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Drone Detection and Classification Using Cellular Network: A Machine Learning Approach

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***Abstract*—The main target of this paper is to propose a preferred set of features from a cellular network for using as predictors to do the classification between the flying drone User Equipments (UEs) and regular UEs for different Machine Learning (ML) models. Furthermore, the target is to study four different machine learning models i.e. Decision Tree (DT), Logistic Regression (LR). Discriminant Analysis (DA) and K-Nearest Neighbour (KNN) in this paper, and evaluate/compare their performance in terms of identifying the flying drone UE using three performance metrics i.e. True Positive Rate (TPR), False Positive Rate (FPR) and area under Receiver Operating Characteristic (ROC) curve. The simulations are performed using an agreed 3GPP scenario, and a MATLAB machine learning tool box. All considered ML models provide high drone detection probability for drones flying at 60 m and above height. However, the true drone detection probability degrades for drones at lower altitude. Whereas, the fine DT method and the coarse KNN model performs relatively better compared with LR and DA at low altitude, and therefore can be considered as a preferable choice for a drone classification problem.**

***Index Terms*—UAV; Drone; Machine learning; 5G; Cellular networks.**

I. INTRODUCTION

Unmanned aerial vehicle (UAV), known as drones are widely used for military applications, border surveillance, foresting and agriculture, monitoring, for search and rescue in emergency operations, and for a personal hobby [1]. The use of drone can potentially and dramatically improve the rescue operation and hence can reduce the number of human casualties. In case of personal drone usage, most of the drone applications are short range and are only suitable in a visual line of sight with the drone. In order to extend the operational range of the drone, recently the manufactures are providing the support of Long Term Evolution (LTE) connectivity for controlling the drone and for sending and receiving the data. Drones equipped with high-definition cameras and LTE connectivity are able to transmit live video streams [2], [3].

Cellular-connected drones provide large operational coverage, high speed for data transfer, robust security, and real time communications. However, it should be noted that the current cellular network was designed to provide services for users located at the ground, and the current cellular networks have not been designed to serve aerial users. The ground-to-drone communication is significantly different from traditional ground-to-ground links. Indeed, there is a strong relationship between the channel characteristics and the flying altitude [4]. As the height above ground increases, the radio propagation becomes closer to Line of Sight (LOS) free-space propagation. Thus, the drone experiences more favorable propagation conditions. On the other hand, the favorable propagation conditions that drones enjoy at high altitude also becomes their limiting factor due interference issue. High flying drone is visible to more number of Base Stations (BS) and hence causes strong interference in uplink direction, and a UE receives strong interference from the interfering BSs. Therefore, the interfering signals can be strong if they are not controlled satisfactorily. This kind of problem is faced in real mobile networks, and therefore requires a measure to limit the use of cellular services by flying drones. A wide-scale deployment of drones can be realized if interference management challenges are addressed properly [3], [5].

In order to provide good QoS for regular UEs and for drone UEs, the mobile operator needs to identify/classify them correctly. Classification based on Machine Learning (ML) is a two-step process, first is the learning step and second is the prediction step. In the learning step, the model is developed/trained based on the given training data. In the prediction step, the trained model is used to predict the response for the given data [6]–[8]. The main target of this paper is to extend the work done in [9], and the main contribution of this paper is to propose a set of features which is to be used by ML approaches to identify the flying drones in the mobile networks. The selected set of features is based on the radio measurement reports transmitted by the drones. The second target of this paper is to compare the performance of four machine learning schemes namely Decision Tree (DT), Logistic Regression (LR), Discriminant Analysis, and K-nearest neighbours (KNN) in terms of classifying between the drone UE and regular UE.

The remainder of this paper is as follows. In Section II, we describe the proposed methods and the evaluation methodology. In Section III, we present the simulation environment and evaluation results for the proposed machine learning solutions followed by the conclusion in Section IV.

II. MACHINE LEARNING APPROACHES

In this section, we briefly explain different machine learning approaches those are considered in this paper for analysis.

