

**ENERGY-BASED DETECTION FOR MULTIPLE
UNAUTHORIZED UNMANNED AERIAL VEHICLES USING
SPIKING NEURAL NETWORKS**

BY

Abdullah Alshammari

A Thesis Presented to the

COLLEGE OF GRADUATE AND INTERDISCIPLINARY STUDIES

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

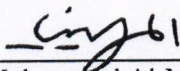
In

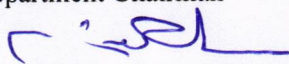
ELECTRICAL ENGINEERING

MAY 2024

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS
DHAHRAN- 31261, SAUDI ARABIA
DEANSHIP OF GRADUATE STUDIES

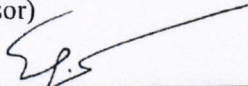
This thesis, written by Abdullah Alshammari under the direction of his thesis advisor and approved by his thesis committee, has been presented and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN TELECOMMUNICATION ENGINEERING.**

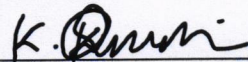

Dr. Mohammed Al-Muhaini
Department Chairman


Dr. Suliman Saleh Al-Homidan
Dean of Graduate Studies

Date _____


Dr. Suhail Ibrahim Al-Dharab
(Advisor)


Dr. Samir Nasser Alghadhban
(Member)


Dr. Khurram Karim Qureshi
(Member)



© Abdullah Alshammari
2024

Dedication

This thesis is dedicated to my father, mother, wife, and my Family.

ACKNOWLEDGMENTS

Praise and glory to Allah, the Almighty with whose gracious mercy we live.

I would like to express my gratitude and profound appreciation to my advisor and thesis committee chairman, Dr. Suhail Ibrahim Al-Dharrab, for his guidance and support throughout the study. I could not have made it without his help; I wish Allah, the Almighty, reward him with all the best. I am also very grateful to my advisors and committee members, Dr. Samir Nasser Alghadhban and Dr. Khurram Karim Qureshi, for their time and effort to review the thesis and provide valuable comments.

My special thanks go to my father and mother for their prayers and kindness, and also to my family for encouraging me to pursue my Master degree. I thank them all for their support and for being next to me all the time. May Allah bless and reward them with all the good things in life.

TABLE OF CONTENTS

ACKNOWLEDGMENTS	V
TABLE OF CONTENTS	VI
LIST OF TABLES	VIII
LIST OF FIGURES	IX
LIST OF ABBREVIATIONS.....	X
ABSTRACT	XI
ملخص الرسالة	XII
CHAPTER 1 INTRODUCTION	1
1.1 Unmanned Aerial Vehicles	2
1.2 Detection of Malicious UAVs	4
1.3 Thesis Contributions	5
1.4 Thesis Outline	6
CHAPTER 2 LITERATURE REVIEW	7
2.1 UAV Detection Techniques.....	7
2.1.1 Radar	7
2.1.2 Optimal/Thermal (Computer Vision)	11
2.1.3 Radio-Frequency.....	11
2.1.4 Acoustic	15
2.2 RSS-based Detection of Malicious UAVs.....	15
2.3 ML-based Detection Techniques	16
CHAPTER 3 PERFORMANCE OF ENERGY-BASED DETECTION FOR SINGLE UAV.....	19

3.1	Problem Statement	19
3.2	System Model	20
3.3	Air-to-Ground Channel Model	21
3.3.1	Probabilistic large-scale path loss.....	22
3.3.2	Small-scale Multipath Fading.....	24
3.4	Results and Discussion	25
 CHAPTER 4 DETECTION AND CLASSIFICATION OF MULTIPLE UAVS USING SPIKING NEURAL NETWORKS		33
4.1	Spiking Neural Networks.....	33
4.2	Literature Review	35
4.3	Model Architecture	38
4.3.1	System Model	38
4.3.2	Dataset	39
4.4	Preprocessing.....	40
4.4.1	Feature Extraction.....	41
4.4.2	Filtering.....	41
4.4.3	Class Imbalance	42
4.5	Hyperparameters.....	43
4.6	Experimental Results	43
4.6.1	Binary classification	44
4.6.2	Multiclassification	45
 CHAPTER 5 CONCLUSIONS AND FUTURE WORK		50
 REFERENCES		51
 APPENDIX A		58
 APPENDIX B		59
 VITAE		60

