

AI-Based Detection of Jamming Attacks In 6G Drone Networks

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Abstract: A single paragraph of about 200 words maximum. For research articles, abstracts should give a pertinent overview of the work. We strongly encourage authors to use the following style of structured abstracts, but without headings: (1) Background: place the question addressed in a broad context and highlight the purpose of the study; (2) Methods: describe briefly the main methods or treatments applied; (3) Results: summarize the article's main findings; (4) Conclusions: indicate the main conclusions or interpretations. The abstract should be an objective representation of the article, it must not contain results which are not presented and substantiated in the main text and should not exaggerate the main conclusions.

Keywords: keyword 1; keyword 2; keyword 3 (List three to ten pertinent keywords specific to the article; yet reasonably common within the subject discipline.)

1. Introduction

The shift from 4G to 5G has been a generational leap has revolutionized connectivity around the world. Despite 5G being still in its early adoption rate at the time of writing [1], the research community is already working on the next generation of wireless communication technologies, 6G. 6G technology is expected to enable a wide variety of new use cases, thanks to the increases in both data rates and latency but this in turn will also bring forth new security challenges, specific to those applications.

One of the main differences between 5G and 6G technology will be the focus of the 6G standard in regards to AI integration. While Software Defined Networks (SDN) have played a key role in improving the efficiency and security of 5G networks, 6G is expected to take this a step further, by integrating artificial intelligence and machine learning directly into the network. This is what the authors of [2] define as the shift from *Softwarization* to *Intelligentization*.

AI integration in 6G networks will greatly strengthen the security of the network against security threats. By leveraging Diagnostic Analytics, a collection of insights into the status of the networks, security teams will be able to train specific AI models to detect and respond to security threats in real-time.

In this paper we will focus on a specific aspect of the security of 6G networks, namely we will provide a machine learning based approach for the detection of jamming attacks in networks of drones.

The paper is divided in 5 sections:

1. **Topic overview:** In this section we will discuss how drones can benefit from integration in 6G network, analyze jamming attacks, their types, mitigation and detection. Finally we will discuss the advantages of an edge AI approach for jamming detection.
2. **Materials and methods:** In this section we will define the scenario that we decided to analyze as well as the dataset, algorithm and evaluation metrics we chose for our tests.

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3. **Numerical Results:** In this section we will present the testing methodology as well as the numerical results that we obtained. 38
4. **Discussion:** In this section we will discuss the results obtained in the previous section and highlight notable trends. 40
5. **Conclusions:** In this section we will summarize the results and discuss possible future research directions. 42

2. Related Works 44

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3. Topic Overview 55

3.1. Drones in 6G Networks 56

Drones, also known as Unmanned Aerial Vehicles (UAVs) are defined as *all aircraft designed to fly without a pilot on board* [3]. This technology has experienced rapid growth in 57

recent years and is expected to keep growing in both the consumer sector as well as the commercial and military sectors [4].

In report 22.886 [5] 3GPP, the organ responsible for the development and maintenance of the 5G standard, identifies some of the envisioned use cases for 5G V2X (Vehicle-to-Everything) communication services. Among these use cases, the report identifies vehicle platooning, advanced and remote driving end extended situational awareness as some of the main benefits of V2V communication. All these use cases can be leveraged by a 6G drone network to achieve fast and reliable drone-to-drone communication, that, with the integration of artificial intelligence would allow the drones to act autonomously in a coordinated manner.

This would prove useful in a variety of fields: from autonomous soil and crop health assessment as well as irrigation in agriculture, delivery of life saving supplies and locating of survivors in disaster response, in the delivery sector as a more eco friendly alternative to traditional delivery options and possibly in the mobility sector as a complement to traditional taxis and public transportation [6].

The effectiveness of drones in the military sector is widely recognized, both for high and low end models. For example, in the Ukraine war even cheap FPV drones mounted with explosives were successfully used to destroy much more expensive equipment [7].

Security against Jamming attacks is crucial in all these applications, especially in a safety critical environment.

