AI POWERED SOLUTION FOR RADIO LINK FAILURE PREDICTION BASED ON LINK FEATURES AND WEATHER FORECAST

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Abstract *– Radio link sustainability gets affected by weather adversities such as snow, fog, cloud, rain, thunderstorm, etc. A proactive solution in radio link failure scenarios is necessary to overcome economic loss and maintain the Quality of Service (QoS). To address the issue, our work contributes towards building a machine-learning-based solution to predict the radio link failure when generic regional weather forecast data, key performance indices of radio link and spatial nature of the data are available. After rigorous data preprocessing, ensembling models like logistic regression, random forest, light BGM, XGBoost and gradient boosting classifiers were trained to predict the Radio Link Failure (RLF) for two cases i.e., day-1-predict and day-5-predict. Since it is a classification use case, the metrics used for our work are precision, recall, and F1 score. The performance of the gradient boosting classifier was better as compared to the other models with an F1 score of 0.95 for both day-1-predict and day-5-predict.*

Keywords – Data preprocessing, key performance indices, machine learning, radio link failure, weather forecast

1. INTRODUCTION

Establishing reliable communications is of prime importance in today's era of telecommunications. One of the challenges the radio engineers face in achieving this is radio link failure. RLF can hinder communication reliability and increase network latency. In extreme cases, for critical applications, if the communication link is interrupted for a longer time it may incur a huge economic loss. In some cases, a radio link failure scenario demands manpower and a larger recovery time to resolve the issue. Research towards RLF prediction has gained attention in Long-Term Evolution – Advanced (LTE-A) networks [1], in 5G [2] which promises to offer Ultra-Reliable Low Latency Communications (URLLC), etc. In fact, RLF is a general problem in any wireless communication network.

There are many factors that contribute to radio link failure among which weather-based disruptions are also of major concern. The Qualit of Service (QoS) of a radio link can be affected by large variations in the weather parameters like rain, temperature, humidity, wind, etc. However, the frequency of operation decides which weather parameter affects the quality of radio connectivity [3]–[5]. There are some passive methods by which some action is taken once the RLF is sensed; some actions taken are initiating the reconfiguring process, changing the antenna direction and polarization, providing low-cost structural support, activating backup virtual machines, redirecting the network traffic, etc [6]. Using such passive methods may sometimes extend the restoration for hours or increase the latency which would incur a huge loss to the service provider/network operator. A proactive approach would be a better solution in such cases. Hence predicting the RLF is one of the problems which researchers are trying to address.

1.1 Problem definition and proposed solution

There is scope for improved proactive solutions to predict radio link failure, especially based on variations in the weather conditions. Estimating the probability of RLF based on weather phenomena is the need of the hour and so is devising an accurate model to predict it. Our work considers the variation in various weather parameters, along with Radio Link (RL) Key Performance Indicators (KPIs), over a large range of geographical features to generalize the prediction model, which in fact is not documented in the existing literature to the best of our knowledge. The primary objective is to predict the event of radio link failure for the next day of measurement and on the subsequent fifth day. The major challenges and contributions of the work are highlighted below.

- With the dataset being in a crude format and highly biased with many features, there is a major effort towards rigorous data analysis to select the most relevant features, class rebalancing and data integration.

- With the processed dataset, in the model-building approach, testing majorly with ensembling Machine-Learning (ML) techniques has been tried.

In the next section, we discuss some of the related works pertaining to the problem statement. In Section 3, complete data analysis has been presented with appropriate visualization. Also, the challenges encountered while dealing with the datasets to select the most appropriate features and structure them have been discussed. The actual flow of data preparation has been presented in Section 4. In Section 5, testing of all the ML algorithms used for model building and for cross-validation and inferencing has been presented. The final results have been analyzed and discussed in Section 6. The work is concluded along with the future scope in Section 7.