LIST OF TABLES

Table 1: Summary of radar-based UAV detection research works	10
Table 2: Summary of works on RF-based multi-UAV detection.	14
Table 3: Summary of works on RF ML Survey	17
Table 4: Data Distribution Ratio	40
Table 5: Balancing segments across the four classes in the dataset	43
Table 6: Hyperparameters	43

LIST OF FIGURES

Figure 1: UAV Applications	1
Figure 2: Anti Drone System	3
Figure 3: Example of intruding UAV with sensed RF signal in presence of interference	20
Figure 4: RF signal propagation from a flying UAV in an urban environment	21
Figure 5: Line-of-sight probabilities across various environments	22
Figure 6: Path loss in dB versus the intruding UAV altitude	24
Figure 7: Energy Detection Technique Block	26
Figure 8: ROC curves for a Rayleigh channel in suburban area with UAV located at $x_D = y_D = 40\text{m}$ and at an altitude $h' = 15\text{m}$	30
Figure 9: ROC curves for a Rayleigh channel in urban area with UAV located at $x_D =$ $y_D = 40\text{m}$ and at an altitude $h' = 15\text{m}$	31
Figure 10: ROC curves for a Rayleigh channel comparing the performance in suburban and urban areas with $P_t = 4\text{ dBm}$, UAV at $x_D = y_D = 40\text{m}$	32
Figure 11: Neurons and the junction between neurons through the synapse.....	34
Figure 12: Spikes from 3 neurons processed in the soma and output is delivered through the axon.....	35
Figure 13: LIF RC circuit [72].....	38
Figure 14: System model for the experiment setup	39
Figure 15: (a) Parrot Bebop [80], (b) Parrot AR [81], (c) DJI Phantom 3 [82]	39
Figure 16: UAV segment with no active amplitude RF signal	42
Figure 17: Accuracy in detection Vs Epoch (Binary).....	44
Figure 18: Confusion Matrix (Binary).....	45
Figure 19: Accuracy vs epoch considering four classes and without filter	46
Figure 20: Confusion matrix considering four classes and without filter.....	46
Figure 21: Accuracy vs epoch considering four classes and with filter	47
Figure 22: Confusion matrix considering four classes and with filter.....	48
Figure 23: Accuracy vs epoch considering CNN, four classes, and with filter	49
Figure 24: Confusion matrix for CNN, four classes, and with filter	49

LIST OF ABBREVIATIONS

CDF	cumulative distribution function
CFAR	Constant false alarm rate
CNN	Conventional Neural Network
DNN	Deep Neural Network
DFT	Discrete Fourier Transform
DRNN	Deep Recurrent Neural Network
DVS	Dynamic Vision Sensor
EO	Electro-optical
EM	Electromagnetic wave
FMWC	Frequency-Modulated Continuous Wave
IR	Infrared
I	In-phase
LoS	Line of sight
ML	Machine Learning
NLoS	Non-line of sight
NN	Neural Network
PCA	Principal component analysis
PDF	Probability density function
Q	Quadrature
RSS	Received signal strength
RCS	Radar Cross Section
ROC	Receiver Operating Characteristic
RF	Radio Frequency
SNN	Spiking Neural Network
SNR	Signal-to-Noise Ratio
SVM	Support Vector Machine
UAV	Unnamed Aerial Vehicles

ABSTRACT

Full Name : [Abdullah Alshammari]
Thesis Title : [ENERGY-BASED DETECTION FOR MULTIPLE
UNAUTHORIZED UNMANNED AERIAL VEHICLES USING
SPIKING NEURAL NETWORKS]
Major Field : [MASTER OF SCIENCE IN TELECOMMUNICATION
ENGINEERING]
Date of Degree : [2024]