3.2. Understanding Jamming Attacks

Jamming attacks are a type of Denial of Service (DoS) attack that aims at disrupting the communication between two or more devices. This is achieved by transmitting a powerful signal on the same frequency as the one used by the devices to communicate. If the jamming signal is strong enough, it is able to overwhelm the legitimate signal, effectively blocking the communication between the devices [6]. Since the ability to communicate is affected, Jamming attacks falls under the umbrella of attacks that target the *Availability* of the service in the CIA triad classification [8]. Jamming attacks can be classified into 5 main categories, based on the attack pattern of the jammer:

- **Constant Jamming:** The jammer continuously transmits a strong signal on the same frequency as the devices it wants to disrupt.
- **Periodic Jamming:** The jammer simply transmits a strong signal on the same frequency as the devices it wants to disrupt for a certain period of time t_a , then stops transmitting for another period of time t_b . This type of jamming attack is particularly effective against devices that are not able to change their frequency and has the ability to disrupt the transmission of a sequence of consecutive packets. [9]
- **Random Jamming:** In random jamming, the jammer is active at random intervals, giving each transmitted packet a probability p of being jammed [9].
- **Reactive Jamming:** A reactive jammer starts transmitting its jamming signal only when it senses energy in the communication channel, indicating that a legitimate transmission is taking place. This type of jamming attack is more power efficient compared to other operation types, as it only transmits its signal when it is needed[16].
- **Smart Jamming:** A smart jammer is a more sophisticated type of jammer that is able to adapt its jamming signal to maximize the disruption of the communication between the devices. Smart jammers are able to modify their attack pattern based on the transmission specifics of the devices they are targeting and are able to adapt to changes in the communication channel[11].

An effective Jamming detection AI model should achieve a high detection score against all the different types of jamming attacks.

3.3. Jamming attacks against drone networks

Jamming attacks are particularly effective against drone networks, as drones usually rely on external input to navigate and operate correctly. If a jammer were able to completely

block the communication between the drone and the base station, the drone would be left without any indication on how to behave and would need to activate an internal failsafe mechanism. This usually comes in the form of either a return to base procedure, a landing procedure or a hover in place procedure. All of these procedures leave the drone in a vulnerable position, as a bad actor could potentially capture the drone and use it for malicious purposes. This is especially true when jamming attacks are used in combination with other types of attacks, such as spoofing attacks.

One real world example of this is the capture of an American drone by Iran in 2011. In December 2011 a Lockheed Martin RQ-170 Sentinel drone operated by the United States Air Force was flying over Iran when its operators lost control of the vehicle. The US government initially claimed that the drone had crashed due to a technical malfunction, but later reports revealed that the drone had been captured by the Iranian military. Iranian electronic warfare specialists claimed to have brought it down using a Jamming attack, that forced the drone into a return to base procedure, in combination with a GPS spoofing attack, that made the drone land into a designated area [12]. After successfully capturing the drone, the Iranian government managed to reverse-engineer the drone and produce a working replica, which was then used in their military operations [13].

3.4. Centralized vs Edge approach for Jamming detection

When presenting a machine learning based approach in an IoT setting, the question of where the AI model should be placed often arises. By their nature, IoT devices, and in turn drones, are usually resource constrained, both in terms of computational power but also in terms of internal storage and battery capacity [14]. This means that complex AI models and algorithms are usually not feasible to be run on the device itself. A centralized approach offloads the computational burden to a central server, that returns the results of the AI model to the device. While this approach might be feasible in some cases, in a real-time situation such as a jamming attack, the latency introduced by the communication with the central server means less time to react to the attack. Also, as jamming attacks degrade or sometimes completely block the communication between the device and the base station, a centralized approach might not be feasible in this case. An lightweight edge approach on the other hand, while not as powerful as a centralized approach, would to provide real-time results to the device and would be able to operate even when the communication is disrupted.

