Stand Alone and Clustered Base Stations Approaches for AI Based Congestion Prediction on ORAN RIC Layer

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***Abstract*—5G/6G will rely heavily on the architect concept of Open Radio Access Network (oRAN). In a such open environment, a near real time processing and decision-making capabilities are an essential requirement. Artificial Intelligent, more specifically, Machine learning is the selected technique to be used in performing the needed processes. In this paper, we are presenting the first look at the performance of selected ML techniques in order to practically test their performance using real Data set gathered in cooperation with the Data analytic Dept. at the Saudi Communications Company in Saudi Arabia. The Data set consist of an hourly measurement of certain network's parameters for the time span of on year and for different seven base stations all are located in Riyadh, Saudi Arabia. Two approaches were studied. in the first one a dataset from one BS only is used for training and testing for different techniques. While, in the second approach, all data from the seven base stations were used instead. Results show that: for a supervised classifier techniques, the Decision tree technique performs the best among the selected techniques with an accuracy of 0.96 and 0.91 for single and all base stations, respectively. For the supervised regression approach the accuracy level was found to be 0.98 and 0.97 for single and all base stations, respectively.**

I. INTRODUCTION

The sixth generation (6G) of wireless cellular systems must cater to radically new services, such as holographic teleportation, connected robotics and autonomous systems (CRAS), extended reality (XR), digital twins, and the metaverse. These bandwidth-intensive applications require the delivery of a 1000× capacity increase compared to current 5G cellular systems. These applications also require multi-purpose wireless functions that could encompass communications, sensing, localization, and control. These requirements can only be attained by boosting the existing wireless spectrum bands at sub-6 GHz and millimeter wave (mm Wave) with abundant bandwidth through the use of terahertz (THz) bands namely 0.1 - 10 THz. One important feature of B5G networks is what's so called Ultra Reliable Low Latency Communications (URLLC) The provision of URLLC is a novel service paradigm offered in 5G networks. Both the reliability aspect, with packet error rates $\leq$ 10-5, and end-to-end latencies 1ms aim at supporting new use cases such as factory automation, autonomous driving, e-health, building automation, and smart cities, to name a few (1). To enable these and other services, the 5G network infrastructure is based on the revolutionary novel concepts of Network Function Virtualization (NFV) and end-to-end Network Slicing (NS) (2). In the NFV approach to network design, many network services such as network address translation, domain name service, and caching are decoupled from propriety hardware and implemented in software that runs on off-the-shelf hardware. The NS concept allows multiple logical networks or slices to operate on a shared physical infrastructure. Each network slice has dedicated resources for computation and storage as well as data-traffic isolation from the other slices to create a true end-to-end virtual network. With NFV and NS, the physical network resources can be optimized to provide URLLC services for safety critical applications such as vehicular communications or remote-robotic-surgery. Another infrastructure evolution to support low latency communications is edge-computing architectures including Mobile Edge Computing (MEC). In the MEC paradigm, many of the data processing tasks are moved to the cellular BS or similar edge node, which also has the ability to cache content, thus minimizing the service time to its proximal network users (1). 5G/6G will relay on the concept of ORAN in order to widening the vendors spectrum and to elevate applications migration to the networks using AI/ML and API tools as depicted in figure 1 (9). Congestion prediction is an essential tool in all application layer of ORAN operations. A need for a near real time system for congestion prediction yields to the usages of AI/ML. In this paper we are aiming in developing an algorithm using classical supervised classifier and supervised regression techniques. for that cause. Preliminary results have been achieved utilizing practice dateset obtained from a local operator in Saudi Arabia. More of RIC functions will be based on this system, such as mobility management. These operations will be carried in the application layer of the ORAN 5G/6G architect as shown in figure 2 (9).

