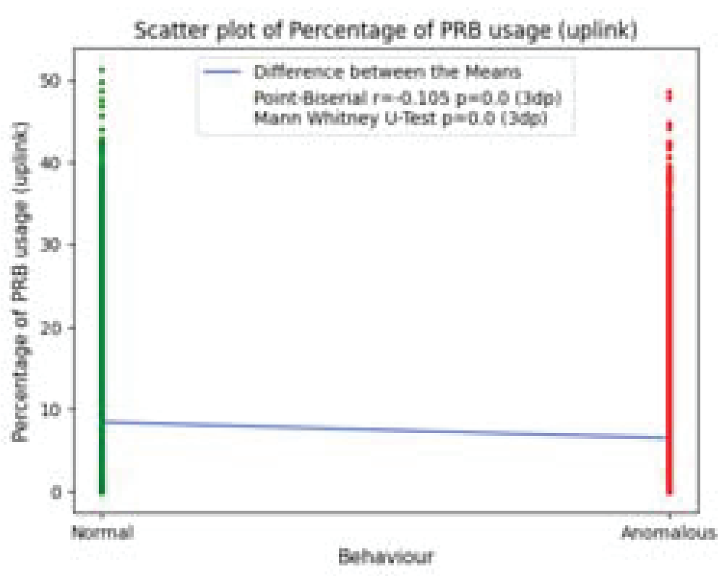
DATA QUALITY

1. Presence of missing data in the rows was tested, no missing data was found and no further action done
2. Outliers were then identified by visualising box plots and plotting any values outside Tukey's Fences [1]
3. Only distinct global outlier identified was in the box plot of Mean UE Devices (uplink) with a value of 2.668



FEATURE IMPORTANCE

1. The non-parametric Chi Square test for homogeneity [2], Point-Biserial correlation [3] and Mann Whitney U test [4] are hypothesis tests used to evaluate predictor feature importance by assessing for statistically significant effects on the outcome feature
2. For example, a scatter plot of Percentage of PRB usage (uplink) shows a difference between the mean values of anomalous and normal cells supported by the statistically significant ($p<0.001$) hypothesis tests
3. Only significant features such as Percentage of PRB usage (uplink) were retained for model training



DATA DISTRIBUTION

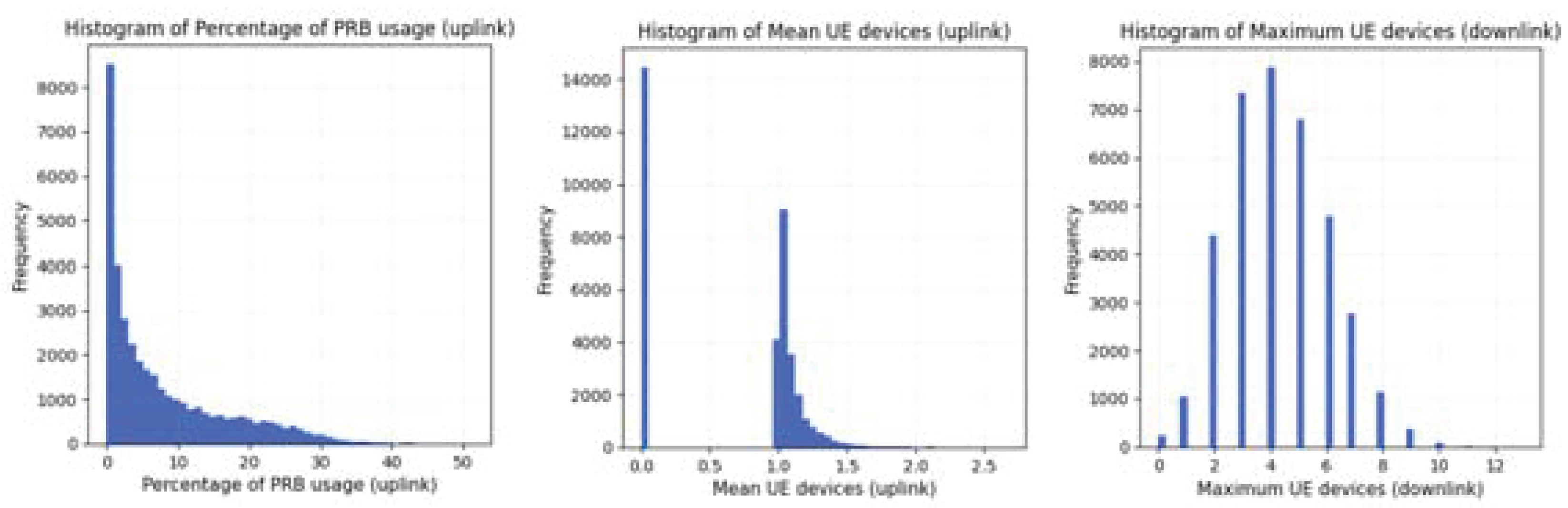
3 types of distributions were observed from the histograms:

(a) Exponential – Peak at 0, long right tail

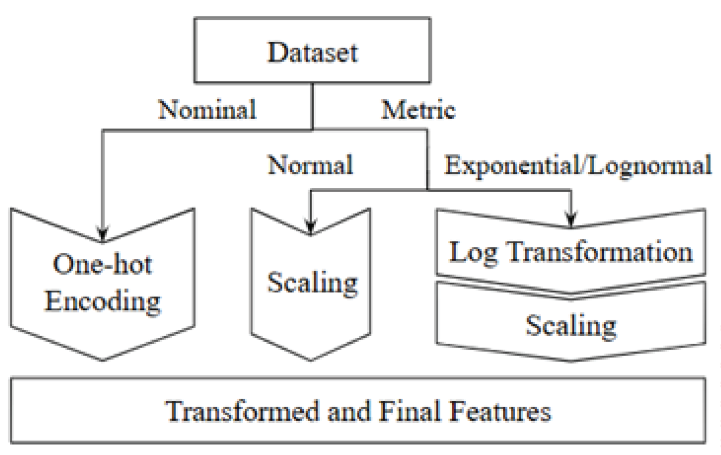
(b) Bimodal-Lognormal – two peaks, lognormal shape

(c) Normal – Gaussian distribution, integer only values

Examples are illustrated below in order from left to right



FEATURE ENGINEERING



Simplified Pre-processor Diagram

NOMINAL FEATURES

1. Two features "Mean UE devices encoded (uplink)" and "Mean UE devices encoded (downlink)" were created from the features "Mean UE devices (uplink)" and "Mean UE devices (downlink)" respectively
2. These features return 1 if the value of the original feature is 0 and 0 if the value is not, extracting information from the bimodal distribution observed
3. "Cell ID" feature under went one hot encoding, resulting in the creation of 33 different features, one for each Cell ID, returning 1 if the ID matches and 0 if it does not

METRIC FEATURES

1. Exponential or Lognormal features identified during Exploratory Data Analysis would undergo a log transformation in order to normalise the data first
2. These features would thereafter undergo scaling along with the normally distributed data, where the feature is scaled to have a mean of 0 and a standard deviation of 1.

The log transformation improves model performance and training stability by normalising the data while scaling ensures that the magnitude of influence each feature has on the ML model is comparable and reduces excessive bias on any specific feature because its original values are greater.

MODEL TRAINING

SELECTED MODELS

The two selected ML models for training are the

1. Decision Tree (DT) model [5],
2. eXtreme Gradient Boosting (XGBoost) model [6]

Where the XGBoost model is an ensemble learning technique that consists of multiple decision trees building upon the residuals of the previous tree.

OBJECTIVE FUNCTION

The chosen objective function for **hyperparameter tuning** is:

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

due to its utilisation of both precision and recall in a manner which scores models with more balanced values higher, making it more suitable for the imbalanced dataset being used