2. RELATED WORK

Although there are good studies to understand and establish the relationships between weather conditions and radio link quality, there are only a few pieces of work in the scope of our problem statement i.e., to predict RLF subjected to weather adversities. The research work in [7], [8] establish that there is negative correlation between signal strength and humidity, whereas temperature seems to be positively correlated with signal strength. In a study on impact of humidity and temperature on radio signal quality [9], the authors claim that temperature plays a significant role, as compared to humidity, in determining the grade of a given radio channel in the ISM band. The impact of weather conditions on the quality of the radio channel is determined by the frequency of operation and the terrain conditions. The effect of wind and rain in tropical forests has been investigated in [10]. The authors modeled the received signal under such conditions and they found that it would fit Rician-K distribution wherein the K-factor would decrease as the wind or rain gets intensified. Effects of weather conditions on radio link quality in Ultra-High Frequency (UHF) in a tropical region were examined in [8]. With their work they could establish that there is an anti-correlation between radio link quality and weather parameters like wind, humidity and temperature, with humidity being the strongest influencer. Authors in [11] established the relationship between specific path attenuation and the rainfall rate in different frequencies of operation like 900 MHz (2G), 1800 MHz (4G) and other 5G. With extensive measurements and evaluation, they infer that the relationship between path attenuation and rainfall rate is linear. The impact of various weather parameters in industrial wireless sensor network setup in the ISM (industrial, scientific and medical) band i.e., 2.4GHz was studied in [12]. With the experimental setup, Received Signal Strength Indicator (RSSI), Link Quality Indicator (LQI) and noise floor readings were measured for each received packet along with environmental information such as temperature, humidity, fog and rainfall. The study concluded that temperature has a major impact on communications, whereas the effect of fog and rain was less severe unless the rainfall would cross 2-3 mm/hour. Signal attenuation in GHz frequency of operation can be dominated by extreme rainfall. Study of the effect of rain attenuation in mm-wave communication is one of the hot topics on which research is focused as we are heading towards 5G and 6G communication technology [13]. An exponential model which would be helpful in modeling and predicting rainfall was proposed in [14] for k-region, which would be helpful in designing communication satellite systems.

Researchers have adopted a proactive approach in predicting the role of weather conditions in the radio environment. Machine learning/artificial intelligence-based solutions are hence being proposed in this direction. In [15], link failure in LTE and 5G networks due to failure in handover is predicted using Recurrent Neural Network (RNN) by continuously monitoring the changes in the Reference Signal Received Power/ Reference Signal Received Quality (RSRP/RSRQ). Their trained model could predict RLF due to handover within a time lapse of a hundred milliseconds. A combination of Long Short Term Memory (LSTM) and Support Vector Machine (SVM) is proposed in [2] to establish a correlation between RLF and various parameters like RSRP, RSRQ, channel quality indicator and power headroom. The authors claimed a validation accuracy of 98% in predicting radio link failure. C. Luo et. al. [16] presented an online scheme called OCEAN for prediction of channel state information of a channel which is affected by various features like frequency band, location, time, temperature and humidity. Another study [17] estimates the radio signal attenuation, based on ensembles of forecast rainfall fields from the latest radar rainfall fields observed, which is nowcasted for 5G networks. The forecast attenuation data obtained from the proposed short-term ensemble prediction system was within the 90% confidence region.

From the above literature survey, we understand that more investigations are required to establish a generalized relation between weather parameters and radio signal strength. Although proactive solutions have been proposed in certain radio environments, there is scope for more research considering different operating conditions. In view of this, it is of interest to carry out studies to predict RLF considering both radio environment and weather conditions over an extended period of time.

3. DATASET DESCRIPTION AND ANALYSIS

3.1 Dataset description

The dataset for our study consists of extensive measurements of both weather conditions and RL KPIs. An illustration of the scenario for the data capture is shown in Fig. 1. With the backhaul links considered, measurements from the weather stations and the radio receiver sites form the key parameters in developing an RLF prediction model. The dataset was a compilation of region-wise data corresponding to several KPIs and corresponding historical weather features along with weather forecasts recorded at the meteorological stations. The distance matrix was used to map weather features recorded at weather stations to approximate weather conditions at radio stations.