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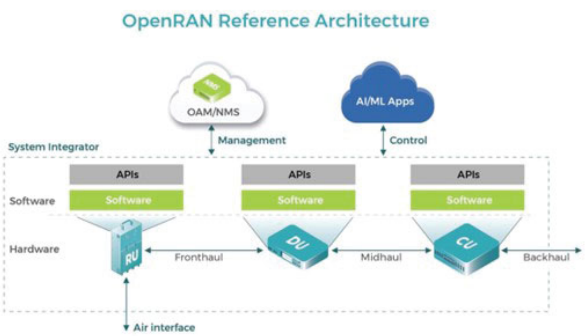


Fig. 1. Open RAN Reference Architecture

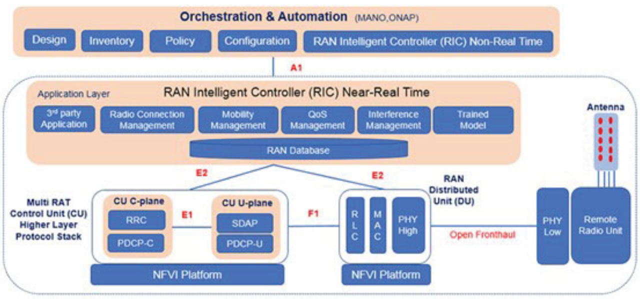


Fig. 2. 6G operational Structure

One of important processes is the QoS management. In order to maintain a certain QoS level, the RAN Intelligent Controller (RIC) has to perform the prediction of network congestion in Near-Real Time. This will be achieved using ML algorithms to predict congestion in any given base station without any control of the backbone network. Recently a practical experiment has been done in adapting machine learning techniques in congestion prediction with an appealing results (3) . In (4), a dataset driven by an emulator on the packet level , for the IoT 5G network have been used as a dataset for different machine learning algorithms. The best performance among the algorithms in predicting the optimum IoT node was the C4.5 Decision tree with an accuracy of 92%. Moreover, path loss prediction for a specific user carried on the cell itself as part of the RIC structure has been investigated in (7). The results revealed that all the adopted machine learning algorithms such as ANN, SVM, and BKNN performed better that the classical empirical models in forcasting the path loss. Finally, A comprehensive view and vision for 6G structure and open focus areas are presented in (8).

II. Dataset pre-processing

Table I defines the attributes of the dataset used in the research and that provided by a local mobile operator in Saudi Arabia.

A real dataset of 8544 records each has five features and one attentively pre- categorized cell. Pre processing was performed by which any non-normal data in any feature, and hence, the whole accompanying record has been removed. Moreover, the threshold level of congestion has been assigned as the mean of the utilization of the dataset.

III. Results and Discussions

In this section we will present the results obtained by performing operation over the dataset for a ,randomly selected one base station out of the seven available cells, using different machine learning algorithms. First, we set the threshold to be the mean of the utilization rate. Secondly, we have executed different algorithms and selected the best performance among them. Finally, the achieved results are presented.

A. Single base station

1) Regression: As seen from Table II, the r2 score which is a measure of the goodness of fit of a model is achieved to be 0.98 using Random Forest Regression technique. Other models performs well as they achieved 0.97 and 0.94 for Linear Regression and Decision Tree Regression, respectively.

TABLE II. Regressors for single base station

Regressor	R2 score	MAE	MSE
Linear Regression	0.97	0.016	0.0006
Random Forest Regression	0.98	0.014	0.0004
Decision Tree Regression	0.94	0.026	0.0012

2) Classification: Four supervised classifier have been selected and studied. The accuracy level was the criteria for selection. Accuracy was measured and presented. An accuracy of 0.9646 has been achieved in Linear Discriminant classifier. All result's are shown in Table III.

TABLE III. Classifiers for single base station

Classifier	Accuracy
Decision Tree	0.9596
G. Naive Bayes	0.9540
KNN	0.9359
Linear Discriminant	0.9646

B. Cluster of base stations

1) Regression: As seen from table IV, the r2 score is achieved to be 0.97 using Random Forest Regression technique. Other models performance is well below level of acceptance. Further research is on going to improve the performance.

2) Classification: Three supervised classifier have been selected and studied. The accuracy level was the criteria for selection. Accuracy was measured and presented. An accuracy of 0.915 has been achieved in Linear Discriminant classifier. All result's are shown in table V The performance here is worse than in using a dataset from single base station, further investigation is ongoing to declare clearly whats better practically: either to keep each cell managed internally by

TABLE I. DATASET ATTRIBUTES DEFINITION

Column	Description
eNodeB	Access site name abbreviated
Hour	Timestamp of when the data is collected
4G_H_DL Latency Huawei (ms)	Average latency aggregated across all users connected to the site in one day
4G_H_DL User Avg throughput Mbps eRAN7	Average downlink throughput aggregated across all users connected to the site in one day
4G_H_LTE Avg RRC Connected Users	Average connected users to the site
4G_H_DL-PRB-Utilization %	Utilization of the site bandwidth
4G_H_Total Traffic Volume MB	Total volume of traffic

