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THEME

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# Detecting Unmanned Aerial Vehicle based on Artificial Intelligence techniques

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khadidja.

# ABSTRACT

## Abstract

In this paper, we propose method for detection of drone and classification using different algorithms of machine learning by recording the RF spectrum. We tried to find the best algorithm we have a good accuracy. In this research we collected the Radio frequency dataset because it is the most efficient detection method in terms of price / quality ratio, we also carried out a preprocessing procedure and a better training we using Cross-Validation technique for evaluating ML models by training several ML models on subsets of the available input data and evaluating them on the complementary subset of the data. We use cross-validation to get many results we chose 10 algorithm of ML and chose the best one of them. Although the airspace contains many waves, including radio frequencies, Wi-Fi ,GPS, resaux mobile ,radar ,wireless data ,UAV...etc. We were able to reach a very acceptable result as a start in this project.

**Keywords:**Artificial intelligence ,Machine Learning, Radio Frequency, Unnamed Aerial Vehicle, classification algorithms

## Résumé

Dans cet article, nous proposons une méthode de détection de drone et de classification utilisant différents algorithmes d'apprentissage automatique en enregistrant le spectre RF. Nous avons essayé de trouver le meilleur algorithme ayant une bonne précision. Dans cette recherche, nous avons collecté le jeu de données Radiofréquence car il s'agit de la méthode de détection la plus efficace en termes de rapport qualité / prix, nous avons également effectué une procédure de prétraitement et une meilleure formation en utilisant la technique de validation croisée pour évaluer les modèles ML en entraînant plusieurs modèles ML sur des sous-ensembles de données d'entrée disponibles et en les évaluant sur le sous-ensemble complémentaire des données. Nous utilisons la validation croisée pour obtenir de nombreux résultats, nous avons choisi 10 algorithmes de ML et choisi le meilleur d'entre eux. Bien que l'espace aérien contienne de nombreuses ondes, notamment les radiofréquences, le Wi-Fi, le GPS, les réseaux mobiles, les radars, les données sans fil, les drones ... etc. Nous avons pu atteindre un résultat très acceptable au début de ce projet.

**Mots clés :** Intelligence Artificielle, ML, RF, UAV, algorithmes de classification.

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# list of Abbreviations

UAV:unmanned aerial vehicle

RF:Radio frequency

ML:machine learning

AI:Artificial intelligence

SNR:Signal-to-noise ratio

## **Chapter 1**

# **General Introduction**

## 1.1 General Introduction

Drones have been around for more than two decades, but their roots date back to World War I when both the U.S. and France worked on developing automatic, unmanned airplanes. However, the last few years have been significant in terms of drone adoption, usage expansion across industries, and global awareness. From technically manning sensitive military areas to luring hobbyists throughout the world, drone technology has developed and prospered in the last few years. Individuals, commercial entities, and governments have come to realize that drones have multiple uses, which include: Aerial photography for journalism and film ,Express shipping and delivery ,Gathering information or supplying essentials for disaster management, Thermal sensor drones for search and rescue operations, Geographic mapping of inaccessible terrain and locations, Building safety inspections ,Precision crop monitoring, Unmanned cargo transport, Law enforcement and border control surveillance ,Storm tracking and forecasting hurricanes and tornadoes. Development of hundreds of more uses of drones are underway due to the multiple investments pouring into this promising industry every day. Even though so many beneficial civilian applications of micro-UAVs abound. but The idea of having drones into the national airspace raises serious safety concerns, Such drones have capabilities and weight limits that enable their use for malicious and harmful purpose for nearly all spectrum of the society which ranges from government facilities and aviation authorities to regular individuals and this deployment in range of civilian became a threat beyond people's security and privacy. Officials said the large number of small aircraft posed a threat. security and privacy can be achieved by accurately detecting and identifying non compliant micro-UAVs. Several techniques have been proposed for micro-UAV detection and classification so far. Often recognized as anti-drone method, is a process to determine the use or presence of drones by the reinforcement of technologies. Several approaches for drones detection have been developed in recent years and most of these approaches are employed on algorithms based on modalities like sound, vision, radar, and Radio Frequency (RF) signal[3] .The reliable detection of drones, however, is a challenging task due to the presence of many objects in the air, such as birds, clouds, and airplanes. [5] Some of these challenges can be addressed by machine learning (ML) which are based on radio frequency (RF) ML can perform pattern recognition using modalities, which cannot be perceived by human's altogether. These include radio frequencies as well as optic and acoustic signals beyond the abilities of human sense organs. The detection and classification technologies specifically those which are based on machine learning (ML), And this is what we will try to address in our work this by improving drone detection using ML. This work organized as follows. Chapter 1 gives an overview of IA and his applications and overview of UAV; chapter 2 describes the experimental setup and detection of UAV with techniques ML and chapter 3 discussion and presents the results; and chapter 4 provides the conclusion.

## **Chapter 2**

# **Background**

## 2.1 Introduction

Artificial Intelligence, or AI, has existed for some time now. If we could develop an AI that could detect drones without humans, what sort of new opportunities could come from the melding of AI with drone technology? In this chapter, we explain what exactly is artificial intelligence and its applications. In addition, give an overview of UAV.

### 2.1.1 Artificial Intelligence

Artificial intelligence is a technology that is already impacting how users interact with, and are affected by, the Internet. In the near future, its impact is likely to only continue to grow. AI has the potential to vastly change the way that humans interact, not only with the digital world, but also with each other, through their work and through other socioeconomic institutions – for better or for worse. Artificial intelligence (AI), sometimes called machine intelligence, is intelligence demonstrated by machines, unlike the natural intelligence displayed by humans and animals [1]. With the help of AI, you can create such software or devices, which can solve real-world problems very easily and with accuracy such as health issues, marketing, traffic issues, etc. With the help of AI, you can create your personal virtual Assistant, such as Cortana, Google Assistant, Siri, etc. With the help of AI, you can build such Robots which can work in an environment where survival of humans can be at risk. AI opens a path for other new technologies, new devices, and new Opportunities. Artificial Intelligence is not just a part of computer science even it's so vast and requires lots of other factors which can contribute to it. To create the AI first we should know that how intelligence is composed, so the Intelligence is an intangible part of our brain which is a combination of Reasoning, learning, problem-solving perception, language understanding.

### 2.1.2 Applications of Artificial Intelligence

Artificial Intelligence has various applications in today's society. It is becoming essential for today's time because it can solve complex problems with an efficient way in multiple industries, such as Healthcare, entertainment, finance, education, etc. AI is making our daily life more comfortable and fast. Following are some sectors, which have the application of Artificial Intelligence:

### 2.1.3 AI in Robotics

Artificial Intelligence has a remarkable role in Robotics. Usually, general robots are programmed such that they can perform some repetitive task, but with the help of AI, we can create intelligent robots, which can perform tasks with their own experiences without pre-programmed.



FIGURE 2.1: application of artificial intelligence

### 2.1.4 AI in Robotics

In the last, five to ten years, AI becoming more advantageous for the health-care industry and going to have a significant impact on this industry. Health-care Industries are applying AI to make a better and faster diagnosis than humans. AI can help doctors with diagnoses and can inform when patients are worsening so that medical help can reach to the patient before hospitalization.

### 2.1.5 AI in Gaming

AI can be used for gaming purpose. The AI machines can play strategic games like chess, where the machine needs to think of a large number of possible places.

### 2.1.6 AI in Finances

AI and finance industries are the best matches for each other. The finance industry is implementing automation, Chabot, adaptive intelligence, algorithm trading, and machine learning into financial processes

### 2.1.7 AI in Data Security

The security of data is crucial for every company and cyber-attacks are growing very rapidly in the digital world. AI can be used to make your data more

safe and secure. Some examples such as AEG bot, AI2 Platform, are used to determine software bug and cyber-attacks in a better way.

### **2.1.8 AI in Automobiles**

It is now advancing towards driverless cars. These cars have incorporated systems that are useful in applying brakes, changing lanes, navigation, and many more. Such cars interpret the pattern in which other cars are moving and try to imitate that in themselves. It is also being worked on in the insurance sector, which can help in fast and more efficient filing of claims and insurances.

### **2.1.9 AI in Business**

A firm can use AI-based solutions by determining what are the weaknesses and strengths and use these solutions to deduce its financial, production-related and CRM and other objectives. It helps in automating tasks that in turn save an awful lot of time and man power.

### **2.1.10 AI in Education**

AI can deliver a better learning experience by adjusting learning as per the needs of each student, and provide universal access to students. It can also automate grading systems. AI can also provide additional support to the students, as required.

### **2.1.11 AI in Government**

Governments have started honing AI to make suitable policies and services. Governments can use AI to counter natural disasters, road accidents, and many such problems a country may face. With the aid of AI-based applications, developers are trying to bring about a change in the way the public sector works. Such apps can reduce costs and errors, save employees from mundane tasks and also help in clearing out backlogs.

### **2.1.12 AI in Manufacturing**

A manufacturer can enhance its production quantity and quality by applying AI to forecast future demand and supply, production planning, material movement, assembling the parts, and all such activities involved in manufacturing.

### **2.1.13 AAI in NLP**

: NLP, acronym for Natural Language Processing, deals with the ability of the computer to understand the natural language of its users. Spell check and autocorrect are two of the most commonly used NLPs. I have a habit of



writing 'Yasss brooo' when I get excited about something. My phone has understood this, and every time I am close to finish typing 'yasss', the keyboard of my smartphone immediately and automatically suggests 'brooo'

## 2.2 Artificial Intelligence Algorithms

Different Artificial Intelligence algorithms can be used to solve a category of problems. In the below section we'll see the different types of algorithms that fall under Classification, Regression and Clustering problems **r7**

### 2.2.1 Classification Algorithms

Classification, as the name suggests is the act of dividing the dependent variable (the one we try to predict) into classes and then predict a class for a given input. It falls into the category of Supervised Machine Learning, where the data set needs to have the classes, to begin with. Thus, classification comes into play at any place where we need to predict an outcome, from a set number of fixed, predefined outcomes. Classification uses an array of algorithms, a few of them listed below :

1. Naive Bayes
2. Decision Tree
3. Random Forest
4. Logistic Regression
5. Support Vector Machines
6. K Nearest Neighbours

Let us break them down and see where they fit in when it comes to application.

#### Naive Bayes

Naive Bayes algorithm follows the Bayes theorem, which unlike all the other algorithms in this list, follows a probabilistic approach. This essentially means, that instead of jumping straight into the data, the algorithm has a set of prior probabilities set for each of the classes for your target. Hence this can be extremely useful in cases where you need to predict whether your input belongs to either a given list of n classes or does it not belong to any of them. This can be possible using a probabilistic approach mainly because the probabilities thrown for all the n classes will be quite low

#### Decision Tree

The Decision Tree can essentially be summarized as a flowchart-like tree structure where each external node denotes a test on an attribute and each

branch represents the outcome of that test. The leaf nodes contain the actual predicted labels. We start from the root of the tree and keep comparing attribute values until we reach a leaf node. We use this classifier when handling high dimensional data and when little time has been spent behind data preparation. However, a word of caution – they tend to overfit and are prone to change drastically even with slight nuances in the training data.

### **Logistic Regression**

It's a go-to method mainly for binary classification tasks. The term 'logistic' comes from the logit function that is used in this method of classification. The logistic function, also called as the sigmoid function is an S-shaped curve that can take any real-valued number and map it between 0 and 1 but never exactly at those limits

### **Support Vector Machine**

An SVM is unique, in the sense that it tries to sort the data with the margins between two classes as far apart as possible. This is called maximum margin separation. Another thing to take note of here is the fact that SVM's take into account only the support vectors while plotting the hyper plane, unlike linear regression which uses the entire dataset for that purpose. This makes SVM's quite useful in situations when data is in high dimensions. Let us try to understand this with an example. In the below figure we have to classify data points into two different classes (squares and triangles)

### **K Nearest Neighbors**

KNN is a non-parametric (here non-parametric is just a fancy term which essentially means that KNN does not make any assumptions on the underlying data distribution), lazy learning algorithm (here lazy means that the "training" phase is fairly short). Its purpose is to use a whole bunch of data points separated into several classes to predict the classification of a new sample point. The following points serve as an overview of the general working of the algorithm:

- A positive integer N is specified, along with a new sample
- We select the N entries in our database which are closest to the new sample
- We find the most common classification of these entries
- This is the classification we give to the new sample

## **2.2.2 Regression Algorithms**

In the case of regression problems, the output is a continuous quantity. Meaning that we can use regression algorithms in cases where the target variable is a continuous variable. It falls into the category of Supervised Machine Learning, where the data set needs to have the labels, to begin with.

## Linear Regression

Linear Regression is the most simple and effective regression algorithm. It is utilized to gauge genuine qualities (cost of houses, number of calls, all out deals and so forth.) in view of the consistent variable(s). Here, we build up a connection between free and ward factors by fitting the best line. This best fit line is known as regression line and spoken to by a direct condition  $Y = a * X + b$ .