For the given use case, we used the dataset having information about the radio link characteristics and weather parameters. The information gathered from meteorological stations consists of station clutter class type and antenna height above ground level. There are 20 unique weather stations and eight clutter class categories. The different clutter classes considered are dense-tree, low-medium urban, airport, open-in-urban, low-sparse-urban, sea, sparse-tree and open land with variable counts in each class. Most weather stations belong to dense-tree clutter class and other classes are in minority. Further, the dataset consists of different clutter classes of radio station sites belonging to the same categories as discussed. There are around 1500 unique radio stations where radio link status has been recorded. Radio station sites mostly belong to the urban clutter class, inland water and greenhouse clutter class type.

The RL dataset consists of around 1,900,000 unique samples. The radio stations considered are of the cellular networks operating in the UHF band. The Key Performance Indicators (KPIs) recorded for radio links consist of information on modulation techniques employed i.e., n-QAM, five operating frequencies, link traffic, additive_bit_error with definite timestamp, maximum_received_signal_ strength. The dataset also contains radio link failure TRUE/FALSE labels. The measurements were recorded for the radio link failures over a period of two years. The features recorded by historical weather measurements at meteorological stations consist of temperature, wind direction, wind speed, humidity, precipitation, precipitation_coefficient and pressure. The measurements were documented for every hour of the day.

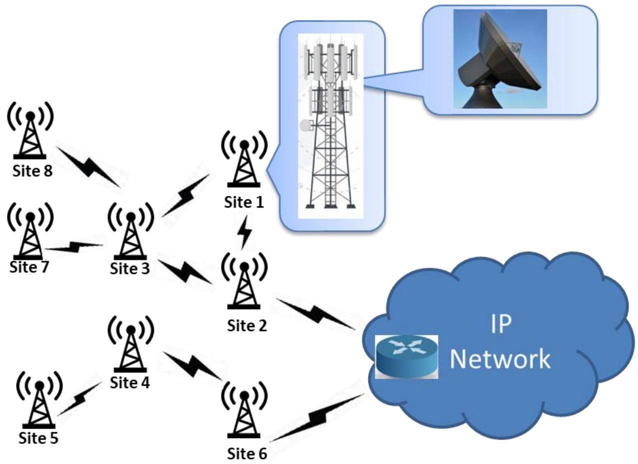


Fig. 1 - Illustration of the operating scenario

3.2 Feature distribution and importance

Radio link samples are highly disproportionate in the dataset and many of the features were visualized as not distributed properly. True radio links are a minority class as compared to false samples. True samples are less than 1% in the available dataset which was addressed by up-sampling the minority class. Fig. 2 shows the feature distribution of some of the important KPIs affecting radio link failure. From the distribution, it is seen that the repeated error count has a very narrow distribution. In case of link unavailable time, the variation in the distribution can be observed.

The joint distribution plot of different KPIs is shown in Fig. 3 and the corresponding correlation is visualized with the heat map in Fig. 4. It can be observed from Fig. 4 that there is moderate correlation between the KPIs considered and the interdependency is less. Machine learning models are built to identify the important KPIs which affect the radio link, keeping RLF as target. Logistic regression, CART decision tree and random-forest classifiers were used iteratively. The findings with the higher coefficient values are the important features. The identified features are repeated_error_count, link_unavailabe_time, link_available_time, error_count, additive_bit_error and maximum_received_signal_strength.