A. Decision Tree (DT)

A Decision tree (DT) is a supervised learning method that can be applied to both classification and regression problems. The Decision tree algorithm is easy to interpret and has a fast prediction speed and requires small memory usage. A DT is a flow chart like tree structure composed of the root node, internal node, branch and the leaf node [6], [7]. The topmost node in a decision tree is known as the root node, and the leaf node represents the class/label or the final outcome of the decision tree. The root node has no incoming edges and the leaf node has no outgoing edges. The internal node represents the test conditions or the decision rule on an attribute, and the branch represents the outcome of that test. The machine learns to partition the data on the basis of the feature/attributes. The best feature is selected using the Feature Selection Measures (FSM) in order to split the data sets. The feature selection measure is a heuristic way of selecting the splitting metric that the data is partitioned in the best possible manner. The FSM provides a rank for each feature, and the feature with the best score is selected as a splitting feature [6], [7]. In this paper, we have evaluated three variants of decision tree (DT) algorithm named as Fine, Medium and Coarse decision tree algorithm. This classification of DT algorithm depends upon the number of leaves used to make distinction between the classes. In coarse DT approach the maximum number of split is 4, whereas in medium and fine DT algorithm the maximum number of split is increased to 20 and 100, respectively [10].

B. Logistic Regression (LR)

The logistic regression (LR) is a method for classifying a given input vector $x = (x_1, x_2, ..., x_n)$ into one of two classes. Logistic regression is applicable to only dichotomous nature of the classification problems. It is based on a model that the logarithm of the odds of belonging to one class is a linear function of the feature vector used for classification shown as follows [11].

$$\ln(\frac{p}{1-p}) = \alpha + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n. \quad (1)$$

As the LR is applicable to only dichotomous problems therefore in Eq. 1 the p is the probability of belonging to one (odd) class and $p-1$ is the probability of belonging to another (even) class, and the fraction $\frac{p}{1-p}$ is defined as the odds ratio. In Eq. 1 the α and $\beta_1, \beta_2, ..., \beta_n$ are regression coefficients/weights and those are estimated based on the input feature data. The most widely used method to estimate these coefficients is the maximum likelihood. Hence, the LR predicts the probability of an outcome which can have only two values, and its probability is limited to values between 0 and 1.

C. Discriminant Analysis (DA)

Unlike the LR method, whose application is limited to classification problems with only two-classes, the Discriminant Analysis (DA) approach can be applied for problems with more than or equal to two classes. There are two types of discriminant analysis considered in this paper and those are named as Linear DA and Quadratic DA. In case of linear DA there are linear boundaries between the classes, whereas there are non-linear boundaries of an ellipse, parabola or hyperbola shape between the classes in quadratic DA [10], [12]. The DA is based on the statistical properties of the data for each class and is based on simplified assumptions. The LDA assumes that the data within each class has a Gaussian distribution and each feature has the same variance. Quadratic discriminant analysis (QDA) provides an alternative approach. Like LDA, the QDA classifier also assumes that the data from each class has Gaussian distribution. However, unlike LDA the QDA assumes that each class has its own variance matrix.

D. K-Nearest Neighbours (KNN)

K-nearest neighbour (KNN) is a classification and supervised learning algorithm. The nearest neighbor classification approach has good predictive accuracy, however it takes comparatively longer time to get trained in comparison with earlier mentioned ML algorithms. In this method, the prediction for a new input x is made through searching the entire training set for the K most similar neighbors [8], [10]. The distance metric is utilized to determine which of the K instances in the training dataset are most similar to a new input. The most popular distance metric is Euclidean distance. The value for K is determined through algorithm tuning. Again, three variants of KNN are considered in this paper named as fine, medium and coarse KNN approaches. This sub-classification of KNN algorithm depends upon the number of neighbors used to make distinction between the classes. In coarse KNN method the number of neighbor is set to 100, whereas in medium and fine KNN method the number of neighbors is set to 10 and 1, respectively. Increasing the number of neighbors increases the prediction accuracy, on the other hand it also increases the training time and reduces the prediction speed [10].