### 2.2.3 Clustering Algorithms

The basic idea behind clustering is to assign the input into two or more clusters based on feature similarity. It falls into the category of Unsupervised Machine Learning, where the algorithm learns the patterns and useful insights from data without any guidance (labeled data set). For example, clustering viewers into similar groups based on their interests, age, geography, etc can be done by using Unsupervised Learning algorithms like K-Means Clustering.

#### K-Means Clustering

K-means is probably the simplest unsupervised learning approach. The idea here is to gather similar data points together and bind them together in the form of a cluster. It does this by calculating the centroid of the group of data points. To carry out effective clustering, k-means evaluates the distance between each point from the centroid of the cluster. Depending on the distance between the data point and the centroid, the data is assigned to the closest cluster. The goal of clustering is to determine the intrinsic grouping in a set of unlabeled data.

### 2.2.4 Ensemble Learning Algorithms

In cases where data is of abundance and prediction precision is of high value, boosting algorithms come into the picture. Consider the scenario, you have a decision tree trained on a data set along with a whole bunch of hyper parameter tuning already performed, however, the final accuracy is still slightly off than you would like. In this case, while it might seem that you have run out of possible things to try, ensemble learning comes to the rescue.

## 2.3 Areas and Applications of Artificial Intelligence

In the below figure, you will see a major number of areas where AI is being used extensively. Let us discuss some of them:

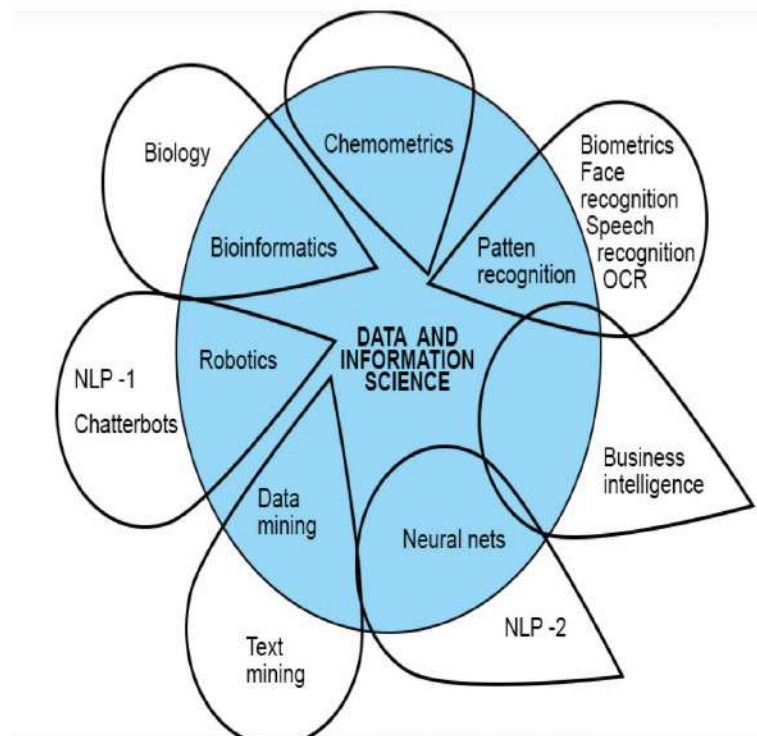


FIGURE 2.2: Areas of artificial intelligence

### 2.3.1 Common-sense reasoning

Common-sense reasoning is one of the branches of Artificial intelligence (AI) that is concerned with simulating the human ability to make presumptions about the type and essence of ordinary situations they encounter every day. These assumptions include judgments about the physical properties, purpose, intentions and behavior of people and objects, as well as possible outcomes of their actions and interactions. A device that exhibits common sense reasoning will be capable of predicting results and drawing conclusions that are similar to humans' folk psychology (humans' innate ability to reason about people's behavior and intentions) and naive physics (humans' natural understanding of the physical world).

### 2.3.2 Learning

Machine learning (vide infra) is the study of computer algorithms that improve automatically through experience and has been central to AI research since the field's inception. Unsupervised learning is the ability to find patterns in a stream of input. Supervised learning includes both classification and numerical regression. Classification is used to determine what category something belongs in, after seeing a number of examples of things from several categories. Regression is the attempt to produce a function that describes the relationship between inputs and outputs and predicts how the outputs should change as the inputs change. In reinforcement learning the agent is rewarded for good responses and punished for bad ones.

The agent uses this sequence of rewards and punishments to form a strategy for operating in its problem space. These three types of learning can be analyzed in terms of decision theory, using concepts like utility. The mathematical analysis of machine learning algorithms and their performance is a branch of theoretical computer science known as computational learning theory. Within developmental robotics, developmental learning approaches were elaborated for lifelong cumulative acquisition of repertoires of novel skills by a robot, through autonomous self-exploration and social interaction with human teachers, and using guidance mechanisms such as active learning, maturation, motor synergies, and imitation.

### 2.3.3 Perception

Machine perception is the ability to use input from sensors (such as cameras, microphones, tactile sensors, sonar and others more exotic) to deduce aspects of the world. Computer vision is the ability to analyze visual input. A few selected sub problems are speech recognition, facial recognition and object recognition.

### 2.3.4 Motion and manipulation

The field of robotics is closely related to AI. Intelligence is required for robots to be able to handle such tasks as object manipulation and navigation, with sub-problems of localization (knowing where you are, or finding out where other things are), mapping (learning what is around you, building a map of the environment), and motion planning (figuring out how to get there) or path planning (going from one point in space to another point, which may involve compliant motion – where the robot moves while maintaining physical contact with an object).r9

## 2.4 Languages and environment of AI

AI researchers have developed several specialized languages for AI research, including Lisp and Prolog. Some of the most important by-products of artificial intelligence research have been advances in programming languages and software development environments. For a number of reasons, including the size of many AI application programs, the importance of a prototyping methodology, the tendency of search algorithms to generate huge spaces, and the difficulty of predicting the behavior of heuristically driven programs, AI programmers have been forced to develop a powerful set of programming methodologies.r9

## 2.5 Machine Learning and Deep Learning

The figure below delineates relationship between artificial intelligence, machine learning and deep learning

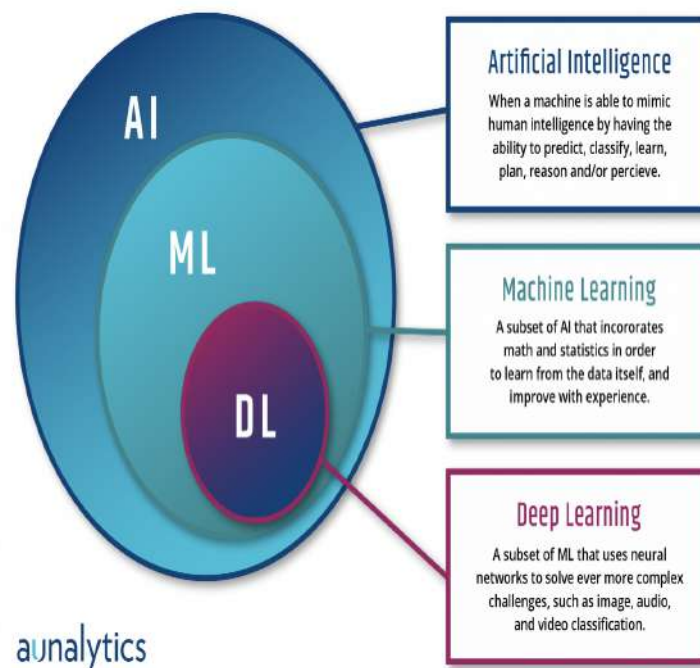


FIGURE 2.3: relation of AI ,ML and DL

## 2.6 AI and ML

Machine Learning is a subset of Artificial Intelligence and it explores the development of algorithms that learn from given data. These algorithms should be able to learn from experience (i.e. the given data) and teach themselves to adapt to new circumstances and perform certain tasks. In programmatic advertising, for example, Machine Learning algorithms help us navigate through the Big Data pool and extract meaningful information, they help us define our most relevant audience and direct our campaign in such way to best meet their preferences. Many AI professionals are not always experienced in ML and vice-versa. Some algorithms are Classification (Neural Network, SVM, CART, Random Forest, Gradient Boosting, and Logistic Regression), Clustering (K-Means Clustering, Hierarchical Clustering, and BIRCH), Regression (Linear/ Polynomial Regression, Curve Fitting), Feature Selection (PCA, ICA, and RFE), Forecasting (ARIMA, ANOVA), and Collaborative Filtering/Recommendation Systems etc. Many data based learning and decision systems are developed using these techniques in areas of Finance, Healthcare, Retail, and E-commerce. Few of the examples are product recommendation system of Amazon, Energy load forecasting in Power industry, Sales Forecasting in retail industry etc.**r9**

List of machine learning algorithms:

1. Decision tree learning:
2. Association rule learning:
3. Artificial neural networks
4. Deep learning

5. Inductive logic programming
6. Support vector machines
7. Clustering
8. Bayesian networks
9. Reinforcement learning
10. Representation learning
11. Similarity and metric learning
12. Sparse dictionary learning
13. Genetic algorithms
14. Rule-based machine learning
15. Learning classifier system

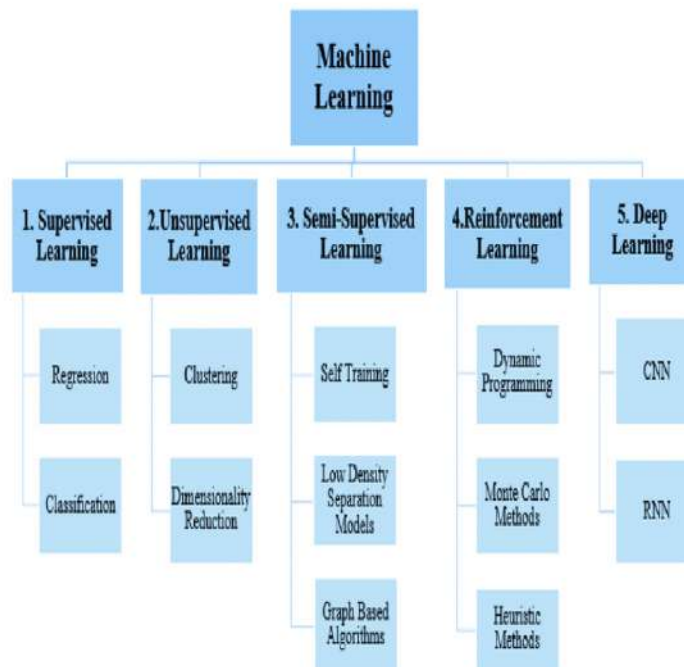


FIGURE 2.4: machine-learning algorithms

## 2.7 Definition of UAV

An unmanned aerial vehicle (UAV) (or uncrewed aerial vehicle commonly known as a drone) is an aircraft without a human pilot on board and a type of unmanned vehicle. UAVs are a component of an unmanned aircraft system (UAS); which include a UAV, a ground-based controller, and a system of communications between the two. The flight of UAVs may operate with various degrees of autonomy: either under remote control by a human operator, autonomously by onboard computers or piloted by an autonomous robot **r10**.

### 2.7.1 Application of UAV

The applications of drones cover a wide range of civil and military applications. Drones can perform both outdoor and indoor missions in very challenging environments **r12**. Drones can be equipped with various sensors and cameras for doing intelligence, surveillance, and reconnaissance missions. The applications of drones can be categorized in different ways. It can be based on the type of missions (military/civil), type of the flight zones (outdoor/indoor), and type of the environments (underwater/on the water/ground/air/space). In Fig. 5, a flowchart of different types of drones' applications is shown [183,184]. As shown in Fig. 5, drones have a variety of applications in our daily life. Drones can have more than two-hundred applications in future according to their types **r13** ; **r14**. For example, these drones can be used for search and rescue missions, environmental protection, mailing and delivery, performing missions in oceans or other planets, and other miscellaneous applications **r15**. These drones can provide a rapid overview around the target area without any danger. Drones equipped with infrared cameras can give images even in the darkness [186]. For instance, because of their reduced dimensions, micro drones can be used for reconnaissance inside buildings. As reported in **r16**, small drones are currently the only way to "look" inside buildings in the battlefield. They can carry specific sensors to locate biological, nuclear, chemical, or other threats **r18**.