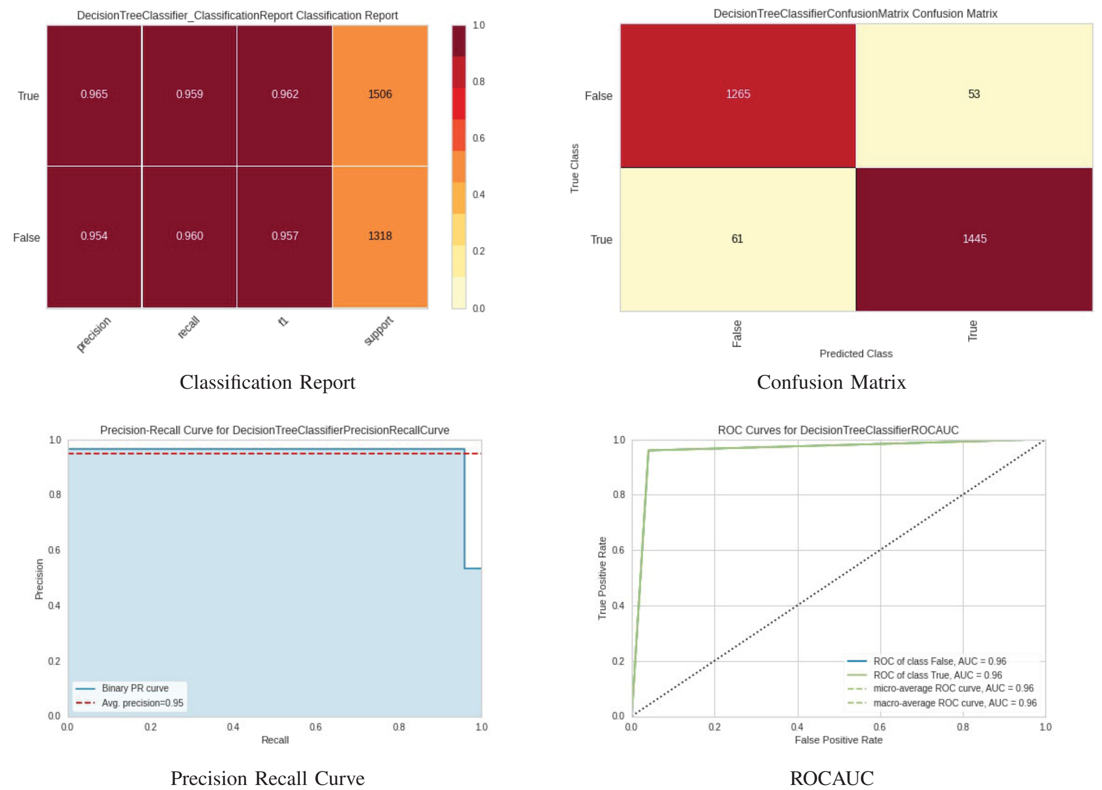


Fig. 3. Decision Tree Classifier for single Base station

its own RIC and its own collected data or to share the environment between cells.

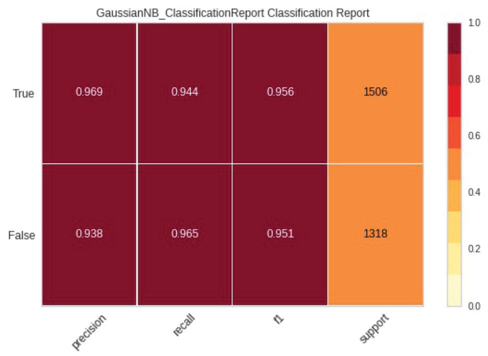
IV. FUTURE WORK

There will be four main areas of extended research, they are:

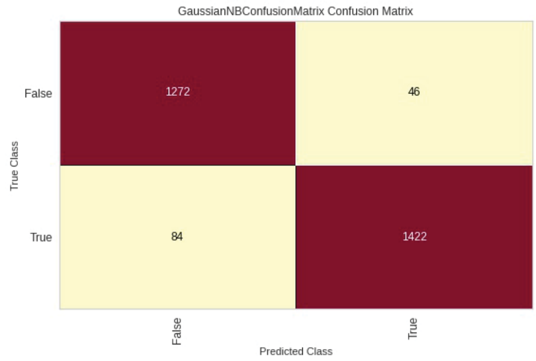
- More advanced machine learning techniques, Deep learning, in particular Deep Reinforcement Learning DRL are to be used in order to enhance accuracy (5), and processing speed.
- The training and verification processes will be executed in phase two of research using Super computing capabilities at KACST since the current data could not be executed in full using classical computers.
- Extra data will be asked to be provided from the local operator in order to represent the network accurately. Data from 5g base stations are preferable if existed.
- Different protocols of the Intelligent controller should be investigated given a real dataset of local environment.
- For various learning tasks, Quantum ML algorithms can provide exponential speed-ups over classical ML algorithms (6), and hence QML will be studied in details using the available data.

TABLE IV: REGRESSORS FOR CLUSTER OF BASE STATIONS

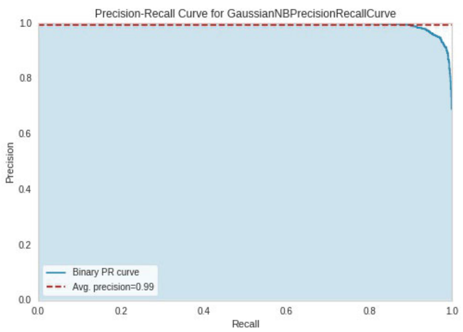
Regressor	R2 score	MAE	MSE
Linear Regression	0.86	0.075	0.0074
Random Forest Regression	0.97	0.024	0.0016
Decision Tree Regression	0.92	0.046	0.0041



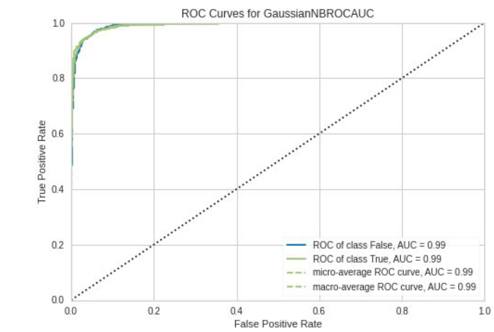
Classification Report



Confusion Matrix

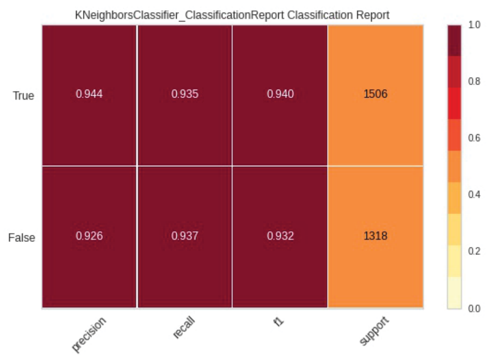


Precision Recall Curve

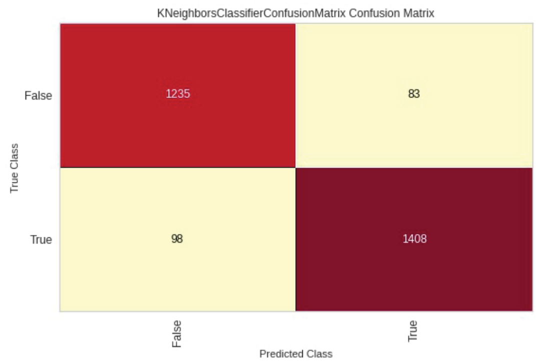


ROCAUC

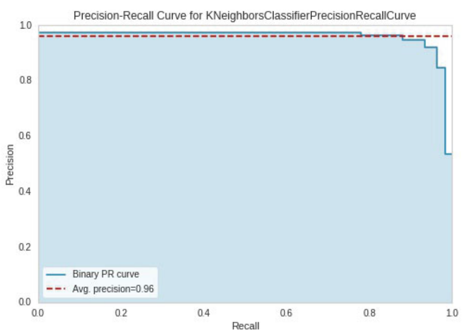
Fig. 4. Gaussian Naive Bayes for single Base station