3.5. Detection and Mitigation of Jamming Attacks

When attempting to mitigate jamming attacks, the first step is always to detect that an attack is taking place. This can be done by monitoring the communication channel for signs of jamming. The most common approaches involve the analysis of metrics such as the Signal to Noise Ration (SNR), the Received Signal Strength Indicator (RSSI) and the Packet Delivery Ratio (PDR) [15]. The most simple way to detect jamming attacks is to set a static threshold for these metrics and trigger an alarm when the threshold is crossed. While this approach easy to implement and might be effective in some cases, it is not able to adapt to changes in the communication channel and might be prone to false positives. Implementing a machine learning based approach for jamming detection would allow the system to adapt to the changes in the communication channel and would be able to provide a more accurate detection of jamming attacks [9]. This is especially useful in mobile scenarios like drone networks, where the environment is constantly changing and the signal strength can vary greatly.

Once an attack is successfully detected, state of the art jamming mitigation techniques, like Direct Sequence Spread Spectrum (DSSS), Frequency Hopping (FHSS) and advanced signal processing techniques can be put in place to mitigate the effects of the attack.

4. Materials and Methods

4.1. Scenario Definition and Attacker Classification

In the proposed scenario we have a flying drone that is subject to a jamming attack. The drone communicates with a ground station and periodically samples the Received Signal Strength (RSS) of the signal it receives. The drone implements a simple unsupervised machine learning algorithm module, trained on nominal traffic RSS values. The module takes the sampled RSS values and classifies them as either normal or anomalous. Thanks to this classification module, the drone is able to determine whether or not a jamming attack is taking place.

We assume that a jammer is deployed in the network and that it starts a jamming attack at a certain point in time by transmitting a strong signal on the same frequency as the one used by the drone to communicate with the ground station. We assume that the jammer is able to completely block the communication between the drone and the ground station, meaning the drone has to rely on its internal classification algorithm to determine if a jamming attack is taking place and react accordingly. We assume that the jammer type is unknown to the drone.

Figure 1 shows a diagram of the proposed scenario.

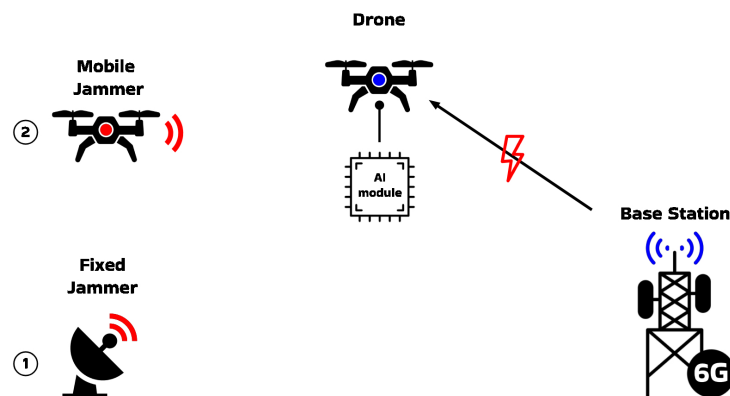


Figure 1. Proposed jamming scenario. The Drone communicates with the 6G base station and receives information about how to behave. The fixed jammer (1) and the mobile jammer (2) target the communication between the drone and the base station. The drone has an internal classification module that is able to detect jamming attacks.

In our scenario, the drone will be subject to two types of jamming attacks, a constant jamming attack and a periodic jamming attack. These types of attacks can be attributed to different types of jammers. The constant jamming attack could be caused by a ground jammer, as maintaining a constant jamming signal requires a large power source, while the periodic jamming attack could be caused by a drone jammer, as drones are usually battery powered and can only jam for a limited amount of time. Employing a periodic jamming attack could help the malicious drone conserve energy and reduce the chances of being detected.

Table 1 shows the attacker classification in the proposed scenario [16]:

Table 1. Attacker classification details.