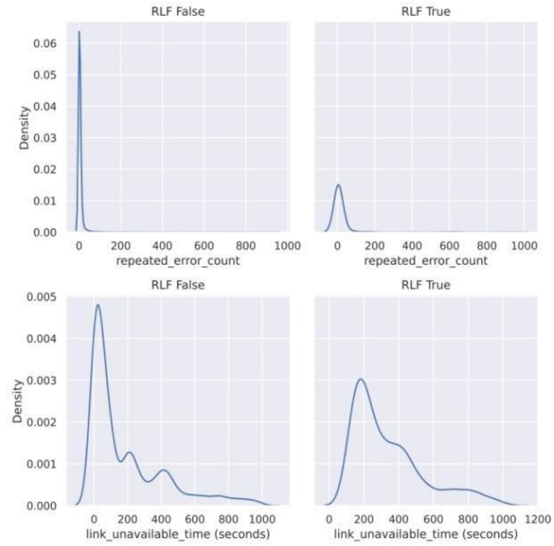


Fig. 2 - Feature distribution of repeated_error_count and link_unavailabe_time

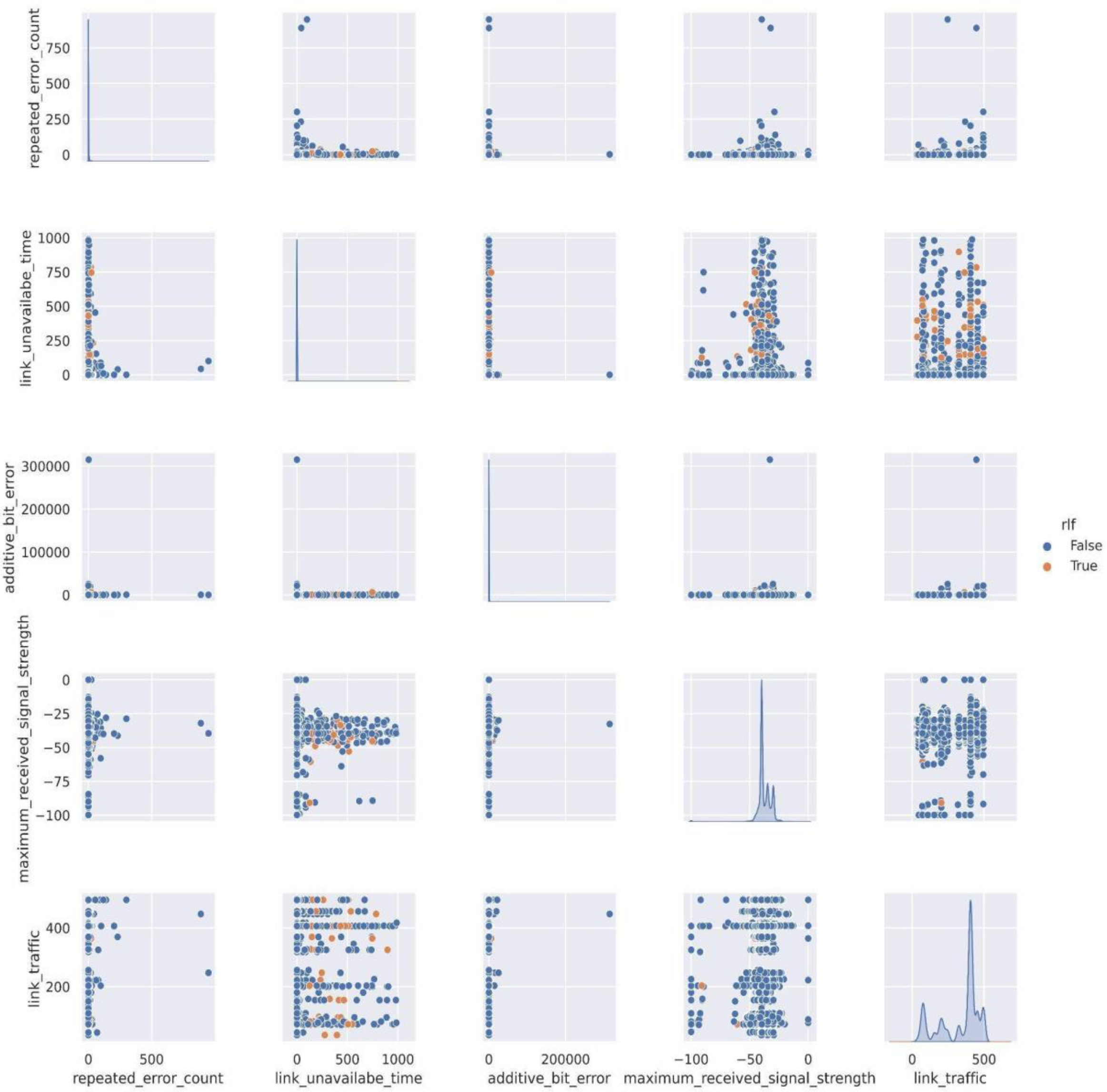


Fig. 3 - Joint distribution plot of KPIs (Color-coded with RLF target)