III. Simulation Methodology

A. Simulation Environment and Problem Definition

The target of this work is to detect the rogue drone utilizing cellular services by using an optimum feature set and ML algorithm. The MATLAB is used as a simulation tool, both for generating the data and for analyzing the performance of different ML approaches in achieving the target. For this research work, static simulations are performed with considerable amount of test points in an agreed 3GPP scenario. An urban environment with homogeneous macro cell deployment is considered. A cloverleaf tessellation with a regular hexagonal grid is used with nineteen macro sites having an intersite distance of 500 m. Where, each macro site has three sectors with fixed 120° angular separation in an azimuth plane as shown in Fig. 1. The base station antennas are mounted at the height of 25 m above the ground. The frequency of operation is 2 GHz utilizing 10 MHz system bandwidth. There are two main types of User Equipments (UEs) considered in this work i.e. drone UEs and regular UEs. The regular UEs are further sub-classified as outdoor ground UEs in Non-Line of Sight (NLOS) environment and

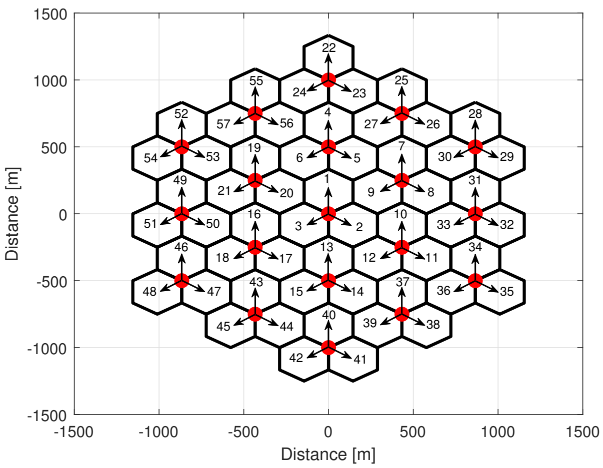


Fig. 1. Simulation scenario.

indoor UEs at different heights i.e. 1.5 m, 11.5 m, 21.5 m, and 31.5 m in NLOS with BS. Similarly, in each simulation scenario the drone UEs are set at the height of 15 m, 30 m, 60 m, 120 m, 200 m and 300 m. It is assumed that drone UEs are in NLOS with BS at 15 m and 30 m height, whereas they are in LOS with BS at 60m and above height. The detailed description about the pathloss and channel models used for drone and regular UEs can be found at [13] and [14]. The focus area for collecting the simulation data is the central site with cell number 1, 2 and 3. There are 27084 samples of each UE type, and those UEs are homogeneously distributed in a focus area. The classification learner app of MATLAB is used to test different machine learning algorithms. We have used the 75% of the total data to train the model and 25% of the data is used to test the trained model for classifying the user as drone UE or regular UE. The summary of the simulation parameters is provided in Table. I.

TABLE I
GENERAL SIMULATION PARAMETERS

Parameters	Unit	Value
Network layout		Cloverleaf
Number of sites	No.	19
Cells per site	No.	3
Intersite distance	m	500
Frequency	GHz	2
System bandwidth	MHz	10
Cell TX power	dBm	46
TX antenna height	m	25
UE type		Drone/Regular
Antenna model		3GPP extended model [15]

An extended 3GPP antenna model proposed in [15] is used to model the antenna radiation pattern in horizontal and vertical domain. The key parameters used in modelling the antenna pattern are Half Power Beamwidth (HPBW) in horizontal domain (θ_H), HPBW in vertical domain (θ_V), Front to Back ratio in horizontal domain (FBR_H), Side Lobe Level in vertical domain (SLL_V), and antenna maximum gain (A_M). The summary of antenna parameters used in this paper is given in Table. II. The main target of the cellular network is to serve the regular users. As the intersite distance is 500 m, therefore the antennas of all cells are downtilted by 6° to limit the coverage of the cell, and to avoid overshooting.

TABLE II
3GPP ANTENNA MODEL PARAMETERS

θ_H [°]	θ_V [°]	FBR_H $[dB]$	SLL_V $[dB]$	A_M $[dBi]$
65	7	30	-18	17.7

B. Features For Training the Model

It is of critical importance to select the correct set of features for training the machine learning algorithm. These features should be available at BS through measurement reports. In this paper, the following three features are considered:

1) Received Signal Strength Indicator (RSSI): It is defined as the sum of the power coming from the serving cell and from the interfering cells, plus the noise available over the system bandwidth.