Classification	Description
Active	The attacker is actively trying to disrupt network operation by transmitting a jamming signal
External	The attack takes place at level 1 of the OSI model, meaning that the attacker is not part of the network
Local	The attack is local, as it is targeted at a specific drone or drone cluster and not at the entire network
Malicious	Jamming attacks are considered malicious as their main goal is to disrupt correct network operation

4.2. Dataset Choice

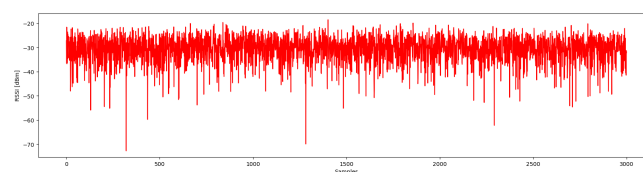
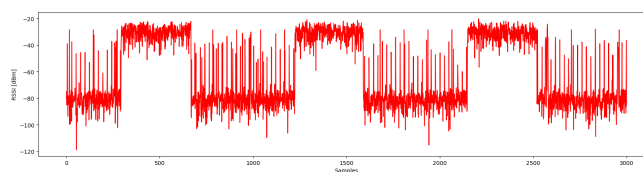
As 6G network traffic is not yet available, we chose an open-source dataset [17] that analyses the RSS values received by a Raspberry Pi 3 that is subject to periodic and constant jamming attacks.

The dataset was created using a software-defined radio (SDR) connected to a laptop that was programmed to transmit a jamming signal using the open source software *GNU Radio*. A second SDR radio was chosen to receive the jamming signal and the RSS values and was connected to a Raspberry Pi 3. The jamming radio operates at a frequency of 2.412 GHz with a Bandwidth of 40MHz, while the Raspberry Pi 3 was programmed to sample the RSS values with a frequency of 32K samples per second.

The dataset contains 3 different *.txt* files that store the RSS values sampled by the Raspberry Pi 3. The first file contains the RSS values sampled during a constant jamming attack, the second file contains the RSS values sampled during a periodic jamming attack and the third file contains the RSS values sampled during normal network operation. The samples are stored in a single column, with each row representing a single sample. The samples use the *dBm* (*decibel-milliwatts*) unit of measurement a logarithmic scale that measures the power of a signal in relation to 1 milliwatt. Conversion can be done using the formula [18] shown in equation 1:

$$P_{dBm} = 10 \cdot \log_{10} \left(\frac{P_{mW}}{1mW} \right) \quad (1)$$

Figures 2 and 3 show respectively plots of the RSS values sampled during a constant jamming attack and a periodic jamming attack.

**Figure 2.** Constant jamming attack RSS values**Figure 3.** Periodic jamming attack RSS values

4.3. Algorithm Choice

When choosing the algorithm for the classification module, we first had to define the requirements that the algorithm had to meet. The algorithm has to be able to classify anomalous samples with a high degree of accuracy, while at the same time being lightweight enough to be run on a resource constrained device like a drone. The training phase should also be fast, as this would allow the drone to redetermine the normal transmission RSS values in a constantly changing environment. If the model didn't periodically redefine normal RSS values, it would be prone to false positives caused by the mobile nature of drones. The model should be also required a limited amount of storage to be run effectively, as drones are usually lacking in internal storage.

The algorithm that best fit these requirements was the *Isolation Forest* algorithm [19]. The Isolation Forest algorithm is a state-of-the-art unsupervised machine learning algorithm for anomaly detection, introduced by Liu et al. in 2008. Unlike traditional anomaly detection algorithms, which require the definition of a normal class, Isolation Forest is able to detect anomalies without explicitly defining the characteristics of the normal class. This is achieved by leveraging the properties of anomalies themselves, i.e. being few and separated from the majority of the data points. The algorithm works by building a forest of isolation trees. Each tree is built by randomly selecting one of the features and then splitting the data points based on a value randomly selected between the minimum and maximum value of the feature. This partitions the data into the left and right branches of the tree. The process is repeated recursively until all the data points are isolated. The height of a node, meaning the number of splits that were required to isolate is used to determine the anomaly score of the data point. The higher the number of splits, the more likely the data point is to be an anomaly. Isolation Forest is an *ensemble* algorithm, meaning that the final anomaly score is calculated by averaging the anomaly scores of all the trees in the forest. More trees mean more accuracy but also more computational power required.