### 2.7.2 Challenge of uav

It is difficult to regulate the flying of small drones. Thousands of small drones are sold every year. These products are available easily online and offline. A small drone can be built even by a novice using easily available parts from the Internet. Even a small drone poses high safety risks to large planes and ground installations like fuel depots. There are occasional instances where operators lose control of their UAV during the flight. There have been no serious accidents so far but there are many reports of criminals using drones to supply illegal and banned items into prisons. The insurance aspect is not fully defined and developed. There are privacy risks to people. Drones can fly high and record visible parts of private property. It can be used to look inside homes through windows. [r10]



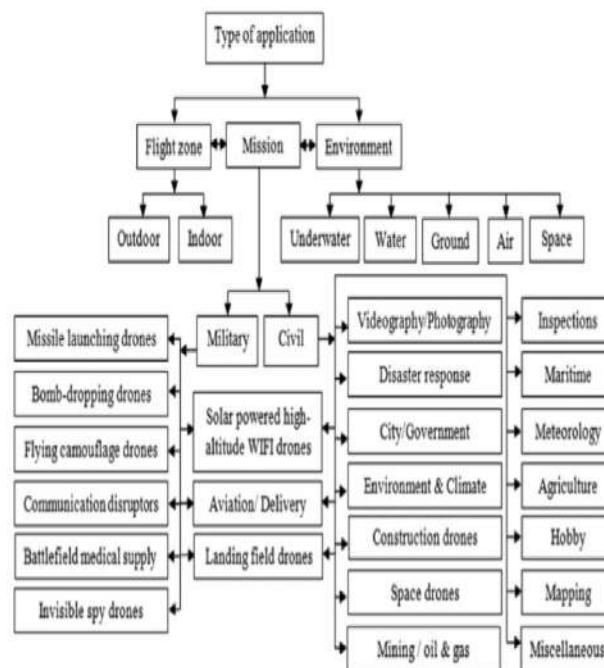


FIGURE 2.5: Classification of drones' applications.

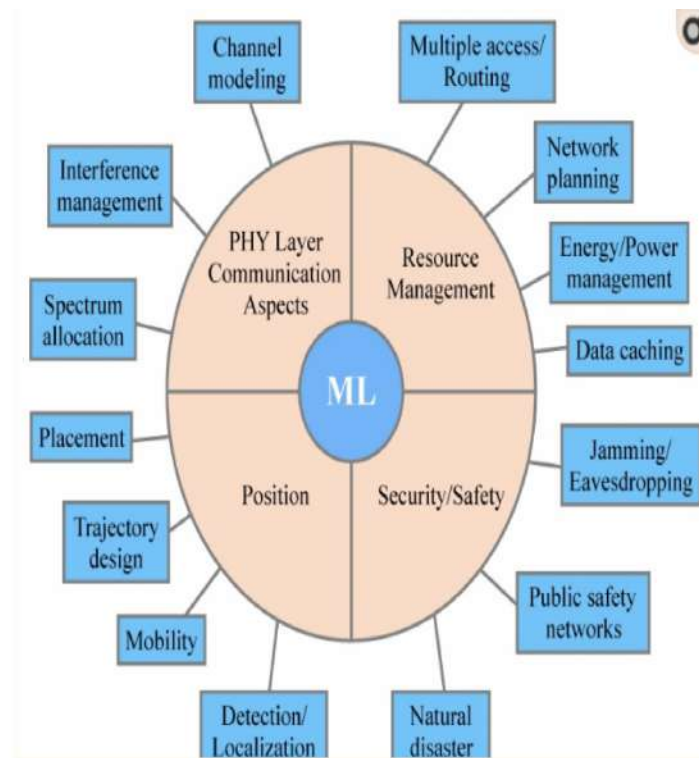
### 2.7.3 IA and UAV

Applications of the AI/ML solutions in UAV-enabled communications are depicted. Generally, the importance of distilling intelligence in wireless communication networks has been outlined in numerous works set of AI/ML techniques for UAV-based communications without focusing on particular AI/ML categories or UAV applications. More specifically, the following contributions are given:

- An exhaustive overview of AI/ML solutions from all possible categories and their application in UAV-based networks is presented.
- A wide range of UAV-enhanced wireless communication issues, ranging from physical layer and resource management aspects up to trajectory design and caching is studied, while wireless security and public safety applications are comprehensively discussed.
- Open issues are identified for both networking and security areas, stimulating further research for the application of AI/ML techniques in UAVs-based networks.

### 2.7.4 Waves + uav

In order to control a drone remotely, you must be able to communicate with it wirelessly. Radio waves are an invisible wave form on the electromagnetic spectrum. Like all things on the electromagnetic spectrum, radio is measured



in hertz (Hz). Extremely low frequency is anywhere from 3Hz to 30Hz and tremendously high frequency is 300 GHz – 3000GHz.

For radio to work, you must have a transmitter to send the messages and a receiver to get the messages. At a rudimentary level, this is how remotely controlling an aircraft is accomplished. More precisely, your transmitter and receiver need to be tuned to the same frequency. To avoid situations such as your drone being controlled by someone else's remote control, devices use a unique identification code to identify a transmission on one particular radio frequency as the transmission it wants to receive. To do this, transmitters and receivers are paired using an RFID or a "radio frequency identification." All information broadcast over RFID is prefixed with an RFID so that the receiver knows that the information it is picking up is for it.

Lower frequencies tend to have a much greater range at lower power than higher frequency devices. Lower frequencies also have a greater ability to penetrate dense objects which is another reason why they are great for remote controlling a drone. However, the lower the frequency, the larger the antenna must be to receive the frequency. Most remote control drones use 900 MHz for transmission. Higher frequencies in the 2.4 GHz range are predominantly used for Wi-Fi. Wi-Fi Controls Wi-Fi used to only be available on computers but as the technology evolved, shrunk, and grew more intelligent, it was integrated into portable devices like phones and tablets. Now there are several million products around the world that are Wi-Fi-enabled so that they can be remotely accessible<sup>18</sup>.

Most drones today are Wi-Fi enabled so that they can broadcast video to a computer, tablet, or Smartphone. Some drones also use Wi-Fi for remote controlling through a tablet or mobile application. The Parrot AR Drone 2.0

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offers high-end interactive controls with their mobile application that runs on an iPhone or iPad . While there are clear benefits to using Wi-Fi with your drone, Wi-Fi works on an ultra-high radio frequency which means that its range is limited to about 600 meters. GPS Global positioning technology has shrunk down enough that it is possible to ping satellites for location data from devices as small as a Smartphone and your drone. GPS is primarily only used to communicate location back to a mobile app. GPS is also used for pre-programming routes. Once programmed, the drone can be cut loose and it will fly in sequence to each of the GPS locations identified.

## **Chapter 3**

### **state of art technology**

## 3.1 motivation

Over the years, the use of drones has become increasingly in the community that we currently live in. Its uses spread outside the military sector and became used in Various commercial activities such as parcel delivery, disaster relief, agriculture and is very famous in the photography business. Drones increased popular for personal use due to the affordability, ease of operation of the drone from Smart devices such as cell phones, tablets, and computers. As such, this increases the likelihood The presence of drones in various environments, especially in government areas and There are many malicious actors seeking to develop drones that are difficult to detect, disruption and exclusion of their threat. And in order to build a safer world, good researchers must work on it improved technologies to detect, combat and destroy malicious drones.

## 3.2 Related work

Unmanned aerial vehicles (UAV) have been the subject of many recent studies. In This chapter, we provide a detailed survey of some relevant research works, in which artificial intelligence techniques have been used to detection of UAV.

## 3.3 MADDOS is an innovative system for detection and neutralization of drones

The MADDOS system is designed to detect the intrusion of unwanted drones by using real time directional measurements of the drone's electromagnetic emissions (including its remote control). The system has no limitation with regard to its detection range. Usually, the detection range is the same (or better) as the usable distance between the operator and the drone, thus depending on the transmitter power of the drone/its operator. Taking into account the various drone types and topography, this range can be up to 50 km or more. The drone detection system can be used virtually anywhere. It is available as a single-site or multiple-site solution and can be adjusted to the characteristics of the respective terrain/area to be monitored.

MADDOS triggers an alarm as soon as a remote control sends a signal, which is even before the actual drone is airborne. Countermeasures can therefore be initiated at a much earlier stage. Multiple graduated alarm zones, simultaneous display of all drones and remote controls, automatic classification of all targets, optical target verification and tracking, real-time recording of all raw data including IQ and video, as well as a simultaneous 2D and 3D view, topographic terrain structures up to complex 3D models of the objects to be secured (airports, cities, industrial plants) – those are the outstanding functions offered by MADDOS. MADDOS can be extended to include an automated, integrated jammer that can effectively prevent a



FIGURE 3.1: MADDOS.

drone from receiving RF contact/signals, thus forcing it into fail-safe mode, e.g. to land or to hover. The interference is extremely selective so that other RF channels are not impaired. Besides being highly selective, the jammer is extremely directional and only jams in the direction of the incoming UAV. It has got extremely high jamming range of up to 8 km and covers up to 16 bands. It also covers most of all commercially available drone models.<sup>19</sup>

### 3.4 Ouranos RF Scanner

Ouranos RF Scanner is designed for detection and direction finding of commercially available drones equipped with a video broadcasting system operating in the standard frequency bands, and also for the detection and direction finding of drone ground station control signals. Not only the direction but also the position of the source can be determined if at least two or more sensors detect the signal OURANOS-RF utilizes the classic AoA type of direction-finding method. This solution provides the best performance with fast response time and fewer limitations. The main advantage is that as soon as any of the sensors capture the signal of interest, the user will get an alarm with direct information included. In many cases, this information is enough for the responsible personnel to trigger the counter activity. As soon as two or more sensors detect the signal, the OURANOS-RF can provide location information as well. In real life, we come across plenty of RF emitting devices irrespective of the location. There might be many interfering signals in a specific band of interest (e.g., 802.11-WiFi standards, Bluetooth, ZigBee,



FIGURE 3.2: Ouranos

etc.) against which the system should perform well. The overlapping signals could degrade the detection performance, classification, and direction-finding. We took these constraints into consideration right from the early stages of the development in order to create a system that can cope with very low SNR and overlapping interference signals. Our systems can also perform very well in the case of strong out-of-band RF signals (e.g., near-field radars, mobile base stations, PMR stations, repeaters).<sup>20</sup>

### 3.5 Drone Detection System -DTS-2458

Rantelon's drone detection system DTS-2458 is based on directional real-time measurement of the RF emissions of the drone and its remote control. It warns the operator when drones are in the vicinity. The system has no limitation regarding the detection range but it is usually comparable to the maximum distance between the drone and the remote controller, i.e. the detection range is dependent on the transmitter power of the drone. The system detects the RF emissions as soon as the emitting device is turned on, allowing to detect the drone before it has taken off. Furthermore, because the system is based on detecting electromagnetic emissions, it is not affected by other flying objects such as birds or balloons. In addition to detecting the direction and presence of the drone, the system is also capable of detecting the direction of the remote controller. The system comprises of a tracking antenna, radio front-end and analysis software. Multiple detector systems can be connected together for accurate geolocation of drones and remotes. The system can also be integrated with other Rantelon jammers.<sup>21</sup>

### **3.6 Drone Detection Approach Based on Radio-Frequency Using Convolutional Neural Network**

Recently, Unmanned Aerial Vehicles, also known as drones, are becoming rapidly popular due to the advancement of their technology and the significant decrease in their cost. Although commercial drones have proven their effectiveness in many day to day applications such as cinematography, agriculture monitoring and search and rescue, they are also being used in malicious activities that are targeting to harm individuals and societies which raises great privacy, safety and security concerns. In this research, we propose a new drone detection solution based on the Radio Frequency (RF) emitted during the live communication session between the drone and its controller using a Deep Learning (DL) technique, namely, the Convolutional Neural Network (CNN). The results of the study have proven the effectiveness of using CNN for drone detection with accuracy and F1 score of over 99.7 and drone identification with accuracy and F1 score of 88.4 . Moreover, the results yielded from this experiment have outperformed those reported in the literature for RF based drone detection using Deep Neural Networks. Index Terms—Drone Detection, Drone Identification, Radio Frequency, Deep learning, DL, CNN, machine learning, ML, Infrastructure Security, Convolutional Neural Networks, RF.22

### **3.7 Micro-UAV Detection and Classification from RF Fingerprints Using Machine Learning Techniques**

in this paper focuses on the detection and classification of micro-unmanned aerial vehicles (UAVs) using radio frequency (RF) fingerprints of the signals transmitted from the controller to the micro-UAV. In the detection phase, raw signals are split into frames and transformed into the wavelet domain to remove the bias in the signals and reduce the size of data to be processed. A naive Bayes approach, which is based on Markov models generated separately for UAV and non-UAV classes, is used to check for the presence of a UAV in each frame. In the classification phase, unlike the traditional approaches that rely solely on time-domain signals and corresponding features, the proposed technique uses the energy transient signal. This approach is more robust to noise and can cope with different modulation techniques. First, the normalized energy trajectory is generated from the energy-time-frequency distribution of the raw control signal. Next, the start and end points of the energy transient are detected by searching for the most abrupt changes in the mean of the energy trajectory. Then, a set of statistical features is extracted from the energy transient. Significant features are selected by performing neighborhood component analysis (NCA) to keep the computational cost of the algorithm low. Finally, selected features are fed to several machine learning algorithms for classification. The algorithms are evaluated



experimentally using a database containing 100 RF signals from each of 14 different UAV controllers. The signals are recorded wirelessly using a high-frequency oscilloscope. The data set is randomly partitioned into training and test sets for validation with the ratio 4:1. Ten Monte Carlo simulations are run and results are averaged to assess the performance of the methods. All the microUAVs are detected correctly and an average accuracy of 96.3 is achieved using the k-nearest neighbor (kNN) classification. Proposed methods are also tested for different signal-to-noise ratio (SNR) levels and results are reported.<sup>23</sup>