2) Signal to Interference plus Noise Ratio (SINR): It is the ratio of the signal power coming from the serving cell to the sum of the power coming from the interfering cells plus noise.

3) Number of reported cells: It is defined as the number of cells for which the UE is making a measurement report. Normally, a UE reports Reference Signal Received Power (RSRP) of the serving cell and of the neighbouring cells with a given measurement threshold with respect to a serving cell. The selection of this feature is based on the fact that high flying drones are expected to be in LOS with numerous cells, and hence it is expected that drone UEs will have comparatively bad SINR compared with regular UEs. Similarly, in case of high flying drones it is expected to have more number of cells within the overlapping window of certain dBs of a threshold with respect to a received power from a serving cell. Therefore, the number of reported cells will be vital in classifying the type of UEs. The combination of these features is used to classify between the regular UE and drone UE.

The Fig. 2(a) shows the number of reported cells in the focus zone for outdoor NLOS regular ground UE, whereas Fig. 2(b-d) show the number of reported cells for the drone UE flying at different heights i.e. 30 m, 120 m, and 300 m, respectively. The color bar shows the number of reported cells. The number of reported cells varies over a wide range. However, the number of reported cells greater than or equal to four is treated as four in Fig. 2 for better visualization. It is interesting to compare Fig. 2(a) and Fig. 2(b) as drone UE was flying at low altitude of 15 m, therefore the number of reported cell profile of drone UE at 15 m height is quite similar to a regular ground UE. However, in Fig. 2(c-d) it is clearly evident that at high altitudes the drone UE is visible to far more number of BSs and hence the number of reported cells is high in case of high flying drones. These results make this feature an interesting choice for the authors to consider it as a part of the feature set for a drone classification problem using machine learning.