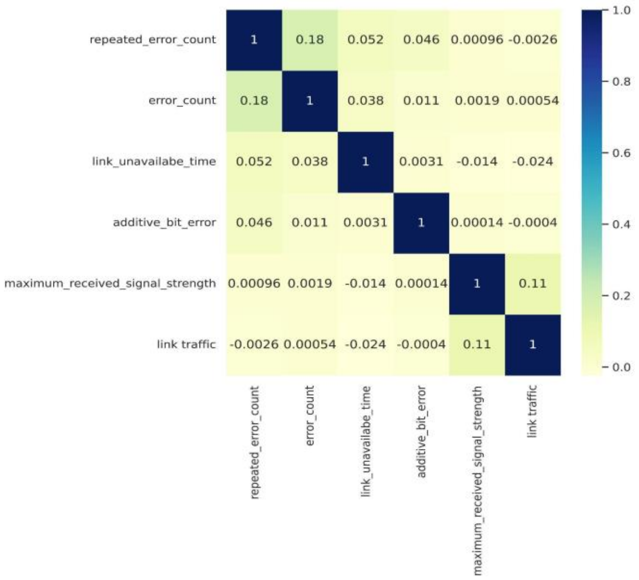


Fig. 4 - Correlation heatmap of important KPIs

3.3 Dataset challenges

Several challenges were encountered with the dataset used and they are listed below.

(i) Spatio-temporal correlation: The location of radio station sites and weather stations is not the same. Weather conditions at radio station sites were required to be approximated by the weather condition recorded at meteorological stations around each radio link site.

(ii) High feature space: RLF depends not only on the weather features but on a combination of multiple other factors like weather conditions (both historical data and forecasts), link performance indicators – operating frequencies, link traffic, received signal strength, bit error rate, modulation scheme, link_unavailable_time, etc. and topological features – clutter class type, radio station ground height, meteorological stations etc.

(iii) Highly imbalanced dataset: Only 0.0612% of the dataset were TRUE radio link failures samples.

4. DATA PREPARATION

In this section, we have discussed the aspects of data preparation and various preprocessing techniques employed.

4.1 Mapping weather station and radio station

The mapping scheme between weather station and radio station is dependent on various factors such as spatial positioning of weather stations and radio station sites, wind direction, terrain conditions, etc. apart from the physical distance. We used the Euclidean distance metric to measure the least distance between the weather station and radio station site. The graph in Fig. 5 shows the distance distribution of the nearest weather station of the available radio stations. This shows that there are quite a good number of weather stations closely located to radio stations. Hence both the sites are mapped and the dataset is prepared accordingly.

4.2 Handling high feature space and categorical features

The dataset contains a large number of both categorical and numerical features. One-hot encoding on categorical features results in a curse of dimensionality. Various feature representation techniques were employed for different types of categorical features such as binary decomposition on the clutter class, level-encoding for weather_dayX in weather station forecast and one-hot encoding for RL KPIs. Clutter class features in radio stations and weather stations and weather_dayX feature in weather forecast were decomposed into binary vectors based on the effect the binary feature would have on the target. The clutter class was decomposed into height, density and other, with binary values representing each clutter class type. Level encoding was used for Weather_DayX features – moisture, cloudy, windy, snow, thunderstorm in weather forecast data. Categorical features with lesser entries are encoded using a one-hot encoding scheme. The parameters 'link-separation', 'equipment_vendor', 'adaptive_modulation', 'operating_frequency_band', 'modulation' were represented using one-hot representation. The dimensionality of input feature space was further reduced by ranking features based on their importance. Iteratively least important features were removed based on the threshold set on the F1 score.