### **3.8 Machine Learning-Based Drone Detection and Classification**

This paper presents a comprehensive review of current literature on drone detection and classification using machine learning with different modalities. This research area has emerged in the last few years due to the rapid development of commercial and recreational drones and the associated risk to airspace safety. Addressed technologies encompass radar, visual, acoustic, and radio-frequency sensing systems. The general finding of this study demonstrates that machine learning-based classification of drones seems to be promising with many successful individual contributions. However, most of the performed research is experimental and the outcomes from different papers can hardly be compared. A general requirement-driven specification for the problem of drone detection and classification is still missing as well as reference datasets which would help in evaluating different solutions.<sup>24</sup>

### **3.9 RF-based drone detection and identification using deep learning approaches**

The omnipresence of unmanned aerial vehicles, or drones, among civilians can lead to technical, security, and public safety issues that need to be addressed, regulated and prevented. Security agencies are in continuous search for technologies and intelligent systems that are capable of detecting drones. Unfortunately, breakthroughs in relevant technologies are hindered by the lack of open source databases for drone's Radio Frequency (RF) signals, which are remotely sensed and stored to enable developing the most effective way for detecting and identifying these drones. This paper presents a stepping stone initiative towards the goal of building a database for the RF signals of various drones under different flight modes. We systematically collect, analyze, and record raw RF signals of different drones under different flight modes such as: off, on and connected, hovering, flying, and video recording. In addition, we design intelligent algorithms to detect and identify intruding drones using the developed RF database. Three deep neural networks (DNN) are used to detect the presence of a drone, the presence of a drone and its type, and lastly, the presence of a drone, its type, and flight mode.

Performance of each DNN is validated through a 10-fold cross-validation process and evaluated using various metrics. Classification results show a general decline in performance when increasing the number of classes. Averaged accuracy has decreased from 99.7 for the first DNN (2-classes), to 84.5 for the second DNN (4-classes), and lastly, to 46.8 for the third DNN (10-classes). Nevertheless, results of the designed methods confirm the feasibility of the developed drone RF database to be used for detection and identification. The developed drone RF database along with our implementations are made publicly available for students and researchers alike.<sup>2</sup>

### **3.10 Conclusion**

With the background from this paper and the ones above, in this thesis will try to extend the finding for detection drone using machine learning

# **Chapter 4**

## **software and material**

## 4.1 Introduction

Since collection and processing of UAV data is a long process, involving data collection, pre-processing RF dataset for creation of a suitable model for results visualization and interpretation. This chapter of the theses describes each step and methods to data collection and analysis to utilize them with leveraged potential and makes a comparison of algorithm of machine learning dedicated for detection of UAV data collection and processing.

## 4.2 Experimental

this experimental developed a drone detector system based on RF signal analysis and classify the drones using a machine learning algorithm The system will be implemented using a software Our approach is based on The drone is made of two fundamental parts which are the remote control and the aircraft. Both communicate with one another using a radio frequency communication link the figure below presents the architecture and components of the experimental. For our RF classification, we will be focusing on the communication between remote controller and drone the remote controller can directly control the drone by means of control, data and video transmission communicate and send information between each other. The majority of controllers use the 2.4 GHz spectrum.

## 4.3 Experimental setup

The setup is shown in Fig. 1. To conduct any experiment using this setup, one must perform the following tasks carefully and sequentially. 1- Turn on the drone under analysis and connect to it using remote controller. 2- Check the drone connectivity and operation by performing simple takeoff, hovering, and landing tests 3- Turn on the Radar to intercept all RF activities and to transfer those to the arduino via the cable connectors to transfer those to laptops 4- Open the LabVIEW programs, installed on the laptops, and select appropriate parameters depending on your experiment and requirements. 5- Start the LabVIEW programs to fetch process and store RF data segments. 6- Stop the LabVIEW programs when you are done with the experiment. 7- We Re-experiment, for a different flight mode. 8- We collected data for deferent scenarios that will be used as the base of our classification the classification using the machine learning testing block with following steps

- 1) Data-set collection.
- 2) Dataset Preprocessing
- 3) Feature Extraction
- 4) Model Training
- 5) Deploying the best performing classifier for inference.

## 4.4 System architecture

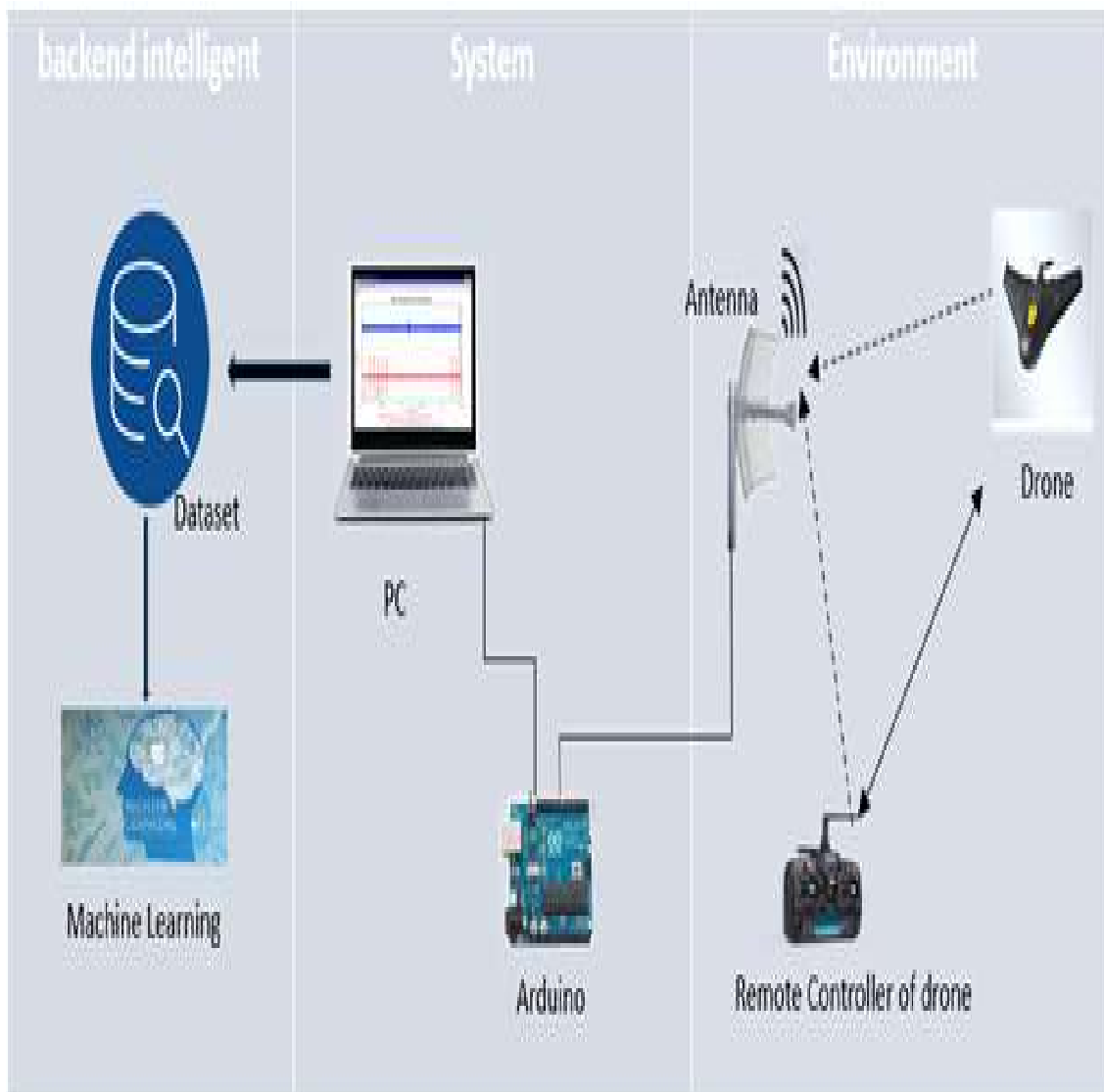


FIGURE 4.1: architecture of the system

### 4.4.1 Hardware components

#### Parrot Disco FPV

Parrot Disco FPV – Easy to fly fixed wing drone, up to 45 minutes of flight time, r32 50 mph top speed, FPV goggles

- Fixed-wing drone that reaches speeds up to 50 mph
- Ultra-precise piloting and extended flight range of up to 1.2 mile with Parrot Sky controller 2
- Immersive flight experience with Parrot cockpit glasses (FPV goggles)
- Shoot full HD 1080P videos and 14Mpx photos with the built-in wide-angle camera. Footage can be captured in RAW, JPEG and DNG format.

- High capacity 2700mAh battery with up to 45 min battery life
- Easy to fly with automatic take-off and landing, assisted piloting controls, anti-stall system, and Return Home functionality
- Compatible Smartphone screen size for the Cockpit glasses: 4.7 - 5.2" / 12 - 13 cm



### Arduino Uno



FIGURE 4.2: .Arduino uno

The Arduino Uno is an open-source microcontroller board based on the Microchip ATmega328P microcontroller and developed by Arduino.cc. The board is equipped with sets of digital and analog input/output (I/O) pins that may be interfaced to various expansion boards (shields) and other circuits. The board has 14 digital I/O pins (six capable of PWM output), 6 analog I/O pins, and is programmable with the Arduino IDE (Integrated Development Environment), via a type B USB cable. It can be powered by the USB cable or by an external 9-volt battery, though it accepts voltages between 7 and 20 volts. It is similar to the Arduino Nano and Leonardo. The hardware reference design is distributed under a Creative Commons Attribution Share-Alike 2.5 license and is available on the Arduino website. Layout and production files for some versions of the hardware are also available<sup>31</sup>. The word "uno" means "one" in Italian and was chosen to mark the initial release of Arduino Software. the Uno board is the first in a series of USB-based Arduino boards; it and version 1.0 of the Arduino IDE were the reference versions of Arduino, which have now evolved to newer releases. The ATmega328 on the board comes preprogrammed with a bootloader that allows uploading new code to it without the use of an external hardware programmer. While the Uno communicates using the original STK500 protocol, it differs from all preceding boards in that it does not use the FTDI USB-to-serial driver chip. Instead, it uses the Atmega16U2 (Atmega8U2 up to version R2) programmed as a USB-to-serial converter

### Labview

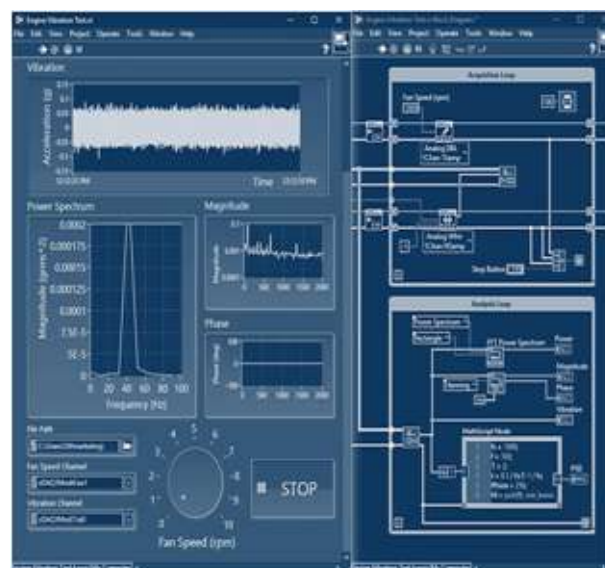


FIGURE 4.3: labview

Laboratory Virtual Instrument Engineering Workbench (LabVIEW) is a system-design platform and development environment for a visual programming language from National Instruments. The graphical language is named "G"; not to be confused with G-code. Originally released for the Apple Macintosh in 1986, LabVIEW is commonly used for data acquisition, instrument

control, and industrial automation on a variety of operating systems (OSs), including Microsoft Windows, various versions of Unix, Linux, and macOS.**r29**  
The latest versions of LabVIEW are LabVIEW 2020 and LabVIEW NXG 5.0, released in May 2020.[2] NI released the free for non-commercial use LabVIEW and LabVIEW NXG Community editions on April 28th, 2020.7. **r30**

### **Antenna**

Features :

Die-cast aluminum construction.  
UV stable light gray powder coat finish.