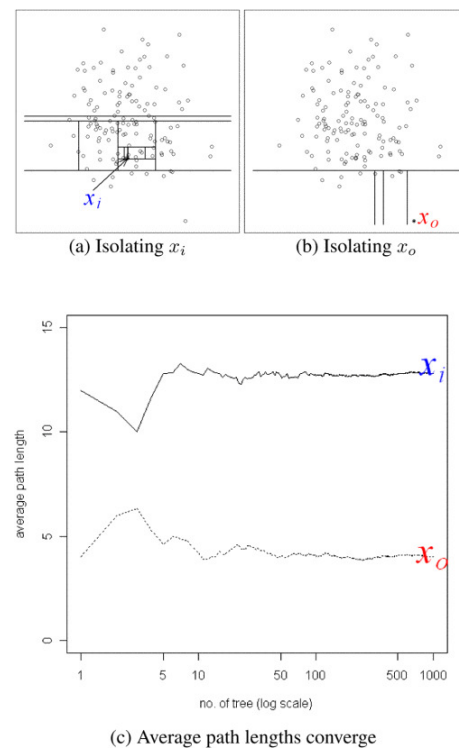


Figure 4. Isolation forest in action. The anomaly x_o is isolated in less splits compared to the normal datapoint x_i [19].

The chosen implementation for isolation forest is the one provided by the *Scikit-learn* library [20] for Python 3. The algorithm was tested on a Desktop PC with an Intel i7-6700 CPU and 16GB of RAM as well as on a Raspberry Pi 3 with a Quad Core 1.2GHz CPU

and 1GB of RAM [21]. The graphs shown are the ones obtained on the Desktop PC for convenience, but the ability of the algorithm to run effectively on a resource constrained device like the Raspberry Pi 3, that has hardware comparable to the one found in high-end commercial drones, was verified.

4.4. Evaluation Metrics

The performance of the model was evaluated using the state-of-the-art evaluation metrics for machine learning classification algorithms. The metrics are all based on the number of true positives, false positives, true negatives and false negatives. A true positive is a data point that is correctly classified as an anomaly, while a false positive is a data point that is incorrectly classified as an anomaly. A true negative on the other hand is a data point that is correctly classified as a normal data point, while a false negative is a data point that is incorrectly classified as a normal data point. The evaluation metrics that we chose to use are the following:

- **Accuracy:** The accuracy is the ratio of correctly classified data points to the total number of data points 2.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

- **Precision:** The precision is the ratio of correctly classified anomalies to the total number of data points classified as anomalies 3.

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

- **Recall:** The recall is the ratio of correctly classified anomalies to the total number of anomalies 4.

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

- **F1 Score:** The F1 score is the harmonic mean of the precision and recall 5.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

The combination of these metrics gives us an insight into the model's performance.

5. Results

5.1. Parameters Tuning

The first phase in our testing methodology was the tuning of the hyperparameters of the model. The tuning was performed by making the parameters vary between a minimum and a maximum value, evaluating the impact on the performance metrics (see section 4.4) and then choosing the best performing parameters. From the parameters available in the *Scikit-learn* implementation of the Isolation Forest, the parameters we decided to tune were the following:

- **n_estimators:** The number of base estimators in the ensemble, i.e the number of isolation trees used to compute the anomaly score of each datapoint.
- **max_samples:** The max number of samples to draw from the dataset to train each tree.
- **contamination:** The amount of outliers present in the dataset used to train the model.

During the tuning phase, the untested hyperparameters were set to their default values of the *Scikit-learn* implementation of the Isolation Forest (2).

Table 2. Scikit-Learn Isolation Forest hyperparameters default values.