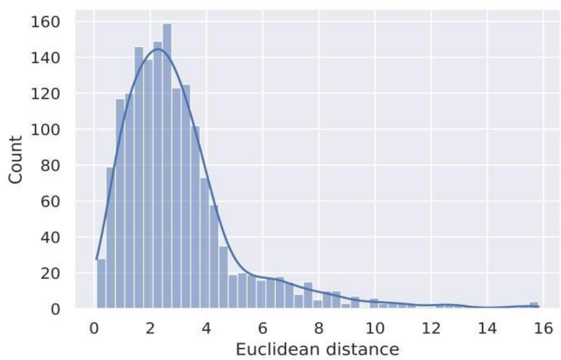


Fig. 5 – Euclidean distance distribution of nearest weather station of radio stations

4.3 Data rebalancing

Due to an unbalanced dataset, the minority class of the RL dataset was up-sampled to improve the ratio using the Synthetic Minority Over-Sampling Technique (SMOTE). SMOTE is a common technique used to up-sample minority classes of the unbalanced datasets. Instead of duplicating observations, it creates new observations along the lines of a randomly chosen point and its nearest neighbors. The original unbalanced dataset was down-sampled by random selection of false labels to obtain the ratio of 1:4 of TRUE v/s FALSE class. This down-sampled dataset was fed into SMOTE to obtain a balanced 1:1 class representation for further model processing. For the day 1 model, around 14636 new samples (12247 TRUE class and 2389 FALSE class) were created by SMOTE.

4.4 Dataset integration

Hourly data samples were aggregated to represent weather conditions on each day at each meteorological station. Weather features were mapped using the mapping scheme across each radio station. Target labels were created based on failure on the next day and also for the next 5th day. The training dataset sample format is shown in Fig. 6.

5. ML MODEL AND INFERENCES

To address two different targets, we have built the models separately for 'day-1-predict' and 'day-5-predict'. The irregularities such as -nan-, -inf- and null values were treated rather than dropping, to retain the less number of TRUE samples. Certain irrelevant features were discarded through the process of feature selection. The dataset was cleaned and structured relevant to the context before passing on to the model. The training dataset was split as 75% train and 25% test dataset. In our approach, ensembling and boosting techniques for model building have been adopted. The first base model was logistic regression and its performance on the dataset was satisfactory. The other ensemble models which were trained and tested include random forest, light BGM, XGBoost and gradient boosting classifiers. The models were trained and an optimized set of parameters were obtained by hyper-paramter tuning. RandomizedSearchCV was used to find the optimized set of model hyper-parameters. Further K-fold cross validation is used, which splits the data into 'n' subsets (n=10), computes the performance of the model and returns an array of all the accuracies. The optimized hyper-parameters and performance metrics for each individual model are tabulated in Table 1 and Table 2 Among the models considered, the gradient boosting classifier performed the best for both the predictions.

Identifiers [Device_ID, Date&time etc.]	RL KPIs	Historical weather features	Weather forecast	Categorical features [binary decomposed vectors, one-hot vectors]	Radio station and weather station info [height]	Target [day-1-predict, day-5-predict]

Fig. 6 - Training dataset sample features

Table 1 - Tuned hyperparameters and performance metrics of different ML models, for day-1-predict

ML Model	Hyper-parameters	Precision	Recall	F1 Score
Logistic regression	C= 0.1, penalty= 'l2',solver='liblinear'	0.89	0.83	0.85
Gradient boosting classifier	{'n_estimators': 250, 'max_depth': 9, 'learning_rate': 1}	0.96	0.93	0.95
XGBoost	{'subsample': 1, 'n_estimators': 800, 'max_depth': 10, 'learning_rate': 0.03, 'colsample_bytree': 1}	0.95	0.94	0.94
LGBM classifier	{'subsample': 1.0, 'num_leaves': 24, 'min_sum_hessian_in_leaf': 0, 'min_data_in_leaf': 20, 'max_depth': 30, 'max_bin': 90, 'learning_rate': 1.0, 'feature_fraction': 0.9, 'bagging_fraction': 1}	0.95	0.94	0.95
Random forest	{'n_estimators': 600, 'min_samples_split': 2, 'min_samples_leaf': 1, 'max_features': 'auto', 'max_depth': 15, 'bootstrap': False}	0.94	0.94	0.94

Table 2 - Tuned hyper-parameters and performance metrics of different ML models, for day-5-predict