8 beam-width and 12 inch coax lead.  
Easy to assemble.  
All weather operation.

Applications:

2.4 GHz ISM Band  
IEEE 802.11b/g/n Wireless LAN Applications.  
WiFi Systems and Long - range Directional Applications.  
Point to Point Systems and Point to Multi-point Systems.  
Wireless Bridges, Back haul Applications and Wireless Video. Systems.**r33**

### **WEKA**

Weka contains a collection of visualization tools and algorithms for data analysis and predictive modeling, together with graphical user interfaces for easy access to these functions.[1]





h

FIGURE 4.4: weka application

The original non-Java version of Weka was a Tcl/Tk front-end to (mostly third-party) modeling algorithms implemented in other programming languages, plus data preprocessing utilities in C, and a Make file-based system for running machine learning experiments. This original version was primarily designed as a tool for analyzing data from agricultural domains,[2][3] but the more recent fully Java-based version (Weka 3), for which development started in 1997, is now used in many different application areas, in particular for educational purposes and research. Advantages of Weka include:


- Free availability under the GNU General Public License.
- Portability, since it is fully implemented in the Java programming language and thus runs on almost any modern computing platform.
- A comprehensive collection of data preprocessing and modeling techniques.
- Ease of use due to its graphical user interfaces.

Weka supports several standard data mining tasks, more specifically, data preprocessing, clustering, classification, regression, visualization, and feature selection. All of Weka's techniques are predicated on the assumption that the data is available as one flat file or relation, where each data point is described by a fixed number of attributes (normally, numeric or nominal attributes, but some other attribute types are also supported).<sup>26</sup> Weka provides access to SQL databases using Java Database Connectivity and can process the result returned by a database query. Weka provides access to deep learning with Deeplearning.<sup>[4]</sup> it is not capable of multi-relational data mining, but there is separate software for converting a collection of linked database tables into a single table that is suitable for processing using Weka.<sup>[5]</sup> Another important area that is currently not covered by the algorithms included in the Weka distribution is sequence modeling.<sup>27</sup>

## laptop

Édition Windows


Windows 7 Édition Intégrale  
 Copyright © 2009 Microsoft Corporation. Tous droits réservés.  
 Service Pack 1




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Système

Fabricant : Toshiba

Évaluation :  [Indice de performance Windows](#)

Processeur : Intel(R) Core(TM) i5-4200M CPU @ 2.50GHz 2.50 GHz

Mémoire installée (RAM) : 8,00 Go

Type du système : Système d'exploitation 64 bits

Stylet et fonction tactile : La fonctionnalité de saisie tactile ou avec un stylet n'est pas disponible sur cet écran

**TOSHIBA**

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Toshiba - support

Numéro de téléphone : 1-800-316-0920

Site Web : [Support en ligne](#)

---

Paramètres de nom d'ordinateur, de domaine et de groupe de travail

Nom de l'ordinateur : TOSHIBA-PC

Nom complet : TOSHIBA-PC

Description de l'ordinateur :

Groupe de travail : WORKGROUP


[Modifier les paramètres](#)

---

Activation de Windows

Windows est activé.

ID de produit : 00426-OEM-8992662-00006



## 4.5 Activity diagram

The following diagram has two main parts, the environment and the system. The first part is the environment we collect data exchanged with drone and remote controller .the second part is our system we have a signal data collection we preprocessing data with processing tools data will structured and filtered for training data set or testing ,we training the model with machine learning algorithms that we have .

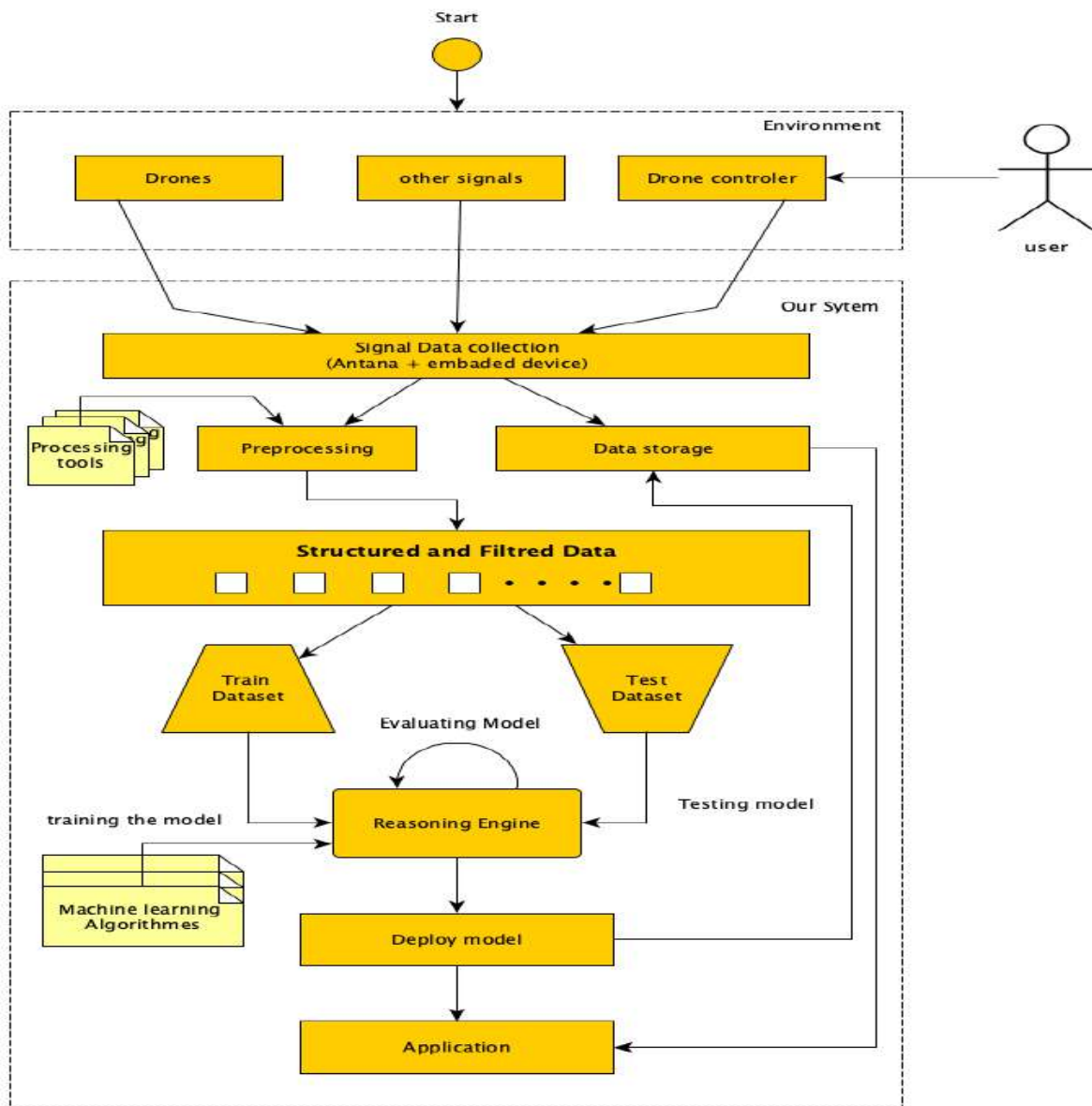


FIGURE 4.5: Activity diagram

## **Chapter 5**

# **DATA AND METHODOLOGY**

This chapter describes the proposed methodology and the automatic drone detection system is also outlined. First, on a system-level and thereafter in deeper detail, both regarding hardware components, and the involved software. after that follows a description of the software running in the drone detection system when it is active, including the graphical user interface. the support software used for such tasks as to collect data and to evaluate the performance after training the data with algorithms of ML is also described. For all parts that include a machine learning feature, the training process is also presented. In our project, we focus on dataset and machine learning algorithms that we are testing with and comparing their results in order to obtain the best model for detecting drones using radio frequency .

## 5.1 The used dataset

Machine learning is about learning from data. Both the quality and quantity of data used in training and testing are vital for learning powerful classification models, the data should cover a wide range of cases. In Our objective the dataset is :

we present an RF based dataset of drones functioning in different modes.

The dataset consists of recorded segments of RF background activities with no drones, and segments of drones operating in different modes such as: off, on and connected, hovering, flying, and video recording, The records are 10.25 seconds of RF background activities and approximately 5.25 seconds of RF drone communications for each flight mode. This has produced a drone RF database with over 40 GB of data encompassing various RF signatures. There are in total 227 segments , each segment consists of two equally sized parts with each part containing 1 million samples, making in total 454 record files. The samples in the segments represent the amplitude of the acquired raw RF signals in the time domain. The segments in the database 34. are stored as comma-separated values (csv) files, this makes the drone RF database easy to load and interpret on any preferred software. Metadata for each segment in the database is included within its filename. It contains the segment Binary Unique Identifier (BUI) to differentiate between the drone's mode followed by a character to determine if it is the first or second half of the segment, and its segment number. For instance, the third segment of the second half of the RF spectrum with BUI = 11010, Phantom drone with flight mode number 3, will have the following filename: "11010H3.csv". [r35]

## 5.2 Methodology

### 5.2.1 Pre-processing

Data Preprocessing is a technique that is used to convert the raw data into a clean data set. In other words, whenever the data is gathered from different sources it is collected in raw format which is not feasible for the analysis<sup>37</sup>.



FIGURE 5.1: Experimental setup for the RF database development. The Bebop drone is shown on the middle, the NI-USRP RF receivers are shown on the right and are connected to the laptops, shown on the left, via the PCIe connectors



FIGURE 5.2: NI USRP-2943R RF receiver

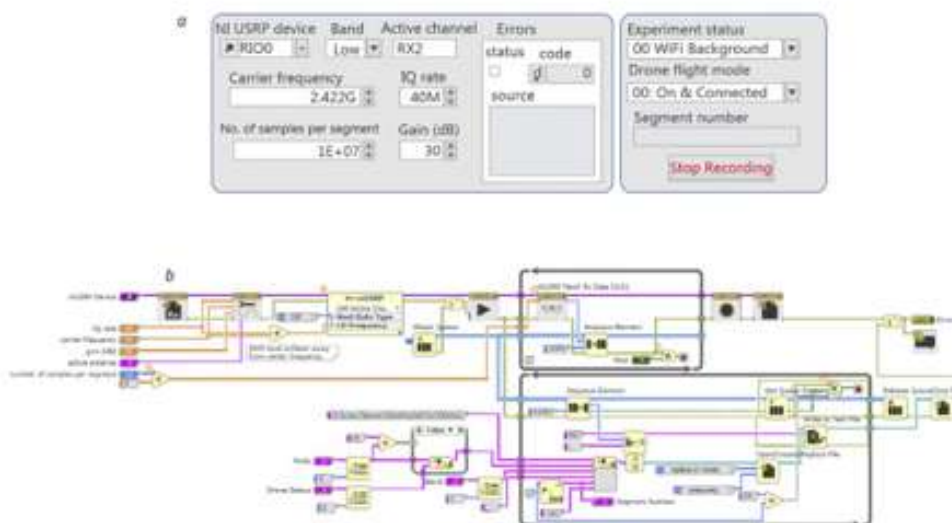


FIGURE 5.3: Front panel of the LabVIEW program installed on the laptops to capture the drones' RF communication r36. b: Block diagram of LabVIEW program

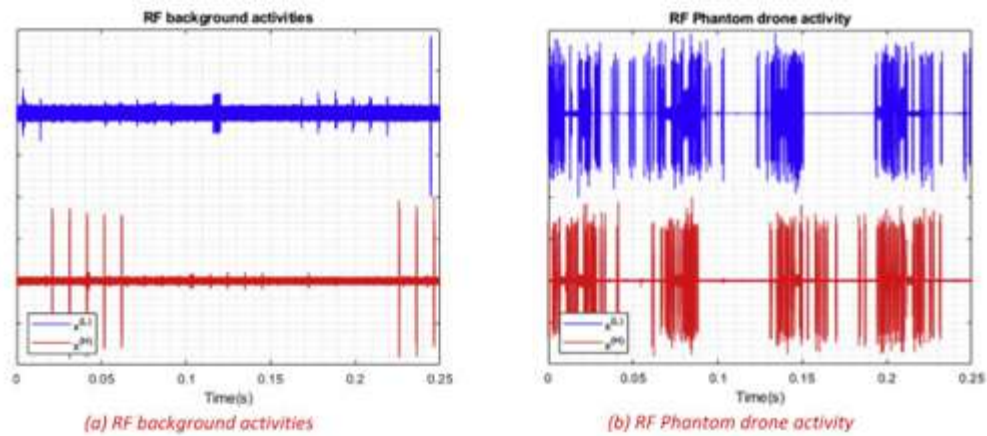


FIGURE 5.4: RF activities plots with normalized amplitudes between 1 and -1. (a) shows segment number 13 of the acquired RF background activities, (b) shows segment number 10 of the acquired Phantom drone activity