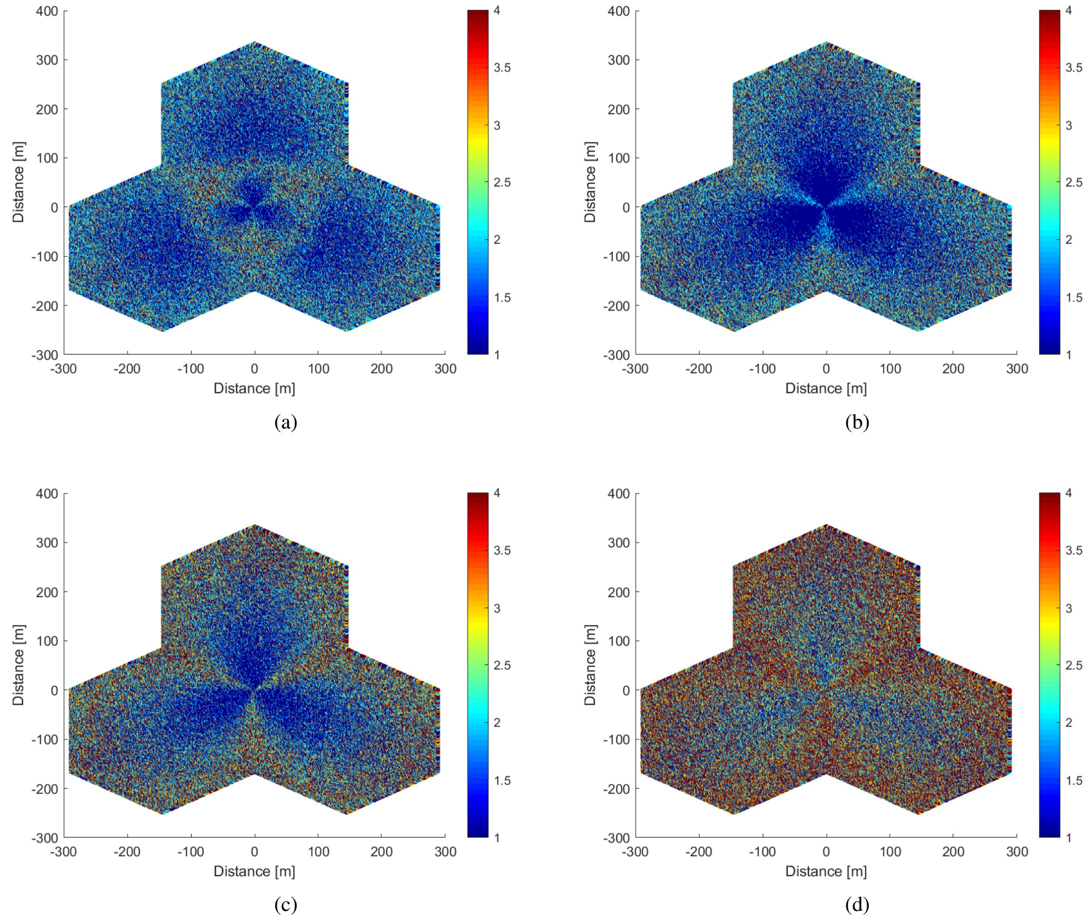


Fig. 2. Number of reported cells within 5 dB threshold, (a) Regular ground UE in NLOS with BS in outdoor environment, (b) Drone UE at 30 m height in NLOS with BS , (c) Drone UE at 120 m height in LOS with BS, and (d) Drone UE at 300 m height in LOS with BS.

C. Performance Metrics

This section defines the performance metrics used for the assessment of different machine learning approaches. The target of this paper is to identify the drone UE as drone UE, therefore the drone detection probability or True Positive Rate (TPR) is considered as one main performance metric. Secondly, it is of equal importance to avoid detecting regular UE as drone UE in order to avoid any unpleasant experience for regular UE. Therefore, the Fale Positive Rate (FPR) is used as second performance metric in this paper. It is essential to use both of these metrics together for checking the performance of machine learning approaches. The objective is to achieve the highest TPR while maintaining the lowest FPR. The TPR and FPR in percentage are defined as given in Eq. 2 and Eq. 3, respectively.

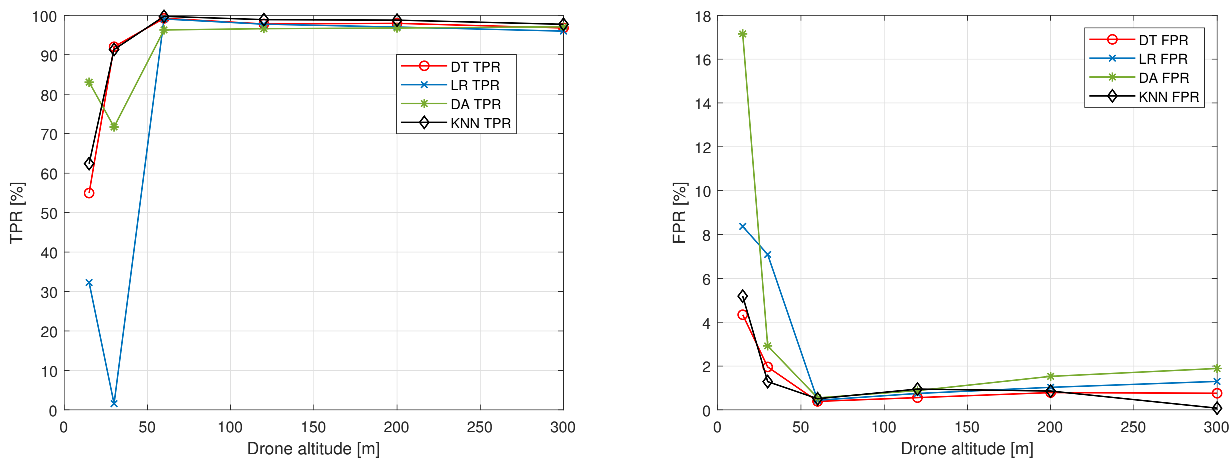
$$TPR = \frac{TP}{TP + FN} * 100. \quad (2)$$