ML Model	Hyper-parameters	Precision	Recall	F1 Score
Logistic regression	C= 0.1, penalty= 'l2',solver='liblinear'	0.82	0.85	0.83
Gradient boosting classifier	{'n_estimators': 250, 'max_depth': 7, 'learning_rate': 1}	0.95	0.95	0.95
XGBoost	{'subsample': 1, 'n_estimators': 800, 'max_depth': 10, 'learning_rate': 0.03, 'colsample_bytree': 1}	0.96	0.94	0.95
LGBM classifier	{'subsample': 0.01, 'num_leaves': 80, 'min_sum_hessian_in_leaf': 0, 'min_data_in_leaf': 20, 'max_depth': 30, 'max_bin': 20, 'learning_rate': 1.0, 'feature_fraction': 0.1, 'bagging_fraction': 0.8}	0.97	0.94	0.95
Random forest	{'n_estimators': 300, 'min_samples_split': 10, 'min_samples_leaf': 1, 'max_features': 'sqrt', 'max_depth': 15, 'bootstrap': False}	0.96	0.93	0.94

6. RESULTS AND DISCUSSION

This section deals with a complete description of the results and relative analysis. The dataset we have used with preprocessing for both train and test is tabulated with the corresponding shape in Table 3. Among all the boosting models, the gradient boosting classifier provided the best result and the corresponding confusion matrices are shown in Fig. 7. It can be seen that the model classifies TRUE failure and FALSE failure with scores greater than 90% in both cases.

The feature importance graph shown in Fig. 8, for day-1-predict and day-5-predict respectively, are derived from the Shapley Additive explanations (SHAP) library. It can be observed that there are highly correlated variables that contribute to the TRUE class prediction. The effect of up-sampling on model performance is shown in Table 4. With up-sampling, the gradient boosting classifier exhibits an increase in F1 score by 0.07, with the same set of hyper-parameters.

Validation performance was observed on the best model for day 1 and day 5 predictions with the corresponding confusion matrices shown in Fig. 9. A set of unseen data (about 5% of the original dataset) was set aside for validation performance. From Table 5, it can be observed that both the models have high F1 scores on an unseen validation dataset. This ensures that the model is not overfitting on the training dataset.

Table 3 – Shape of the dataset used for class prediction

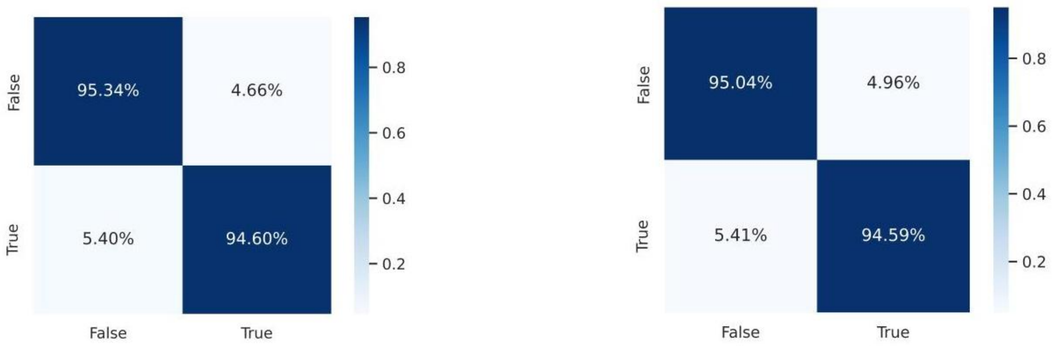
Sample train shape (x,y)	Day-1-predict	(4113, 63)
	Day-5-predict	(4107, 107)
Sample test shape (x,y)	Day-1-predict	(1371, 63)
	Day-5-predict	(1369, 107)

Table 4 – Comparison of effect due to up-sampling on model performance

	F1 Score without up-sampling	F1 Score with up-sampling
Day-1-predict	0.88	0.95
Day-5-predict	0.88	0.95