Parameter	Default Value
n_estimators	100
max_samples	'auto'
contamination	0.1

During he tuning process, as well as the subsequent model testing phase, the model was evaluated using as input normal traffic samples concatenated with jamming attack samples (see code snippet 1). This was done to simulate a real-world scenario where the model has to be able to classify correctly anomalous samples but also reduce the number of false positives during normal operation.

Algorithm 1 Test input definition

```
1: normalTraffic ← ReadAndParseFile(NORMAL_TRAFFIC_FILE, normal_traffic_size)
2: jamming ← ReadAndParseFile(JAMMING_FILE, jamming_size)
3: testInput ← Concatenate(normalTraffic, jamming)
```

The values whe chose for *normal_traffic_size* and *jamming_size* are shown in table 3.

Table 3. Dataset sizes used for the tuning and testing phases.

Dataset	Size
jamming samples n.	2000
nominal samples n.	20000

The dataset is purposefully unbalanced, as jamming attacks are usually rare events compared to normal network operation.

In figure 5 we can see a representation of the input signal in the case of a constant jamming attack. The proposed results, unless otherwise specified, are based on the input signal shown in the figure which employs constant jamming. Periodic jamming always showed comparable trends as constant jamming in all the tests performed.

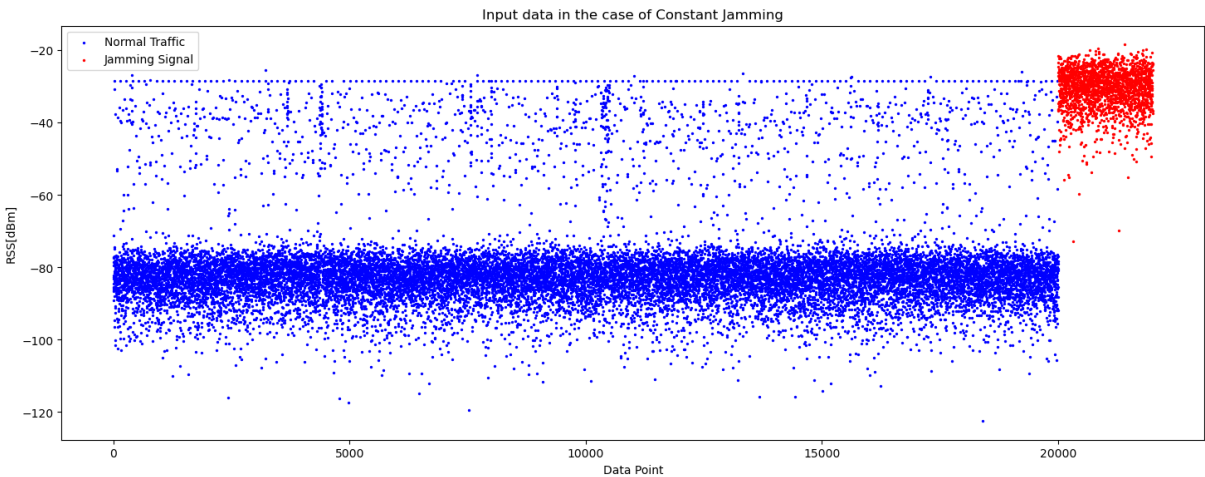


Figure 5. Input signal in the case of Constant Jamming. The jamming signal is concatenated with the normal traffic signal.

5.1.1. *n_estimators* tuning313

The first parameter that we decided to tune was the *n_estimators* parameter. The tuning314

values are shown in table 4.315

Table 4. *n_estimators* tuning values.