$$FPR = \frac{FP}{FP + TN} * 100. \quad (3)$$

In Eq. 2, TP denotes a number of samples with True Positive value and FN denotes the number of samples with False Negative value. True positive means detecting drone UE as drone UE, whereas false negative means detecting drone UE as ground UE. Similarly, in Eq. 3 the FP denotes a number of samples with False Positive value and TN denotes the number of samples with True Negative value. Here the false positive means detecting the ground UE as a drone UE, and a true negative means detecting the ground UE as a ground UE. The third performance metric included in this paper is the Area Under ROC Curve (AUC), where ROC stands for Receiver Operating Characteristic. The value of AUC corresponds to the probability of correctly detecting which of the UE is drone type and which of the UE is regular type. The value of AUC lies in the range of 0 and 1.The AUC value of 1 corresponds to the ability of the machine learning approach to perfectly classify the UE as a drone UE or a regular UE. The goal is to achieve as high value of AUC as possible. Higher the value of AUC, the better is the prediction performance of the ML algorithm.

IV. Simulation Results and Discussion

This section provides simulation results and discusses about the performance comparison of four different approaches of



(a)

(b)

Fig. 3. Drone detection, (a) True positive rate (TPR), and (b) False positive rate (FPR).

ML algorithms. As mentioned earlier in Section II that different variants of decision tree (DT), discriminant analysis (DA), and K-nearest neighbour (KNN) are considered in this paper. However, due to limited space and for better visualization, the results of only best performing variant of each ML approach are shown here. The post analysis of the acquired results revealed that in terms of considered performance metrics the fine DT, quadratic DA, and the coarse KNN method provides the best results among their class variants. Therefore, later the results presented in Fig. 3 and Fig. 4 are with respect to fine DT, quadratic DA, and coarse KNN methods.

The Fig. 3(a) and Fig. 3(b) show the TPR and FPR of different ML approaches for drone detection as a function of drone altitude. The target is to achieve high TPR while maintaining as low FPR as possible, preferably zero or close to zero. Therefore, it is important to analyze both the Fig. 3(a) and Fig. 3(b) together. It is possible to achieve high probability of detecting a drone correctly with a high false positive rate. As it is shown in Fig. 3(a) that with DA method the TPR is 83% and 71.7% for drone flying at 15 m and 30 m altitude, respectively. However, in Fig. 3(b) the FPR is around a high value of 17.1% and 2.9% at 15 m and 30 m altitude. On the other hand, DT and KNN methods have shown some resemblance in their performance for all considered drone heights. The achieved TPR is 54.9% and 92% with DT method, given the FPR of 4.3% and 2% for 15 m and 30 m high flying drones, respectively. Whereas, the KNN offers the TPR of 62.4% and 91.3% while keeping the FPR of 5.2% and 1.3% for 15 m and 30 m high flying drones, respectively. In [9], it was shown that with their given features set and ML algorithm, the drone detection probability was limited to 5% and 40% while meeting the zero FPR at the height of 15 m and 30 m, respectively. It clearly shows that the features set considered in this paper is strong and handy compared the one provided at [9]. For low flying drones the logistic regression method performs significantly worse than other ML approaches. All the considered ML approaches show good results for drone flying at 60 m and above heights as shown in Fig. 3(a) and Fig. 3(b). At low height the radio propagation condition of the regular UE is similar to the flying drone UE, therefore it is difficult and challenging to distinguish between them. Whereas, high flying drones have different radio characteristics from regular ground UEs or indoor UEs, and hence the TPR is high for all ML approaches at high altitudes. In [9], the drone detection probability is around 90%, whereas in this paper DT, LR, and KNN has a drone detection probability of above 99% with small FPR of 0.5% or less. It is difficult to rate the better one between the DT and KNN method.

Fig. 4 shows area under ROC curve (AUC) for different ML approaches. The AUC curve can be considered as a good accuracy indicator and it is a measure of quality of the classifier. It is already stated and shown earlier that the fine DT and the coarse KNN method showed an almost identical performance, and it can also be seen in Fig. 4 as AUC value if 0.95 for coarse KNN and 0.94 for fine DT for detecting 15 m high flying drone. The value of AUC for these two approaches is raised to 0.99 for 30 m high flying drones, and then for the rest of the drone heights the AUC value is 1. The AUC result shown in Fig. 4 shows that for high flying drones i.e. 60 m and above heights all of the considered ML approaches had shown a similar performance and were able to detect drone properly. However, it is difficult and critical to detect the low flying drones, and for low flying drones DT and KNN are the two preferred approaches with a feature set considered in this paper. In the light of the performance results acquired in this paper, the fine DT and coarse KNN is ranked as best suited ML approach for drone classification, and it is followed by quadratic DA and finally the LR method is placed at the last place. Finally, the summary of TPR and FPR results of all considered ML approaches is given in Table III.