Unnamed aerial vehicles (UAVs) or drones have been adopted widely for many applications. As the UAV industry and related technologies flourish and expand, the concern of security breaches, and associated threats, drive the essential need for an accurate and reliable real-time detection system. In this thesis, we will provide a literature review on drone detection techniques; and more specifically on the machine learning adoption for Radio Frequency (RF)-based detection. Moreover, we formulate the detection problem of an intruding UAV considering proper sampling of unknown sensed signal, unknown line-of-sight or non-line-of-sight conditions, multipath propagation, and practical system parameters of energy-based detectors. Based on that, closed-form mathematical expressions are derived for the false alarm and detection probabilities. For the challenging problem of multiple intruding UAVs, we propose Spiking Neural Networks (SNNs) based on a real RF measurement/dataset. A promising accuracy of 96.5 % has been achieved for the classification with meticulous and proper pre-processing.

ملخص الرسالة

الاسم الكامل: عبدالله سالم الشمري

عنوان الرسالة: الكشف المعتمد على الطاقة عن الطائرات المتعددة بدون طيار باستخدام الشبكات العصبية النبضية

التخصص: ماجستير العلوم في هندسة الاتصالات

تاريخ الدرجة العلمية: مايو 2024

تستخدم الطائرات بدون طيار على نطاق واسع وفي العديد من التطبيقات. ومع ازدهار وتوسع صناعة الطائرات بدون طيار والتقنيات ذات الصلة، فإن القلق بشأن الخروقات الأمنية والتهديدات المرتبطة بالطائرات الغير مصرح لها يدفع لحاجة ملحة إلى تطوير نظام كشف دقيق وموثوق للكشف عنها في وقت قياسي. في هذه الأطروحة، سنقدم مراجعة للأبحاث السابقة المتعلقة بتقنيات الكشف عن الطائرات بدون طيار؛ وبشكل أكثر تحديداً حول اعتماد التعلم الآلي للكشف عنها بناء على الترددات الراديوية. علاوة على ذلك، قمنا بصياغة رياضية لمسألة الكشف عن الطائرات بدون طيار الغير مصرح لها مع الأخذ في الاعتبار عدة جوانب عملية منها العينات الزمنية المناسبة من الإشارة المستشعرة غير المعروفة، وظروف خط البصر مع الطائرة بفرضية أنه غير معروف مسبقاً، والانتشار أو التلاشي للإشارات الراديوية، وعدد من المعاملات العملية للنظام المقترح والمعتمد على الإشارة المستقبلية. وبناء على ذلك تم اشتقاق العبارات والنماذج الرياضية وحساب احتمالات الإنذار الكاذب والكشف الصحيح. أما بالنسبة للتحدي المتمثل في وجود عدة طائرات غير مصرح لها في آن واحد، نقترح الشبكات العصبية النبضية حيث تم تحليل الأداء بناءً على بيانات حقيقية للتردد الراديوي لطائرات دون طيار. وتم تحقيق دقة واعدة بنسبة 97.5% للتصنيف من خلال معالجة مسبقة ودقيقة لبيانات الإشارات.

CHAPTER 1

INTRODUCTION

In the past years, the knowledge of industrial technologies has flourished in different aspects which resulted in the sensor technology revolution. Unmanned Aerial Vehicle (UAV) is one of the emerging promising solutions that is playing an important part in this period. This has a great impact on the UAV market and application. There are different applications for UAV utilization, and it is no longer limited to military use since the cost is decreasing and the technology is advancing. Besides the military application, commercial, and non-commercial civilian application can be divided [1]. UAV can be used, in military application, to gather intelligent information by identifying locations or taking pictures of enemy. Such UAV will have attached camera and acoustic sensor for later analysis and processing. It can be also used in aggressive way by jamming enemy communication or attaching by throwing bomb or being self-destructive. Figure 1 depicts some of the UAV applications.