<i>n_estimators</i>	Values
Minimum	1
Maximum	50
Step	1

The effect on the evaluation metrics of the model is shown in figure 6.316

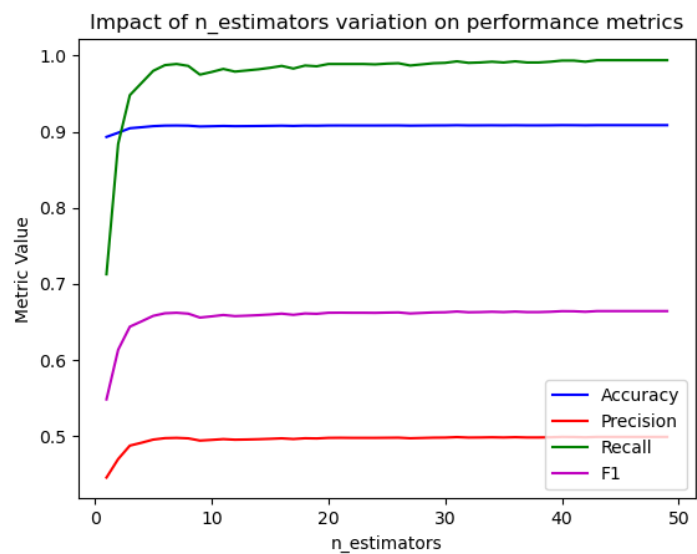


Figure 6. *n_estimators* tuning results.317

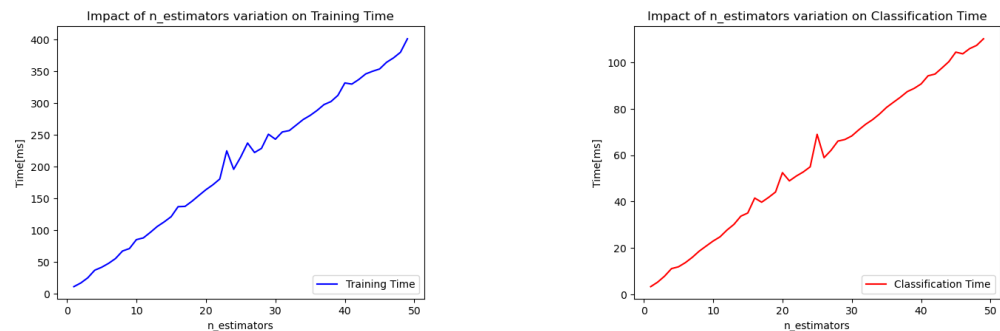
As we can see from the graph, a growing number of estimators initially correlates with318

a better model performance, but after a certain point the performance stabilizes. In graphs319

7a and 7b is shown that the time required both for training and classification increases320

linearly with the number of estimators. This means that choosing an appropriate number321

of estimators is crucial, as it can greatly affect the model performance.



(a) *n_estimators* training time.322

(b) *n_estimators* classification time.323

Figure 7. Comparison of *n_estimators* training and classification times.324

We decided to choose ***n_estimators* = 15**, as it provided a good balance between322

model performance and computational resources required. The model metrics keep slowly323

improving up until 45 estimators, but the minimal performance increase was not worth324

such a large increase in training and classification time, especially considering the resource-constrained nature of the scenario.

5.1.2. max_samples tuning

The second parameter that we decided to tune was the *max_samples* parameter. As shown in table 5, the tuning values were chosen to be between 1 and 20000, i.e the same number of normal traffic samples in the test input.

Table 5. max_samples tuning values.

max_samples	Values
Minimum	1
Maximum	100
Step	1

From figure 8 we can see that the model performance is not greatly affected by the *max_samples* parameter. This is most likely due to the great difference in RSS values between the normal traffic samples and the jamming attack samples, meaning the model can develop the capability to correctly classify the input even with a small training set.