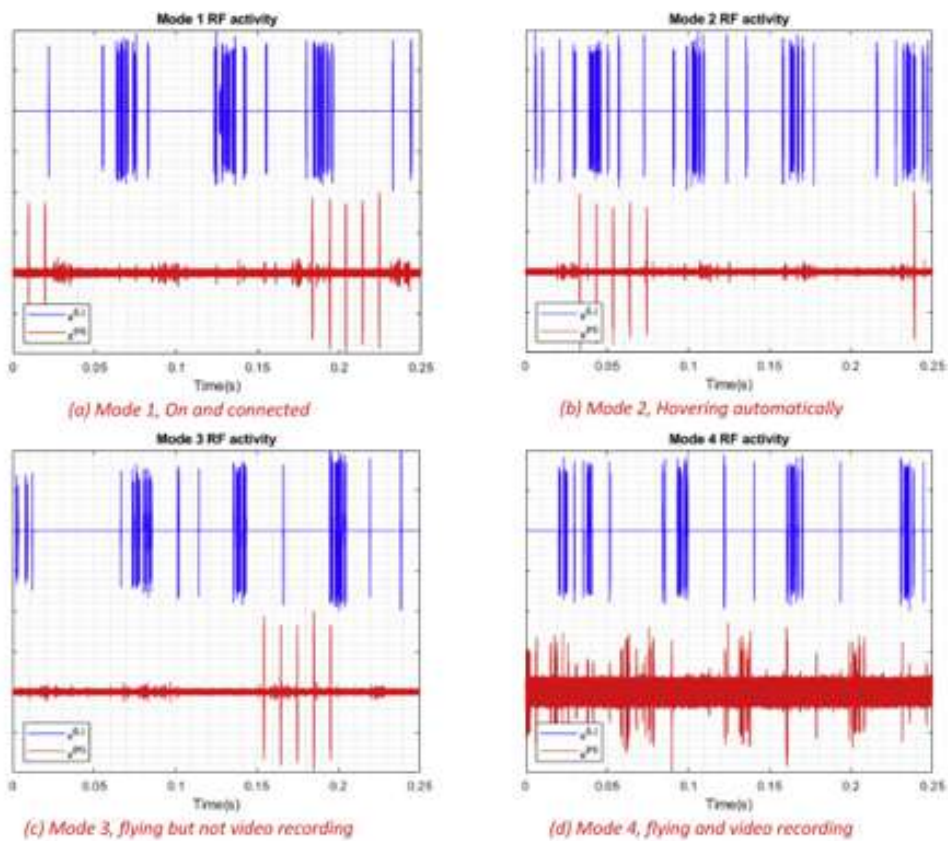


FIGURE 5.5: Different snippets of RF activities for different flight modes for the Bebop drone with normalized amplitude between 1 and -1. Each figure shows the segment number 1 of each flight mode

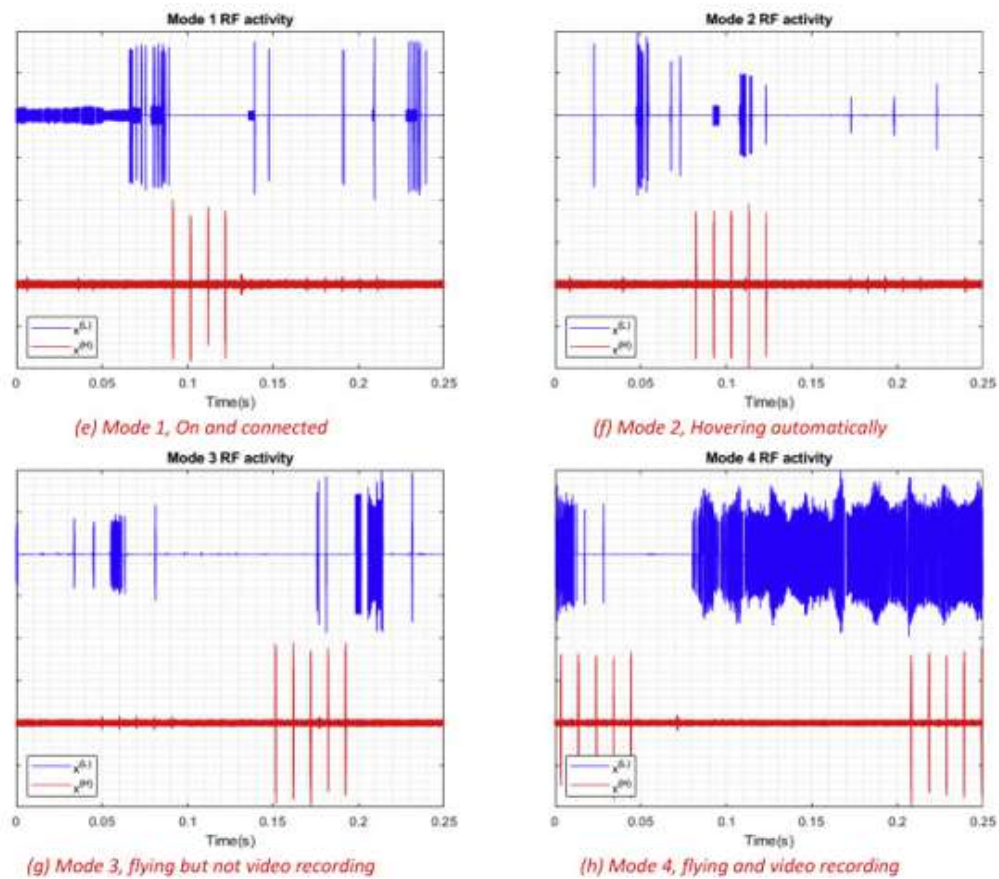


FIGURE 5.6: Different snippets of RF activities for different flight modes for the AR drone with normalized amplitude between 1 and -1. Each figure shows the segment number 1 of each flight mode



| Drone Type | Segments | Samples             | Ratio  |
|------------|----------|---------------------|--------|
| Bepop      | 84       | $1.680 \times 10^6$ | 37.00% |
| AR         | 81       | $1.620 \times 10^6$ | 35.68% |
| Phantom    | 21       | $420 \times 10^5$   | 9.25%  |
| No Drone   | 41       | $820 \times 10^5$   | 18.06% |

Table 1. Details of the developed drone RF database showing the number of raw samples and segments for each drone type.

FIGURE 5.7

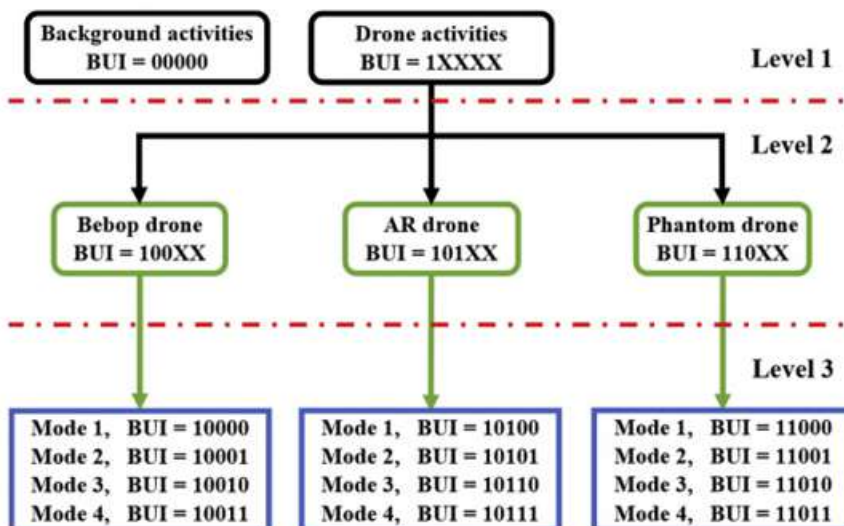


FIGURE 5.8: Experiments to record drones RF signatures organized in a tree manner consisting of three levels. The horizontal dashed red lines define the levels. BUI is a Binary Unique Identifier for each component to be used in labelling

Raw RF signal data is complex valued. In this work, there are several data preprocessing stages we have used to set up data and they are listed below:

### 5.2.2 data cleaning

is the process of detecting and correcting (or removing) corrupt or inaccurate records from a record set, table, or database and refers to identifying incomplete, incorrect, inaccurate or irrelevant parts of the data and then replacing, modifying, or deleting the dirty or coarse data **r38**.

### 5.2.3 Instance selection

(or dataset reduction, or dataset condensation) is an important data preprocessing step that can be applied in many machine learning (or data mining) tasks. Approaches for instance selection can be applied for reducing the original dataset to a manageable volume, leading to a reduction of the computational resources that are necessary for performing the learning process. Algorithms of instance selection can also be applied for removing noisy instances, before applying learning algorithms. This step can improve the accuracy in classification problems **r39**.

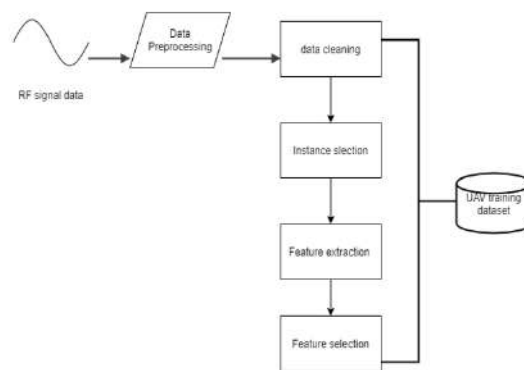
### 5.2.4 Feature extraction

starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction. **r40**

### 5.2.5 feature selection

Also known as variable selection, attribute selection or variable subset selection, is the process of selecting a subset of relevant features (variables, predictors) for use in model construction. Feature selection techniques are used for several reasons: • simplification of models to make them easier to interpret by researchers/users, **r10** • shorter training times, • to avoid the curse of dimensionality, • enhanced generalization by reducing overfitting **r41** (formally, • reduction of variance) **r42**

- After that, we created a program in Java to convert a file that contained data from a text file containing unorganized data, and the data were continuous values into an organized excel file and the values were all in a specific field. And after that Data labeling Y takes the value 'yes' when the data haven radio frequency raw of drone and labeled 'no' for data without RF raw of drone.



### 5.3 Pre processing steps example

1-The SNR of the received RF signal varies with the distance and transmitted power of the wireless source. Higher SNRs can be achieved in multiple ways **r43**, **r44**. One such way is the use of the wavelet transform for removing the bias in the received RF signals and de-noising up to a certain extent.**r43**, **r45**, **r46**. The use of wavelets provides the two-fold advantage compared to the traditional time domain and Fourier domain analysis **r47**. One is the improvement in the SNR (de-noising) and other in the data compression without loss of information. The former aspect is important to improve the detection capability. The latter aspect is important for low complexity system design which result in faster detection algorithms. In this study, a three-stage wavelet decomposition is used, Low-pass  $g[n]$  and high-pass  $h[n]$  filters of the Haar transform are chosen due to their simplicity. Each filter is followed by a down sampler, Wavelet coefficients obtained after the third level are considered as inputs to the detection algorithm both for training and testing the RF signals. An example of the RF signal received from the microUAV controller of DJI Matrice 100 and the corresponding wavelet transformed signal It is clear from the figure that the wavelet transform removes the bias and reduces the number of samples while preserving the structure associated with the original raw signal **r48**

2-Data preprocessing can be divided into the following two steps: Step 1: Perform start-point detection of original signals, signal envelopes of different preambles after the interception of start-point detection are shown in Fig.8(a), Fig. 9(a) and Fig. 10(a). **r49**

```

1
2
3 public class test {
4
5
6     public static void main(String[] king) {
7
8         file f = new file();
9
10        String lines[] = f.Read_from_file("backgroundrf.txt");
11
12        System.out.println(lines[0]);
13        System.out.println();
14
15        String lineX = lines[0];
16
17        System.out.println(lineX.substring(1, lineX.length()).split(",")[0]);
18
19
20        User_Excel_file User_Excel_file = new User_Excel_file();
21
22        Object [][] o = new Object[1000][100];
23
24        System.out.println(lines.length);
25        for(int i = 0 ; i< 1000; i++) {
26            System.out.println(lines[i]);
27            try {
28                for(int j = 0 ; j< 100; j++) {
29
30                    o[i][j] = lines[i].substring(1, lines[i].length()).split(",")[j];
31
32                }
33            } catch (Exception e) {
34
35            }
36
37        }
38
39    }
40
41    User_Excel_file.Write_infile(o, "RFdataDRONE.xls");
42
43    // System.out.println(lines[1]);
44    // System.out.println();
45    // System.out.println(lines[2]);
46
47 }