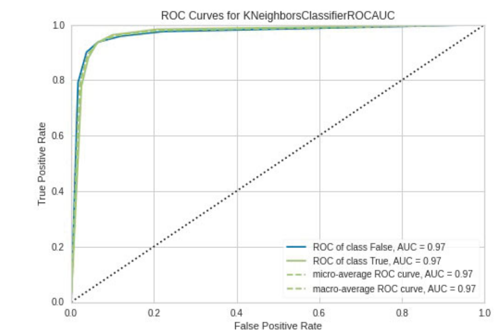
Classification Report



Confusion Matrix

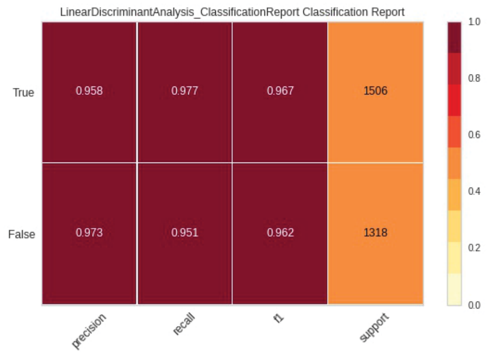


Precision Recall Curve

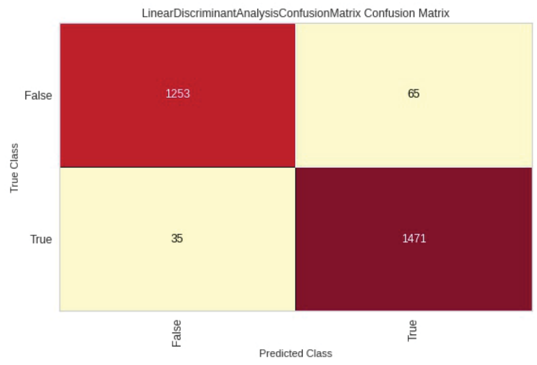


ROCAUC

Fig. 5. K Nearest Neighbor Classifier for single Base station



Classification Report



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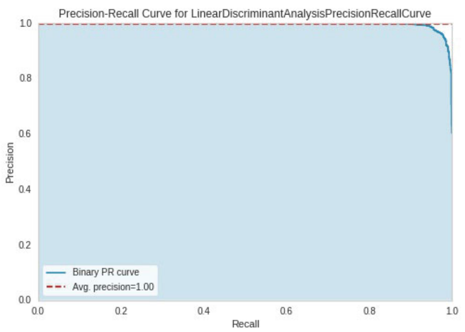
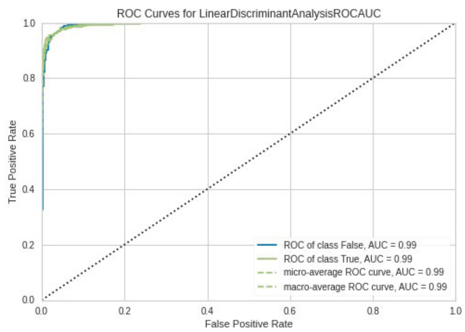
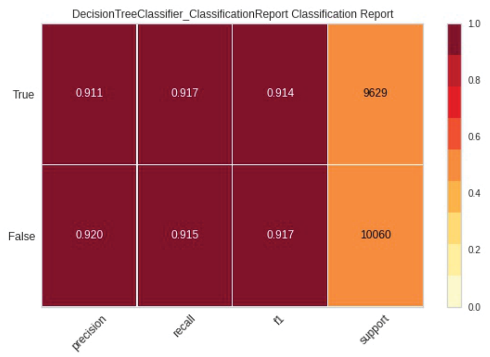


Precision Recall Curve



ROCAUC

Fig. 6. Linear discriminant analysis for single Base station



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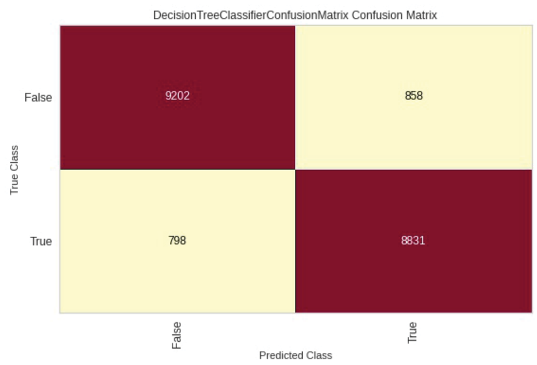