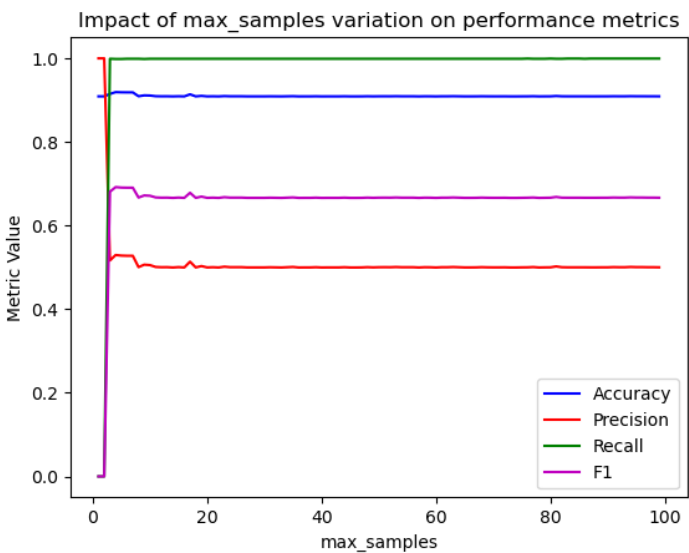
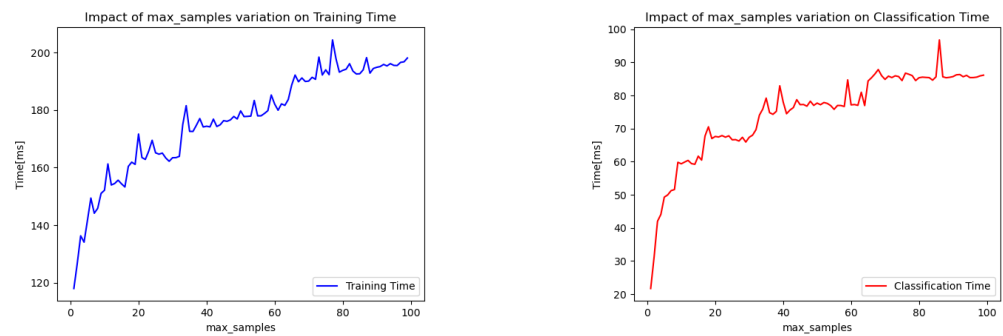


Figure 8. max_samples tuning results.

Still, as the model has to build bigger trees, the *max_samples* parameters as considerable influence on the training and classification time, as shown in figure 9. Given minimal performance differences but the impact on the time metrics, chose the value of *max_samples* = 10.



(a) max_samples training time.

(b) max_samples classification time.

Figure 9. Comparison of max_samples training and classification times.

6. Discussion

Authors should discuss the results and how they can be interpreted from the perspective of previous studies and of the working hypotheses. The findings and their implications should be discussed in the broadest context possible. Future research directions may also be highlighted.

7. Conclusions

This section is not mandatory, but can be added to the manuscript if the discussion is unusually long or complex.

8. Patents

This section is not mandatory, but may be added if there are patents resulting from the work reported in this manuscript.

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Abbreviations

The following abbreviations are used in this manuscript:

SDN	Software Defined Networks	
UAVs	Unmanned Aerial Vehicles	
3GPP	3rd Generation Partnership Project	
V2X	Vehicle to Everything	
FPV	First Person View	
DOS	Denial Of Service	
SNR	Signal to Noise Ratio	
RSSI	Received Signal Strength Indicator	
PDR	Packet Delivery Ratio	
CIA	Confidentiality, Integrity, Availability	
IoT	Internet of Things	
AI	Artificial Intelligence	
DSSS	Direct Sequence Spread Spectrum	
FHSS	Frequency Hopping Spread Spectrum	
OSI	Open Systems Interconnection	
dBm	Decibel-milliwatts	

Appendix A

Appendix A.1

The appendix is an optional section that can contain details and data supplemental to the main text—for example, explanations of experimental details that would disrupt the flow of the main text but nonetheless remain crucial to understanding and reproducing the research shown; figures of replicates for experiments of which representative data are shown in the main text can be added here if brief, or as Supplementary Data. Mathematical proofs of results not central to the paper can be added as an appendix.

Table A1. This is a table caption.

Title 1	Title 2	Title 3
Entry 1	Data	Data
Entry 2	Data	Data

Appendix B

All appendix sections must be cited in the main text. In the appendices, Figures, Tables, etc. should be labeled, starting with “A”—e.g., Figure A1, Figure A2, etc.

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