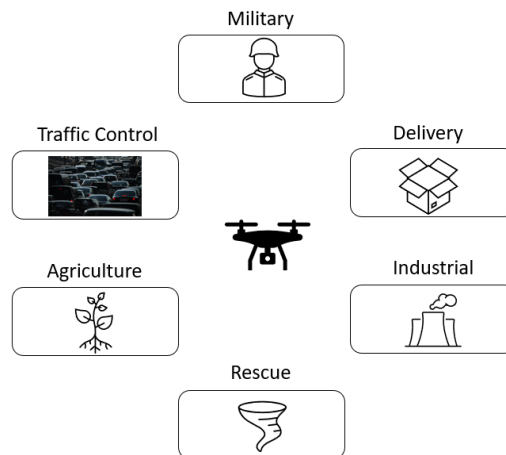


Figure 1: UAV Applications

Civilian non-commercial applications for UAV are utilized in different government organization sectors such as monitoring borders and traffic jams. The advantage of UAV in this application over classic monitoring system like fixed camera is the flexibility of covering bigger footage with low cost. An important time for non-commercial application is during disaster relief like fire or earth quick. It can gather intelligent information about fire spread and support to fight as well without risking the firefighter life. For the commercial application, UAV are used in agriculture, industrial, and delivery sectors. Farmers using UAV for different tasks like soil survey, plantation, crop growth monitoring and analysis [2]. With more organized and developed regulation for UAV, industrial companies started using UAV in different applications like inspection of elevated area or monitoring the safety of employee in critical risk activities. For delivery application, UAV are being used in delivering lightweight product, vaccination, and war aid resource in inaccessible area [1]. All these applications have more impact in terms of human effort reduction, cost optimization, time saving, and business growth.

1.1 Unmanned Aerial Vehicles

Now a days, the application of utilizing drones becomes more such as commercial, agriculture, medical, industrial, and military. The applications market needs are expanding, such as disaster management, emergency services, information technology applications, cargo inspection, or movie filming, for example Shakhathreh et al. [3]. As a result, the potential risk is increasing as well. UAVs have been intensively studied and progressed during the last 30 years. Currently, in real life, we can most of the time observe various public and non-public application use of UAVs, also vastly known as drones.

With advancement in UAV development and the continuous utilization of UAV application, threats and damage, and negative impact it may cause are rising as well. For example, UAV intercept current aviation operations, breaks personal privacy, and threatens public and national security. Moreover, the regulation and rules in this regard are still not fully developed; and there are many UAVs are still not yet licensed or registered. Unauthorized UAVs have been recognized as of highest priority both in military and civilian applications. Such UAVs may be used by malicious organization for hacking critical communication systems or to compromise important infrastructure, or they might be controlled by drone users which may cause threats if flying in unauthorized areas This resulted in the development of the anti-drone technologies. As shown in Figure 2, anti-drone systems are used to defend against drone violations or terrorism and are required to be advanced to overcome existing and future drone threats. The first step in the anti-drone system is detecting the UAV and recognizing its presence. This is important to distinguish between UAV and bird for example. Some anti-drone systems have the feature of UAV classification which identifying the individual UAV feature like the flying mode, model of UAV, and consumer of the UAV.



Figure 2: Anti Drone System

One of the important anti-drone stages is tracking. This is critical to be able to know the direction of the UAV and speed for better counter measure. The last stage of anti-drone system is the UAV neutralization which could be divided into physical and non-physical neutralization [1]. Jamming, spoofing, high power electromagnetic waves, and Laser are examples of the non-physical neutralization. Jamming is a technique used to send a disrupted noisy signal which has the same frequency band as the UAV control. By this, the SNR between the UAV and controller will be low preventing them from controlling the UAV. For spoofing, it is the process of manipulating the UAV to control it or drive it away from the restricted area by sending manipulated signal. High power electromagnetic wave is used to send a strong disrupted directed EM wave to damage the internal part of the UAV. On the other hand, physical neutralization is used to bring down the UAV by direct contact like net, counter UAV, and missile.