```

FIGURE 5.9: Java program for organizing and arranging data

```

-2.000000,0.000000,5.000000,2.000000,3.000000,7.000000,-1.000000,6.000000,-2.000000,3.000000,-3.000000,4.000000,0.000000,4.000000,0.000000,-3.000000,3.000000,-3.000000,-5.000000,0.00
000000,3.000000,2.000000,4.000000,-1.000000,6.000000,-1.000000,5.000000,1.000000,2.000000,-2.000000,-1.000000,-1.000000,2.000000,-2.000000,2.000000,3.000000,3.000000,2.000000,-4.0000
000000,5.000000,4.000000,-1.000000,1.000000,-4.000000,5.000000,-6.000000,1.000000,-5.000000,-4.000000,-2.000000,-7.000000,1.000000,-4.000000,2.000000,-3.000000,3.000000,0.000000,4.00
000000,-3.000000,2.000000,-4.000000,-2.000000,2.000000,3.000000,2.000000,0.000000,0.000000,2.000000,-2.000000,1.000000,-1.000000,1.000000,3.000000,5.000000,-4.000000,3.000000,-3.000000,
000,-3.000000,6.000000,-2.000000,3.000000,1.000000,2.000000,-5.000000,1.000000,-3.000000,0.000000,-2.000000,-2.000000,0.000000,-2.000000,2.000000,-4.000000,-1.000000,-2.000000,-2.0000
000000,1.000000,1.000000,0.000000,-3.000000,0.000000,-2.000000,3.000000,0.000000,2.000000,2.000000,1.000000,6.000000,0.000000,0.000000,0.000000,3.000000,-2.000000,1.000000
1.000000,-2.000000,5.000000,-2.000000,0.000000,4.000000,1.000000,0.000000,4.000000,1.000000,4.000000,0.000000,7.000000,0.000000,1.000000,0.000000,0.000000,3.000000,1.000000,0.000000
000,-2.000000,2.000000,1.000000,5.000000,-3.000000,1.000000,-1.000000,0.000000,3.000000,-1.000000,2.000000,0.000000,-4.000000,3.000000,-2.000000,-2.000000,0.000000,1.000000,2.000000,-
2.000000,0.000000,0.000000,3.000000,2.000000,0.000000,3.000000,-6.000000,2.000000,-2.000000,0.000000,-3.000000,2.000000,0.000000,2.000000,-1.000000,1.000000,2.000000,1.000000,0.0000
000,-3.000000,0.000000,2.000000,1.000000,-1.000000,4.000000,-2.000000,2.000000,3.000000,0.000000,0.000000,3.000000,-4.000000,-2.000000,-4.000000,0.000000,-2.000000,1.000000,1.000000,
0000,2.000000,0.000000,0.000000,4.000000,0.000000,0.000000,2.000000,-1.000000,-1.000000,-1.000000,-1.000000,-3.000000,5.000000,-1.000000,-4.000000,1.000000,1.000000,-1.000000,-1.0000
0,1.000000,-3.000000,-3.000000,4.000000,-6.000000,-2.000000,0.000000,-4.000000,-2.000000,-2.000000,1.000000,2.000000,1.000000,-2.000000,3.000000,-3.000000,-5.000000,1.000000,2.000000,0
3.000000,3.000000,-7.000000,4.000000,-1.000000,0.000000,-1.000000,-2.000000,3.000000,-3.000000,0.000000,-1.000000,3.000000,0.000000,-1.000000,-1.000000,-1.000000,-2.000000,2.000000,-4
4.000000,4.000000,2.000000,-4.000000,-1.000000,1.000000,2.000000,-6.000000,-1.000000,1.000000,-3.000000,4.000000,3.000000,2.000000,4.000000,0.000000,2.000000,-2.000000,7.000000,1.000
1.000000,-3.000000,-2.000000,-3.000000,1.000000,3.000000,-4.000000,4.000000,-2.000000,-3.000000,-1.000000,-1.000000,-1.000000,1.000000,-2.000000,1.000000,1.000000,1.000000,-1.000000,5
00,-4.000000,3.000000,2.000000,0.000000,0.000000,0.000000,-2.000000,3.000000,-7.000000,-1.000000,-3.000000,-5.000000,2.000000,0.000000,-3.000000,1.000000,-1.000000,-1.000000,3.000000,
00,-3.000000,-2.000000,0.000000,1.000000,-2.000000,-4.000000,0.000000,1.000000,-1.000000,0.000000,3.000000,-2.000000,-4.000000,2.000000,0.000000,-3.000000,-3.000000,3.000000,2.000000,
5.000000,-3.000000,0.000000,-1.000000,-1.000000,-3.000000,1.000000,2.000000,0.000000,-2.000000,2.000000,2.000000,-3.000000,3.000000,-4.000000,2.000000,-2.000000,-3.000000,1.000000,2.0

```

FIGURE 5.10: Data before organizing it in the program

|    | AZ        | BA        | BB        | BC        | BD        | BE        | BF        | BG        | BH        | BI        | BJ        | BK        | BL        |
|----|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| 1  | x52       | x53       | x54       | x55       | x56       | x57       | x58       | x59       | x60       | x61       | x62       | x63       | x64       |
| 2  | 0         | 0         | 0         | 0         | 0         | 0         | 0         | 0         | 0         | 0         | 0         | 0         | 0         |
| 3  | 0         | 0         | 0         | 0         | 0         | 0         | 0         | 0         | 0         | 0         | 0         | 0         | 0         |
| 4  | 0.000000  | -2.000000 | 1.000000  | -2.000000 | 1.000000  | 2.000000  | -1.000000 | 4.000000  | 1.000000  | 0.000000  | 0.000000  | -3.000000 | 2.000000  |
| 5  | 0.000000  | 1.000000  | 5.000000  | -1.000000 | 5.000000  | 0.000000  | 4.000000  | -2.000000 | 0.000000  | -1.000000 | 4.000000  | 4.000000  | -4.000000 |
| 6  | -4.000000 | -2.000000 | -2.000000 | 0.000000  | 2.000000  | 0.000000  | -1.000000 | 0.000000  | 4.000000  | 3.000000  | -3.000000 | 2.000000  | -2.000000 |
| 7  | 1.000000  | 2.000000  | -2.000000 | 2.000000  | -1.000000 | 2.000000  | 3.000000  | 0.000000  | -1.000000 | -1.000000 | -1.000000 | 1.000000  | 1.000000  |
| 8  | 2.000000  | -7.000000 | 5.000000  | -3.000000 | 4.000000  | 1.000000  | 1.000000  | -3.000000 | 2.000000  | -2.000000 | 0.000000  | 2.000000  | -2.000000 |
| 9  | 1.000000  | -7.000000 | -1.000000 | 0.000000  | 2.000000  | -1.000000 | 3.000000  | 0.000000  | -3.000000 | -2.000000 | -5.000000 | 4.000000  | -2.000000 |
| 10 | 1.000000  | -2.000000 | 1.000000  | -2.000000 | -1.000000 | 2.000000  | 5.000000  | -3.000000 | 0.000000  | -3.000000 | 2.000000  | -2.000000 | -6.000000 |
| 11 | -1.000000 | -1.000000 | -1.000000 | -1.000000 | -1.000000 | -3.000000 | -2.000000 | 3.000000  | -6.000000 | 1.000000  | 0.000000  | 1.000000  | 2.000000  |
| 12 | 3.000000  | 0.000000  | -4.000000 | -1.000000 | 0.000000  | -3.000000 | -1.000000 | -2.000000 | 3.000000  | -2.000000 | -1.000000 | 1.000000  | 1.000000  |
| 13 | 0.000000  | 3.000000  | 1.000000  | -2.000000 | 1.000000  | 0.000000  | 4.000000  | 0.000000  | 1.000000  | -1.000000 | -1.000000 | -4.000000 | -3.000000 |
| 14 | -1.000000 | 1.000000  | 3.000000  | -1.000000 | 1.000000  | -5.000000 | 5.000000  | -3.000000 | -1.000000 | 0.000000  | -1.000000 | 3.000000  | -1.000000 |
| 15 | -3.000000 | 1.000000  | 0.000000  | 1.000000  | -1.000000 | 5.000000  | 2.000000  | -2.000000 | 0.000000  | 2.000000  | 2.000000  | -4.000000 | 1.000000  |
| 16 | -2.000000 | 2.000000  | 1.000000  | -1.000000 | 3.000000  | 1.000000  | 0.000000  | 0.000000  | -3.000000 | -3.000000 | 2.000000  | 0.000000  | -1.000000 |
| 17 | -1.000000 | -2.000000 | 2.000000  | 1.000000  | 0.000000  | 2.000000  | -3.000000 | 2.000000  | -5.000000 | -5.000000 | 0.000000  | -4.000000 | -3.000000 |
| 18 | -2.000000 | -3.000000 | -2.000000 | -2.000000 | 2.000000  | -2.000000 | -2.000000 | 2.000000  | -3.000000 | -5.000000 | -4.000000 | 3.000000  | -2.000000 |
| 19 | -2.000000 | 3.000000  | -2.000000 | 2.000000  | -2.000000 | -3.000000 | 2.000000  | -1.000000 | -3.000000 | -3.000000 | 1.000000  | -4.000000 | 2.000000  |
| 20 | -3.000000 | -2.000000 | 0.000000  | 3.000000  | -1.000000 | -1.000000 | 1.000000  | -1.000000 | 0.000000  | -1.000000 | 1.000000  | 3.000000  | 1.000000  |
| 21 | -2.000000 | 2.000000  | 0.000000  | 1.000000  | 0.000000  | 0.000000  | 1.000000  | 1.000000  | 2.000000  | 4.000000  | 2.000000  | 0.000000  | -1.000000 |
| 22 | -2.000000 | 3.000000  | -1.000000 | -4.000000 | 0.000000  | -4.000000 | -1.000000 | -3.000000 | 1.000000  | 0.000000  | 1.000000  | 1.000000  | -2.000000 |
| 23 | 6.000000  | -4.000000 | 1.000000  | 1.000000  | 1.000000  | 0.000000  | 0.000000  | 1.000000  | 1.000000  | -1.000000 | 2.000000  | 2.000000  | 0.000000  |

FIGURE 5.11: Data after organizing it in the program

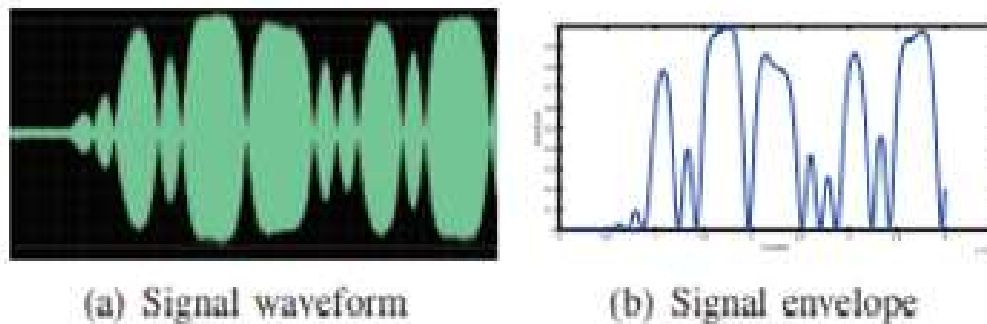


FIGURE 5.12: Signal waveform and envelope of 802.11b

Step 2: Perform envelope extraction of signal envelopes produced in Step 1. The information of signal envelopes and peaks are plotted in Fig. 4(b), Fig. 5(b) and Fig. 6(b) [49].

## 5.4 - Training Data Collection

dataset is a collection of RF communication signals records acquired from number of drones, namely Bebop, AR and Phantom which were operating in different modes along with background activities. Furthermore, The dataset consists of 227 segments . The next step was to go into the csv file and delete variables that have no correlation to helping the computer find where the drone is operating at such as the time. Since Figure 10 showed that the time remained the same throughout the scanning of multiple frequency buckets, it was removed for the time being. The csv file was edited to mark the sections of frequencies in which the drone was known to be operating which, as noted above.

The csv file was filtered to show only those frequencies and a column called "Y" was added to the end. Then the " Y" column was marked with

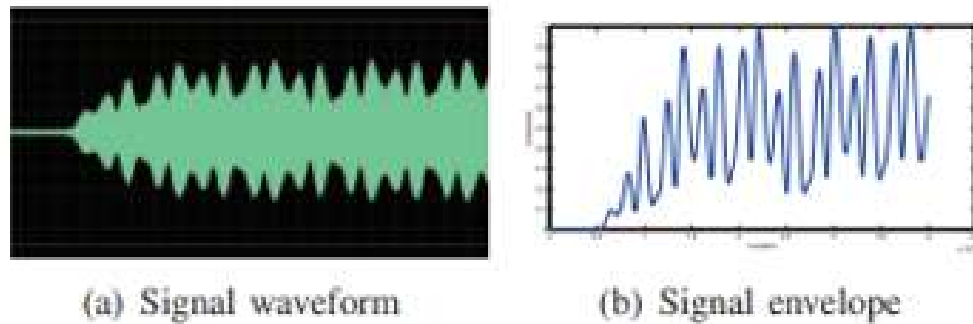


FIGURE 5.13: Signal waveform and envelope of 802.11n

a yes and the rest of the frequencies where the drone was known to be not operating were marked with a no. -Then we used Weka to train data on machine learning algorithms. the first type of machine learning model used was a Bayes –naiveBayes model. Table 1 shows the confusion matrix from this model and Table 2 shows the Accuracy, Error, False Positive rate, and the True Positive rate. Accuracy defines how often the model predicted correct. Error describes how often the machine predicted incorrectly.

|             | Predicted: Yes       | Predicted: No        |
|-------------|----------------------|----------------------|
| Actual: No  | 313 (True Negatives) | 48 (False Positives) |
| Actual: Yes | 72 (False Negatives) | 216 (True Positives) |

Table 1: naiveBayes Confusion Matrix from Raw of drone Model.