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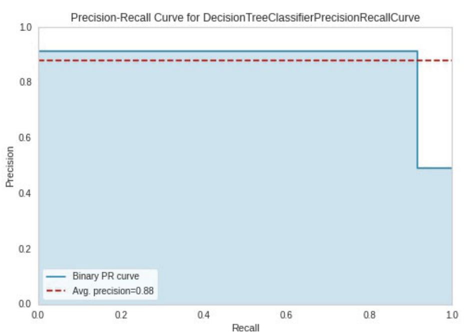
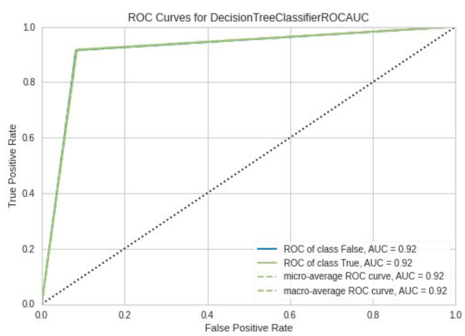
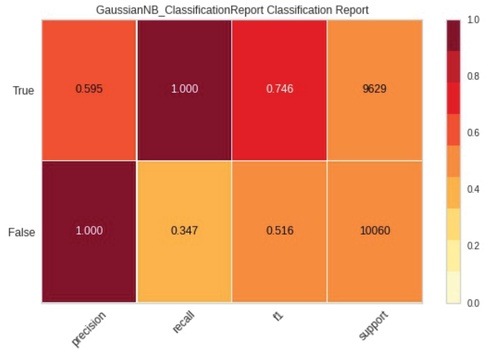


Precision Recall Curve

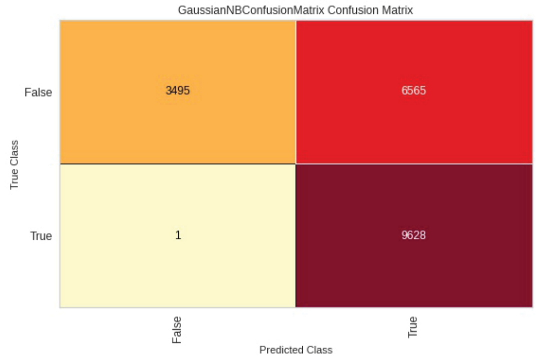


ROCAUC

Fig. 7. Decision Tree Classifier for cluster of base stations



Classification Report



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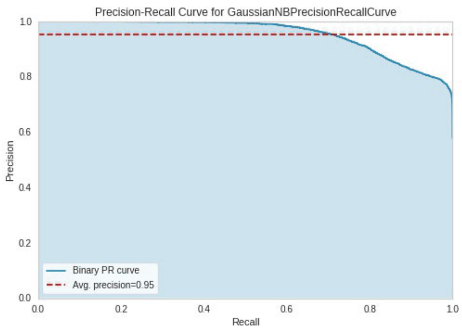
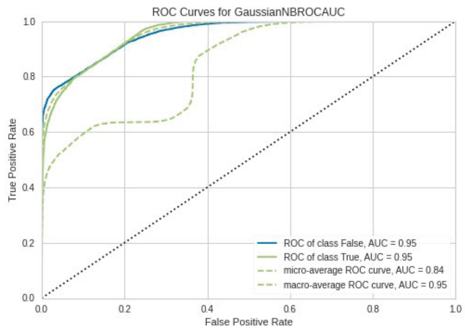
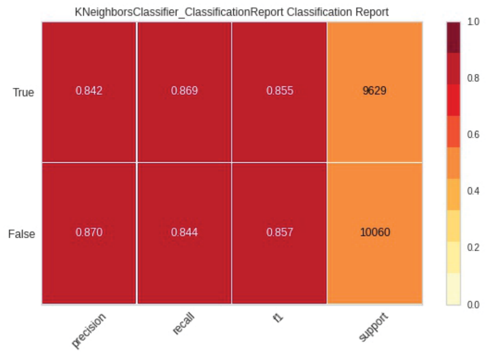