1.2 Detection of Malicious UAVs

In the last few years, UAVs have caught the attention of different levels of companies, organizations, government, and even at personal level. These UAVs mostly use open network to carry out a specific mission during a limited time with low cost. UAVs have shown their contribution during environmental crises aid and covid-19 pandemic as well. With promising development of UAVs, it becomes easy to learn programming and flying, inexpensive, and readily available. However, with such positive impact, there is another side of this impact which is the negative part. The illegal use of UAVs like spying drug trafficking, and terrorism are increasing as well. Despite the formulated regulation for UAVs, the easiness of purchasing these UAVs has become easier.

In March 2023, there was an attempt to assassinate President of Russia, Putin, by UAV which managed to pass through all advanced defense and detection system of Russia but failed by being shot down over the Kremlin [4]. Such malicious UAV attack could have had a severe impact on any government or organization. Therefore, an anti UAV system to detect illegal UAV is very important. There are different UAV detection techniques that are developed and used to detect malicious UAVs like radar and RF. Flying over low altitude in relatively low speed, and with small radar cross section makes the detection of intruding drones/UAVs a real challenge. Moreover, the accuracy to distinguish between a UAV and similar flying birds, or continuous tracking and monitoring of UAV in term of size of needed equipment is challenging factors as well [5]. Therefore, an accurate and real-time detection system is needed.

1.3 Thesis Contributions

Drones and UAVs are becoming popular in many potential civilian and environmental applications. The present counter UAV systems rely fundamentally on radar, electro-optical/infrared (EO/IR), RF directional finding (RFDF), and acoustic sensors. RSS-based detection methodology is an excellent technique for unknown signals specifically in environments with non-line of sight. One challenge is to properly model the system to use RSS measurement to detect multiple intruding RF-controlled UAVs in a complex environment with large pathloss and eventually low SNRs. This requires an accurate statistical model for UAVs and formed ground-to-air channels. Therefore, this thesis will study UAV models including the RF signal of the UAV and develop energy-based detection technique for UAV considering proper statistical model for the channel between

UAV and sensing node. Furthermore, we utilized SNN for multi-UAV classification despite the challenges research encounters to achieve excellent accuracy. Moreover, we proposed preprocessing technique utilized for the raw RF data to allow SNN model achieve high accuracy.

The main contributions in this thesis are

- Deriving closed-form mathematical expressions for the false alarm and detection probabilities using a simple energy-based RF sensing for single UAV detection. These expressions are derived considering proper sampling of unknown sensed signal, unknown line-of-sight or non-line-of-sight conditions, multipath fading, and other practical system parameters.
- Proposing a novel machine learning technique using Spiking Neural Networks for a real RF measurements/dataset to detect and classify multiple UAVs. This has been benchmarked with an existing method in literature in terms of accuracy, and the insights on the advantages of the proposed architecture have been elaborated.

1.4 Thesis Outline

In this thesis, the structure will be as follows. In Chapter 2, the literature review on several UAV detection techniques will be discussed and reviewed including the machine learning methods used in this problem. In Chapter 3, the system model and problem formulation will be explained; and detailed derivation for a single intruding UAV detection will be illustrated. In Chapter 4, the multi-UAV detection and identification will be experimented, and the results on the classification performance will be discussed as well. Finally, the conclusions and future work are in Chapter 5.

CHAPTER 2

LITERATURE REVIEW

In this chapter, various detection techniques will be discussed. This includes radar, computer vision, radio frequency, and acoustic technique. Moreover, a brief introduction about the Received Signal Strength principle and its application for UAV detection. Finally, a survey about UAV detection utilizing machine learning models.

2.1 UAV Detection Techniques

With the rapid evolvement in technology, there are different techniques being utilized for drone detection. In this subsection, an overview of the sensing technology that is utilized for detection is presented. Moreover, the advantages and disadvantages of each technique are explained as well.

2.1.1 Radar

The radar sensing technique is based on sending a radio wave signal and receiving the reflected signal from the targeted object. The reflected signal will carry important information that is called Doppler signature. Based on that, important information like distance, speed, and direction are extracted. Unlike the RF system, the radar system does not require active communication between drone and the controller. Moreover, the radar system is not affected by foggy, dusty, or cloudy weather; and it can function in non-line of sight (NLoS) as well. On the other hand, small RCS are difficult to capture by radar. In addition, there are high path loss when transmitting at higher bandwidth.