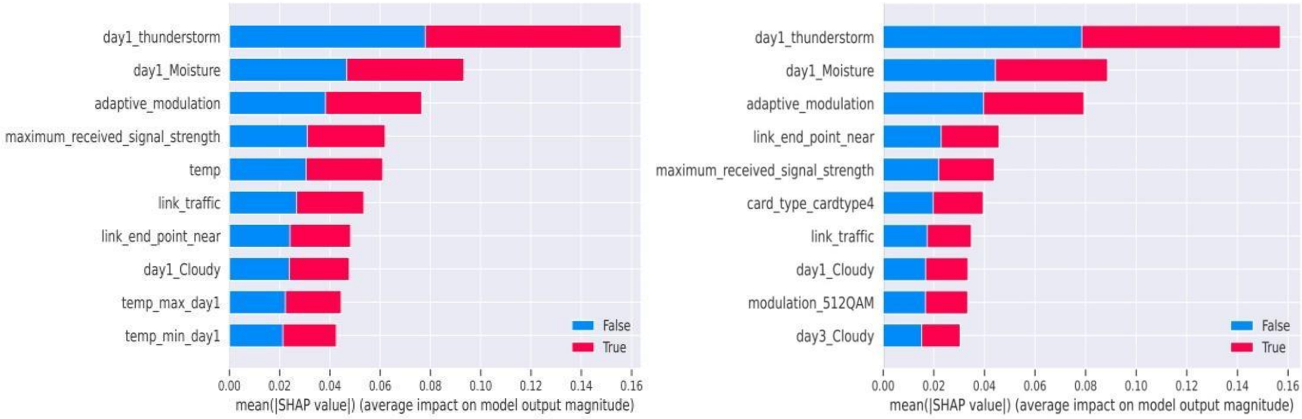
Table 5 - Validation performance of the model

Validation Performance	F1 Score
Day 1 Predict	0.96
Day 5 Predict	0.97



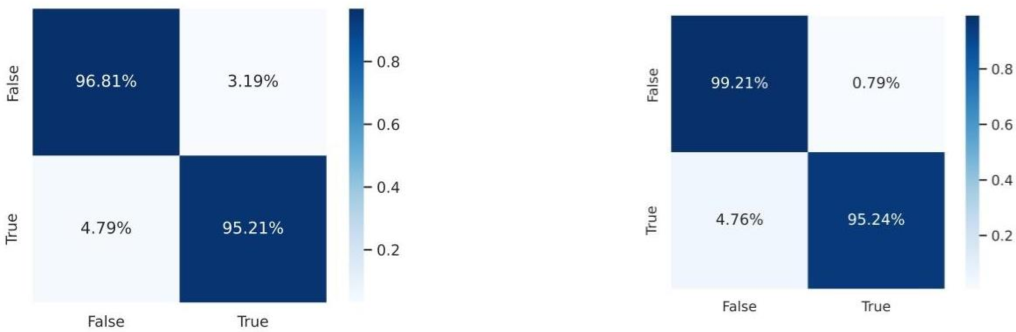
(a) (b)

Fig. 7 - Confusion matrix for best model for (a) day-1-predict (b) day-5-predict



(a) (b)

Fig. 8 - Feature importance of (a) day-1-predict (b) day-5-predict



(a) (b)

Fig. 9 - Confusion matrix of validation performance for (a) day-1-predict (b) day-5-predict

7. CONCLUSION

Radio link failure depends on various factors which include weather factors such as temperature, humidity and radio link KPIs, etc. In this work, a machine-learning-based solution was proposed to predict the radio link failure when a generic regional weather forecast data, radio link KPIs and spatial nature of the data (regions of weather station and radio station) are available. Though the dataset had a good number of samples, narrow distribution for many features was observed through visualization, which indeed was a challenge for the work. Hence the data was processed rigorously and subsequently ensembling models were trained to predict the RLF for two cases i.e., day-1-predict and day-5-predict. We also presented how the gradient boosting classifier rendered the best performance. The presence of thunderstorm and moisture in day-1 forecasts have a major impact on predicting radio link failures.

The inferences drawn using the prediction model would help the engineers to understand major causes of failure and would try to work on action to reduce its effects. Accurate predictions can save man-hours as many RL changes require a field engineer in person. It provides a better understanding of the role and significance of different weather conditions and thereby helps in field deployment and planning in the future in the long term. Also, the predictions help in carrying analytics of cost factor due to RLF and devise techniques that could be used to reduce link failures. In future, we would like to extend our work implementing the complete pipeline for productionalization of the model using necessary industry frameworks.

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