FIGURE 5.14: naiveBayes Confusion Matrix from Raw of drone Model

We used Cross Validacion and trained and tested data using 10 machine learning algorithms and got the result shown in the table below, which contains Correctly Classified Instances and Incorrectly Classified Instances. results from this method gave good accuracy, but a low true positive rate. this is It can work as a decent detection algorithm. Moreover, he is not It takes a lot of computational time. In an effort to get a better detection rate, the ClassificationViaRegression classification model was the best model drone detection classifier

| TP Rate       | FP Rate | Precision | Recall | F-Measure | MCC   | ROC Area | PRC Area | Class |
|---------------|---------|-----------|--------|-----------|-------|----------|----------|-------|
| 0,773         | 0,000   | 1,000     | 0,773  | 0,872     | 0,790 | 0,998    | 0,998    | no    |
| 1,000         | 0,227   | 0,808     | 1,000  | 0,894     | 0,790 | 0,998    | 0,998    | yes   |
| Weighted Avg. |         | 0,884     | 0,111  | 0,906     | 0,884 | 0,882    | 0,790    | 0,998 |

Table 2: naiveBayes Detailed Accuracy

| Algorithm machine learning            | Correctly Classified Instances | Incorrectly Classified Instances |
|---------------------------------------|--------------------------------|----------------------------------|
| Bayes -naiveBayes                     | 51.1628 %                      | 48.8372%                         |
| Functions-logistic                    | 58.1395 %                      | 41.8605 %                        |
| Lazy-IBK                              | 48.8372 %                      | 51.1628 %                        |
| Meta-Bagging                          | 48.8372 %                      | 51.1628 %                        |
| Meta -<br>ClassificationViaRegression | 60.4651 %                      | 39.5349 %                        |
| Misc-inputmappedclassifier            | 51.1628 %                      | 48.8372 %                        |
| Rules-Decisiontable                   | 53.4884 %                      | 46.5116%                         |
| Rules-ZeroR                           | 51.1628 %                      | 48.8372 %                        |
| Tree-Randomforest                     | 44.186 %                       | 55.814 %                         |
| Tree-randomtree                       | 51.1628 %                      | 48.8372 %                        |

1 Table 2. Detection Rate

this table is the result of our classify of RF dataset the teen algorithm with weka application

## Chapter 6

### General conclusion

In this project and from the experiment and results shown so far, we can successfully classify signals that are being transmitted from drones. Using the machine learning training and testing we observed that out of the different classification algorithms, ClassificationViaRegression works best and provide the highest accuracy. Our goal is to be able to improve this accuracy by identifying new features from the test statistics that can be added to the classification model. So far, we have been able to test the addition of signal standard deviation and median and even though accuracy increased a little validation of RF based signal classification using the trained model created from the machine learning algorithm so far has a prediction accuracy which is not very high at this point. And as stated earlier, we hope to change this and intend to continue to carry out more training, testing and analysis so as to increase the prediction of the classification. Different approach will be employed in collecting and testing the data.



# Bibliography

- [1] <https://www.iwm.org.uk/history/a-brief-history-of-drones>
- [2] <https://www.businessinsider.com/drone-technology-uses-applications>
- [3] Drone Detection Approach Based on Radio-Frequency Using Convolutional Neural Network Sara Al-Emadi, Felwa Al-Senaid Department of Computer Science and Engineering Qatar University Doha, Qatar
- [4] Machine Learning-Based Drone Detection and Classification: State-of-the-Art in Research September 2019 IEEE Access PP(99):1-1 DOI: 10.1109/ACCESS.2019.2942944
- [5] <https://en.wikipedia.org/wiki/Artificialintelligence>
- [6] <https://www.educba.com/artificial-intelligence-application>
- [7] <https://www.edureka.co/blog/artificial-intelligence-algorithms>
- [8] ARTIFICIAL INTELLIGENCE (AI) March 23, 2017 by Dr Rajiv Desai
- [9] [https://en.wikipedia.org/wiki/Unmanned\\_aerial\\_vehicle](https://en.wikipedia.org/wiki/Unmanned_aerial_vehicle)
- [10] <https://onlinemasters.ohio.edu/blog/the-benefits-and-challenges-of-uavs/>
- [11] <http://air-vid.com/wp/20-great-uav-applications-areas-drones/>
- [12] <https://www.microdrones.com/en/applications/>.
- [13] R.J. Yan, S. Pang, H.B. Sun, Y.J. Pang, Development and missions of unmanned surface vehicle, *J. Mar. Sci. Appl.* 9 (4) (2010) 451–457
- [14] R. Stuchlík, Z. Stachoň, K. Láska, P. Kubíček, Unmanned Aerial Vehicle–Efficient
- [15] ] R.J. Bachmann, Biologically inspired mechanisms facilitating multimodal locomotion for areal micro-robot, in: *Proceedings of the 24th International Unmanned Air Vehicles Conference*, Bristol, UK, 2009.
- [16] P.M. Miller, Mini, micro, and swarming unmanned aerial vehicles: A baseline study, *Library of Congress Washington DC Federal Research DIV*, November, 2006.
- [17] <https://www.dummies.com/consumer-electronics/drones/understanding-how-your-drone-is-controlled>

- [18] 1-MADDOS MADDOS is an innovative system for detection and neutralization of drones <https://maddos.pl/?gclid=EAIaIQobChMIhpi27t3U6wIVBwCGCh2MBg3nEAAAYAS> (consulted 06-09-2020)
- [19] DYMSTEC,CO.,LTD.»ANTI DRONE » OURANOS RF SCANNER <http://www.dynamicshielding.com/anti-drone/ouranos-rf-scanner/> (consulted 04-09-2020)
- [20] Rantelon Ltd., Akadeemia tee 23, EE12618 Tallinn, Estonia [www.rantelon.com](http://www.rantelon.com), [rantelon@rantelon.com](mailto:rantelon@rantelon.com), <https://rantelon.ee/wp-content/uploads/2018/06/DTS-2458>
- [21] Drone Detection Approach Based on Radio-Frequency Using Convolutional Neural Network .Al-Emadi S. Al-Senaïd F.2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies,
- [22] Micro-UAV Detection and Classification from RF Fingerprints Using Machine Learning Techniques .Ezuma M. Erden F.Guvenc I.IEEE Aerospace Conference Proceedings (2019)
- [23] Machine Learning-Based Drone Detection and Classification: State-of-the-Art in Research .Taha B.Shoufan A.IEEE Access (2019)
- [24] RF-based drone detection and identification using deep learning approaches Al-Sa'd M. F. Al-Ali A. Erbad A.Future Generation Computer Systems (2019)
- [25] (en) Ian H. Witten, Eibe Frank, et Mark A. Hall, Data Mining: Practical machine learning tools and techniques,3e édition, Morgan Kaufmann, 2011(ISBN 978-0-1237-4856-0), 629 pages [présentation en ligne [archive]]
- [26] (en) G. Holmes, A. Donkin and I.H. Witten, « Weka: A machine learning workbench » [archive], Proc Second Australia and New Zealand Conference on Intelligent Information Systems, Brisbane, Australia, 1994 (consulté le 25 juin 2007) [PDF]
- [27] (en) S.R. Garner, S.J. Cunningham, G. Holmes, C.G. Nevill-Manning, and I.H. Witten, « Applying a machine learning workbench: Experience with agricultural databases » [archive], Proc Machine Learning in Practice Workshop, Machine Learning Conference, Tahoe City, CA, USA, 1995 (consulté le 25 juin 2007), p. 14–21 [PDF]
- [28] "NI Releases Free Editions of Flagship Software: LabVIEW". [www.businesswire.com](http://www.businesswire.com). 2020-04-28. Retrieved 2020-04-28.
- [29] "Announcing LabVIEW 2019 SP1 and LabVIEW NXG 4.0". Forums. National Instruments.
- [30] <http://medea.mah.se/2013/04/arduino-faq>

- [31] <https://www.amazon.com/Parrot-Disco-FPV-minutes-goggles/dp/B01JYRII4Y>
- [32] <https://www.amazon.ca/L-Com-HG2424EG-NM-5PK-Cast-Mini-Reflector-Antenna/dp/B004EF1VT6>
- [33] DJIOnline(2018) URL <https://www.dji.com/phantom-3-standard> Google Scholar.
- [34] M. S. Allahham, M. F. Al-Sa'd, A. Al-Ali, A. Mohamed, T. Khattab, and A. Erbad, "Dronerf dataset: A dataset of drones for rf-based detection, classification and identification," *Data in Brief*, vol. 26, 2019. DOI: 10.1016/j.dib.2019.104313.
- [35] Mohammad Al-Sa'd, et al. RF-based drone detection and identification using deep learning approaches: an initiative towards a large open source drone database *Future Gener. Comput. Syst.*, 100 (2019), pp. 86-97, 10.1016/j.future.2019.05.007
- [36] <https://www.geeksforgeeks.org/data-preprocessing-machine-learning-python/>
- [37] Wu, S. (2013), "A review on coarse warranty data and analysis" (PDF), *Reliability Engineering and System*, 114: 1–11, doi:10.1016/j.res.2012.12.021.
- [38] S. García, J. Luengo, and F. Herrera, *Data preprocessing in data mining*. Springer, 2015.
- [39] Sarangi, Susanta; Sahidullah, Md; Saha, Goutam (September 2020). "Optimization of data-driven filterbank for automatic speaker verification".
- [40] Bermingham, Mairead L.; Pong-Wong, Ricardo; Spiliopoulou, Athina; Hayward, Caroline; Rudan, Igor; Campbell, Harry; Wright, Alan F.; Wilson, James F.; Agakov, Felix; Navarro, Pau; Haley, Chris S. (2015). "Application of high-dimensional feature selection: evaluation for genomic prediction in man".
- [41] Gareth James; Daniela Witten; Trevor Hastie; Robert Tibshirani (2013). "An Introduction to Statistical Learning".
- [42] O. A. Alyt, A. S. Omar, and A. Z. Elsherbeni, "Detection and localization of rf radar pulses in noise environments using wavelet packet transform and higher order statistics," *Progress In Electromagnetics Research*, vol. 58, pp. 301–317, 2006.
- [43] A. Ciancio, S. Patten, A. Ortega, and B. Krishnamachari, "Energy-efficient data representation and routing for wireless sensor networks based on a distributed wavelet compression algorithm," in *Proc. International conference on Information processing in sensor networks*, Nashville, Tennessee, 2006, pp. 309–316

- [44] J. Wang, S. Tang, B. Yin, and X.-Y. Li, "Data gathering in wireless sensor networks through intelligent compressive sensing," in Proc. IEEE Int. Conf. Comput. Commun. (INFOCOM), Orlando, FL, 2012, pp. 603–611.
- [45] K. Hassan, I. Dayoub, W. Hamouda, and M. Berbineau, "Automatic modulation recognition using wavelet transform and neural networks in wireless systems," EURASIP J. Adv. Sig. Processing, vol. 2010, p. 42, 2010.
- [46] K. Hassan, I. Dayoub, W. Hamouda, and M. Berbineau, "Automatic modulation recognition using wavelet transform and neural networks in wireless systems," EURASIP J. Adv. Sig. Processing, vol. 2010, p. 42, 2010.
- [47] G. Strang, "Wavelet transforms versus fourier transforms," Bulletin of the American Mathematical Society, vol. 28, no. 2, pp. 288–305, 1993.
- [48] M. Ezuma, F. Erden, C. K. Anjinappa, O. Ozdemir, and I. Guvenc, "Micro-UAV detection and classification from RF fingerprints using machine learning techniques," 2019, arXiv:1901.07703. [Online]. Available: <https://arxiv.org/abs/1901.07703>
- [49] Z. Shi, M. Huang, C. Zhao, L. Huang, X. Du, and Y. Zhao, "Detection of LSSUAV using hash fingerprint based SVDD," in Proc. IEEE Int. Conf. Commun. (ICC), May 2017, pp. 1–5.