There are some research studies on the use of FMWC radar systems to detect a single UAV in a relatively short range. Drozdowicz et al. in [6] used a 35 GHz FMCW radar for drone detection. The authors presented two operation modes: Area mode and barrier mode. In the area mode, a wide beam was used for drone detection in specific areas, while in the barrier mode they used a narrow beam radar for low false alarm and highly reflective area. With 1 GHz bandwidth, velocity of 10m/s and SNR of 10 dB, the drone was detected experimentally with a distance of 90m. Shin et al., in [7] has utilized a K-band FMCW radar system for high sensitivity, linearity, and flatness to detect low radar cross section drones. A fiber optic link is used between the transmitter and receiver to reduce the leakage. As a result, the system was able to detect small drones with distance of 500m. A low-cost K band FCW radar was developed by Zulkifli and Balleri in [8] for detection of small micro drones. With 1.5 m, the system was able to detect the min drones of 3 cm size with 4 propellers of 2.4 cm length. In [9], authors considered, in addition to the drone detection, the tracking capability based on phase-interferometry were evaluated. It was shown that micro drones can be detected and tracked by applying the joint range-Doppler-azimuth processing. Features extracted from the range-Doppler-azimuth domain can be used to identify drones and for the classification purpose as well.

As for the case of multiple UAV detection, which is a challenge to identify and distinguish them from the background clutter. The research problem of the detection of the multiple UAVs have been addressed in [10] and [11]. Yang et al. in [10] used a 12-channel phased array radar with high resolution capability for detection of closely spaced drones (355m). A Pulse Compression and Fast Fourier Transform operation is utilized to obtain doppler matrix where individual drone will be visible. If a single drone is present, a beamforming

and CFAR technique is implemented to get the range and velocity. However, if the threshold is exceeded where more than one drone has similar velocity and range, a super resolution method is implemented to identify the angle to be able to distinguish the closely spaced drones. In [11], the author derived the interdependence between Signal-to-Noise Ratio (SNR) and small UAV Radar Cross Section (RCS). The results of dynamic flight test series performed to assess the detection performance of three drones by pulse Ku-band short range battlefield radar were presented.

The classification and tracking of these multiple UAVs, in addition to the detection, were investigated as well. In [12], Zheng et al. proposed a method based on the Dechirp-keystone transform and frequency selective reweighted trace minimization is used to accurately detect and localize the drone's swarms. With a range of 561m, a group of three drones mathematically and by simulation were detected using FMCW signal and a band of 10 MHz. In [13], Zheng, Chen, et al. used a radar with coprime array where coherent long-time integration and gridless sparse technique are applied for detection and localization of swarm of drones. The LTI technique provides an enhancement in the SNR and the doppler resolution, while the gridless sparse technique enhances the DOA. Mathematically and numerical calculation, an LFMCW radar signal was simulated for detection of three drones with distance of 555m.

Convolution neural network for the classification drones was used by the authors in [14], and to identify them compared to non-drones. The extracted feature from the micro-Doppler signature of tested object was fed to the CNN as training testing test. Using FMCW radar signal with 94 and 24 GHz band, an accuracy of 94.4 % for four classes and 98.3 % for two classes was obtained for a max distance of 120m. In [15], Mendis et al.

used a deep learning based doppler radar sensor system for detection and classification of micro drones. The received discrete time signal from the doppler radar is processed to generate the spectra correlation function (SCF); and then the Deep Belief Network classification method is used to classify the signature of the SCF. With 2.4 GHz RF CW signal, the system experimentally was able to detect and classify the micro drones with accuracy more than 90% while SNR is greater than 0 dB.

For long range capability, the authors in [16] used Holographic Radar (HR), a 3-D, L-Band, which can obtain a high detection sensitivity. The Doppler signature for several micro-drones in pragmatic clutter conditions were examined. These enriched feature measurements can be used by machine learning algorithms to qualify for reliable and accurate detection of drones. In Table 1, a summary of research works on the radar-based detection for single and multiple malicious UAVs.