TABLE III
SUMMARY OF PERFORMANCE RESULTS OF DIFFERENT MACHINE LEARNING ALGORITHMS

Case	Fine DT		Med DT		Coarse DT		LR		Linear DA		Quadratic DA		Fine KNN		Med KNN		Coarse KNN	
	TPR	FPR	TPR	FPR	TPR	FPR	TPR	FPR	TPR	FPR	TPR	FPR	TPR	FPR	TPR	FPR	TPR	FPR
15m	54.9	4.3	74.1	9.5	12.0	0.9	32.3	8.4	49.9	14.4	83.0	17.1	59.3	8.0	57.8	5.1	62.4	5.2
30m	92.0	2.0	83.8	1.7	73.9	2.5	1.6	7.1	3.0	13.8	71.7	2.9	88.8	2.1	90.5	1.1	91.3	1.3
60m	99.2	0.4	98.5	0.6	95.6	1.9	99.1	0.4	100.0	9.0	96.3	0.6	98.2	0.3	99.3	0.3	99.7	0.5
120m	97.8	0.6	97.9	1.4	96.8	3.3	97.7	0.8	98.7	7.2	96.6	0.9	96.8	0.6	98.2	0.6	98.9	1.0
200m	97.9	0.8	96.8	1.3	90.9	2.1	97.0	1.0	99.8	8.6	96.8	1.5	95.8	0.8	98.2	0.7	98.8	0.9
300m	96.8	0.8	95.4	1.0	89.9	2.1	96.0	1.3	98.4	7.9	97.1	1.9	95.5	0.9	96.6	0.7	97.7	0.1

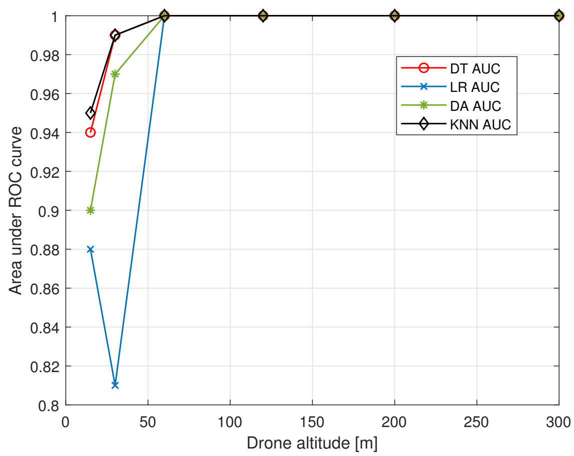


Fig. 4. Area under ROC curve.

V. CONCLUSION

In this paper, we have proposed a suitable set of features for machine learning models and have compared the performance of four different ML algorithms in identifying the flying drones in a mobile network. The feature set includes the RSSI, SINR, and the number of reported cells with 5 dB overlapping window with respect to the serving cell received power. In this paper, different variants of four considered ML algorithms were evaluated by using a homogeneous macro-cellular network in an agreed 3GPP scenario. Simulation data was acquired using static drone User Equipments (UEs) at different height and other regular UEs in an outdoor and indoor environment. It was found that at 60 m and above height the decision tree, logistic regression, and K-nearest neighbour has a drone detection probability or in other words the true positive rate of above 99% with a small false positive rate of 0.5% or less. However, the drone detection probability degrades at lower drone heights. The acquired simulation results showed the TPR of 54.9% and 92% with DT method, while maintaining the FPR of 4.3% and 2% for 15 m and 30 m high flying drones, respectively. Similarly, the KNN offered the TPR of 62.4% and 91.3% while keeping the FPR of 5.2% and 1.3% for 15 m and 30 m high flying drones, respectively. Therefore, the DT and the KNN are the two preferred approaches with a feature set proposed in this paper for identifying the flying drone with good TPR and FPR values.

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