Precision Recall Curve

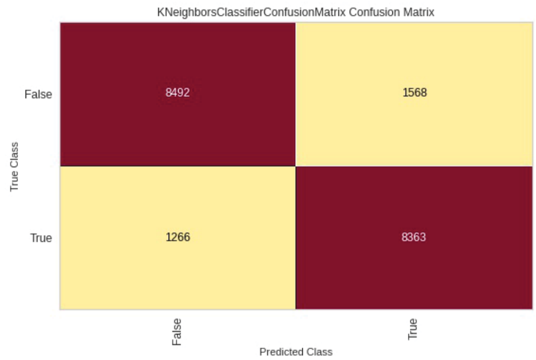


ROCAUC

Fig. 8. Gaussian Naive Bayes for cluster of base stations



Classification Report



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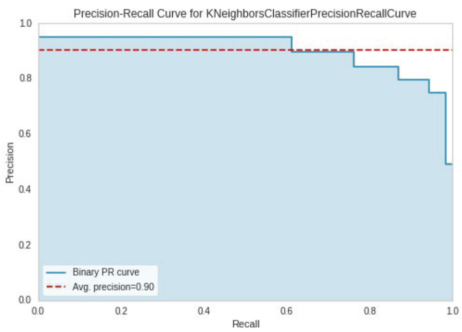
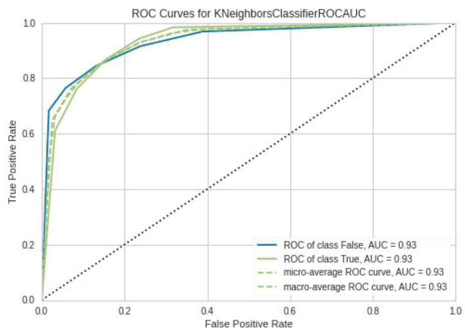
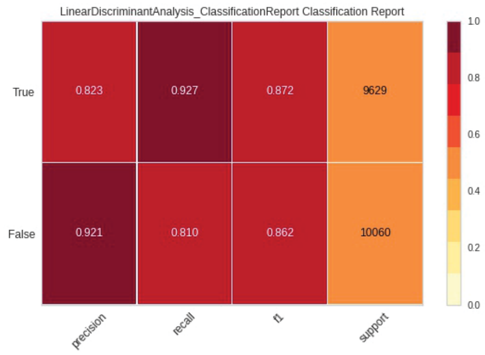


Precision Recall Curve

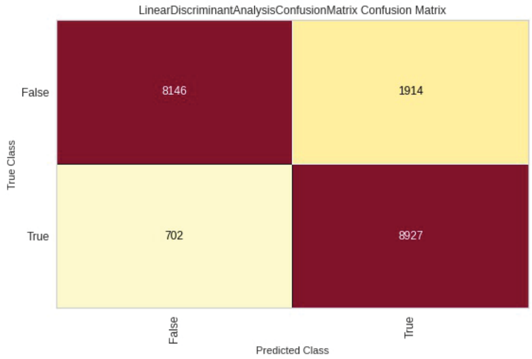


ROCAUC

Fig. 9. K Nearest Neighbor Classifier for cluster of base stations



Classification Report



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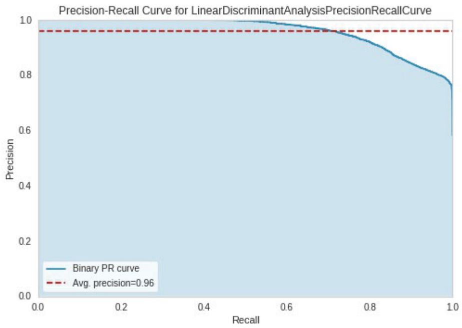
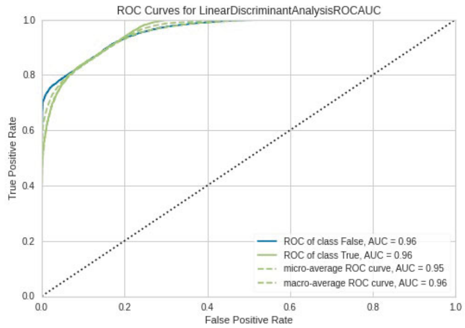


Precision Recall Curve



ROCAUC

Fig. 10. Linear discriminant analysis for cluster of base stations

TABLE V. CLASSIFIERS FOR ALL BASE STATIONS

Classifier	Accuracy
Decision Tree	0.915
G. Naive Bayes	0.669
KNN	0.854
Linear Discriminant	0.867

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