Table 1: Summary of radar-based UAV detection research works

Work	Range	Radar Information	No. of Drones	Methodology	Detection/Localization
[6]	30 – 90m distance 5 meter above ground	35 GHz FMCW radar narrow beam radar 1 GHz bandwidth 10dB SNR multi-rotors - small drones	1	Experimental	Detection
[7]	15-500m	distributed FMCW radar K-band radar 24.59 GHz leakage cancellation 75 dB 500 MHz bandwidth	1	Experimental & Basic mathematical model	Detection
[12]	555m angle 5-12	10 MHz bandwidth 10 GHz	3	Experimental & mathematical model	Detection & Localization
[10]	270-355m angle 4.42 to 2.98	C-band 10 MHz bandwidth multi-channel phased array radar	3	Experimental & mathematical model	Detection
[13]	555m	LFMCW radar 10 MHz bandwidth 10 GHz	3	Mathematical Model	Detection & Localization
[14]	30-120m	FMCW radar K-band radar 24 GHz W-band radar	3	Experimental	Detection & Classification (UAV & birds)

		94 GHz 0-30 dB (10 mostly)			
[15]	3m	2.4 GHz continuous-wave Doppler radar Tx 5 dBm	3	Experimental	Detection & Classification
[8]	2.5m	24GHz K-band FMCW radar 480 MHz Bandwidth	1	Experimental	Detection
[16]	5 Km	L band 2 MHz Bandwidth	3	Experimental	Detection & Classification
[9]	32m	C-Band at 5.8 GHz 300 MHz Bandwidth 19 dBm Tx power	1	Experimental	Detection & Tracking
[11]	1 - 2 Km	Ku-Band radar	3	Mathematical Model	Detection

2.1.2 Optimal/Thermal (Computer Vision)

Another approach for detecting a drone is a computer vision-based detection. Same for radar detection, the computer vision detection does not require an active RF transmission. However, computer vision-based techniques have weak performance in a bad environment such as dust, fog, or rain weather. Moreover, the computer vision cannot detect an object in NLoS condition. Nevertheless, computer vision is a great tool for detection when combined with other technique(s) as hybrid system.

2.1.3 Radio-Frequency

The radio frequency (RF) technique is based on scanning and listening to the active transmission communication signal between the controller and the drone. For the public available and off-the-shelf drones, the operator controlling the drones usually uses 2.4 GHz band. One of the advantages of using RF is the low cost of the sensor that also can detect long-range targets. However, the main drawback of the RF is the need for active transmission, which is not always the case, such as self-controlled or programmed drones.

There has been a growing interest among researchers in using RF-based detection integrated with advanced signal processing, or machine learning methods to detect single and multiple UAVs [17]-[20]. In [21], Nie et al. proposed the use of Wi-Fi signal and created the RF fingerprint to detect and identify the drones. The fractal dimension (FD), axially integrated bispectra (AIB), and square integrated bispectra (SIB) are used to extract the drone's RF fingerprint after being detected. The principal component analysis (PCA) algorithm is used to reduce the extracted feature; and the neighborhood component analysis algorithm is used to weigh its dimension. These extracted drone fingerprints are stored as training and testing data. Two scenarios were selected, indoor with SNR 10 dB, and outdoor 3 dB. The average identification accuracy of these features is 100%, 97.23%, and 96.11% for FD, AIB, and SIB respectively in indoor. On the other hand, the outdoor scenario accuracy is 100%, 95%, and 93.5%.

Based on machine learning models, the authors in [22]-[23] investigated the UAV detection accuracy using received RF signals. For instance, Xu et al. in [22], used the machine learning algorithms (KNN), Neural Network (NN), Convolutional Neural Network (CNN), Support Vector Machine (SVM), in their proposed system. They first used the PCA to minimize the size of the signal data set that is obtained by using the Short Time Fourier Transform to the raw control signal data. The raw data is transformed into an energy distribution matrix where time and frequency information are included. After that, the signal is transformed into spectrogram; and fed to different machine learning algorithms like KNN, NN, CNN, SVM, and DT. With a distance of 7m from the RF detector, the SVM has the highest accuracy (98.52%), but with the longest time of training. On the other hand, the DT has less time training, but with lower accuracy (93.39 %). Al-Emadi and Al-Senaïd

in [24] used the emitted RF signal during the communication between the drone and its controller for detecting purpose. A deep learning technique was used by utilizing CNN. The accuracy detection is 99.7% while the identification is 88.4%.