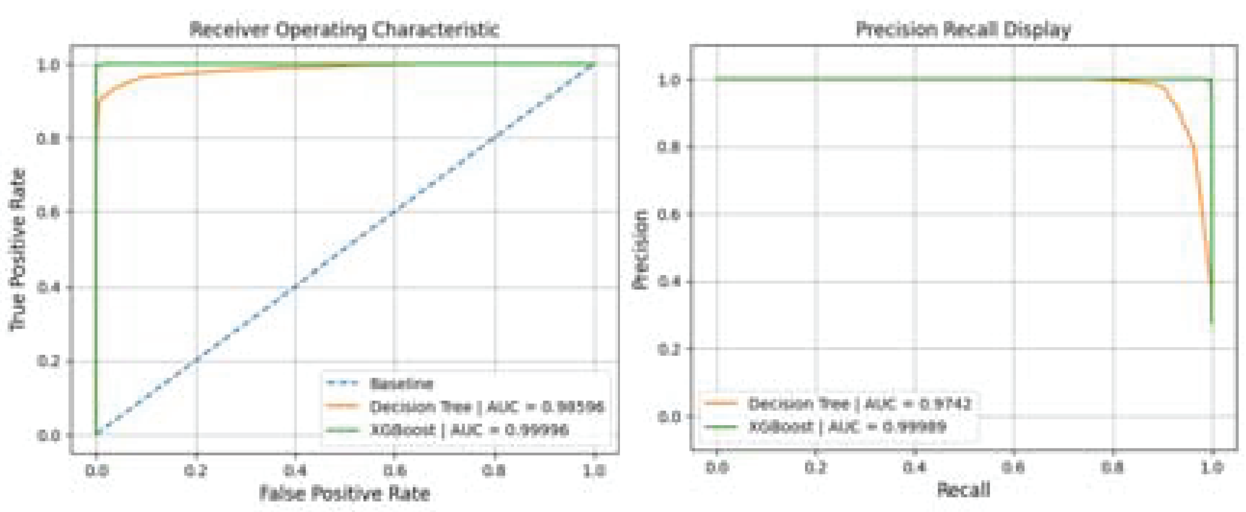
HYPERPARAMETER TUNING

1. Stratified 10-fold validation splits the processed training dataset into a new validation (10%) and training dataset (90%) over 10 folds
2. An Optuna study is created, in the first trial a random set of hyperparameters is chosen from specified ranges
3. For each fold, the models are subsequently fitted with the chosen hyperparameters on the new training data and tested on the validation data to obtain a F1 score for that fold
4. Mean F1 score of all the folds is then calculated
5. In the following trial, the hyperparameters will be tuned using Optuna's [7] optimisation algorithm based on the mean F1 score of the previous trial, aiming for a maximised F1 score
6. The best performing hyperparameters that results in the highest F1 score is the final model

RESULTS AND DISCUSSION

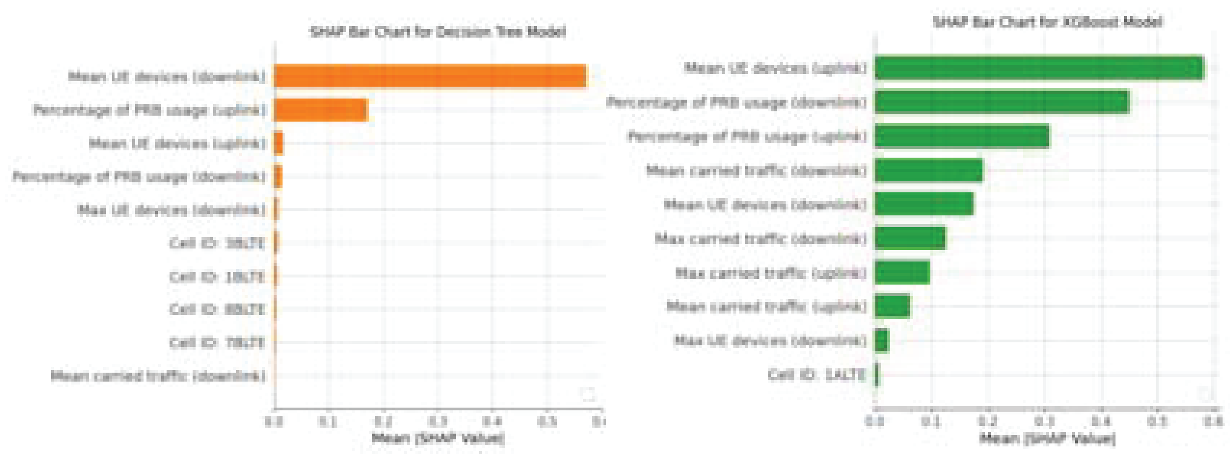
MODEL EVALUATION

The XGBoost model had performed better than the DT model at all possible thresholds, coming exceedingly close to being a perfect model of having an Area Under the Curve (AUC) of 0.999 for both the ROC curve and PRD, which was greater than the DT model's AUC values of 0.986 and 0.974 for the ROC curve and PRD.



MODEL EXPLANATION

The DT model is heavily influenced by mainly two features, "Mean UE devices (downlink)" and "Percentage of PRB Usage (uplink)". Similarly, the XGBoost model is most influenced by the same two features but with reversed communication directions.



CONCLUSION

The DT model and XGBoost model demonstrate exceptional model performance across all evaluation metrics and show promising implementation potential predominantly in the latter model.

FUTURE WORKS

1. Explore the development of a dynamic RRM system capable of reconfiguring the identified anomalies from the ML models
2. Utilise data from multiple deployments and minimise location-specific data
3. Incorporation of MLOps (Machine Learning Operations) for the continued training and adaptation of the ML models in foreign LTE deployments.

REFERENCES

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WEBSITE APPLICATION

A Graphical User Interface (GUI) was created to assist in the usage and evaluation of the ML models

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YDSP Young Defence Scientists Programme

DSTA Defence Science & Technology Agency

DSO National Laboratories