For a long-range detection of up to 3km, Zhang et al. in [23] proposed and used an artificial neural network algorithm where slope, kurtosis, and skewness of the received RF signal were utilized. Drone and non-drone signals in indoor or laboratory environment signals were used for training and evaluation purposes. Based on this proposed algorithm with improved utilization of the aforementioned features, the recognition rate is greater than 82%.

For the detection of a larger number of drones, there have been several researchers considering deep learning techniques due to their high performance and accurate results. In [25], authors investigated detection and classification of drones with presence of the wireless interference. They proposed a multistage detector that can distinguish the transmission signal between the controller and the drones from the background noise and wireless/Bluetooth signal. With 10 dB SNR of the receiver, the accuracy of detection is 99.8% and false alarm of 2.8% where the signal is transferred into two-state Markov models. Once the RF signal is detected, an energy transient concept is used before feeding the data to the ML for classification. 15 different drones' transmission signals were studied, and the system has a classification accuracy of 98.13%.

Ezuma et al. in [26] used RF fingerprint of the transmitted signal from the drone controllers for the detection and classification of the drones. In the detection stage, the raw signal data are split into frames where a naïve Bayes approach is used to check the presence of the drones with detection accuracy of 96.3%. For the classification, the energy transient signal

is used which is less susceptible to noise and can work with different modulation techniques. After feeding the selected features to several machine learning algorithms, the highest classification accuracy for 14 drones is 96.84% for SVM method.

The identification of the manufacturing/model was investigated in [27] by Soltani et al. where they highlighted the issue of identifying of drones from the same manufacturer but different users/operators. The authors utilized the neural network to learn the imperfection in the transmitted waveform. A multi-classifier two step score-based aggregation method is proposed where the RF data augmentation is used to enhance the robustness of the neural network. Moreover, the multi-classifier scheme is used for detecting new drones. The classification accuracy of the multi-classifier improved to 95% while the new drone's detection accuracy was 99%.

The work in [28] by Hoffmann et al. focused on RF-based drone detection and classification as well utilizing the transmitted signal's frequency signature. A novel RF drone dataset using commercial drones was created and a deep comparison between a two-stage and combined detection and classification framework was presented. The YOLO-lite architecture is regenerated from the original and changed to perform combined drone signal detection and classification. Through detailed comparisons, it has been found that the YOLO-lite framework provides better detection performance compared to the GoF sensing and a good classification performance comparable to the DRNN classifier. In Table 2, a summary of research papers on RF-based for multi-UAV detection is provided.

Table 2: Summary of works on RF-based multi-UAV detection.

Work	Frequency & Bandwidth	Detection Accuracy	No. of Drones	Methodology	Use of Machine Learning
[25]	2.4 GHz antenna 24 dBi antenna	99.8% accuracy 10 dB receiver	17	Experimental & mathematical model	Yes

[26]	2.4 GHz band 6 GHz Bandwidth	84% detection at 10 dB SNR 100% detection at 12 dB SNR	14	Experimental	Yes
[22]	2.4 GHz band 30 MHz Bandwidth		4	Experimental	Yes
[21]	2.4 GHz band 6 GHz Bandwidth	97.23% at 10 dB	2	Experimental	Yes
[27]	2.4 GHz band 5 GHz Bandwidth		7	Experimental & basic mathematical model	Yes
[24]	2.4 GHz band	99.8% accuracy single 85.8% accuracy Multiple	Multiple		Yes
[23]	2.4 GHz band	82% detection for 3 km	Multiple	Experimental	Yes
[28]	2.4 GHz band	96% detection at -3 dB SNR	9 drones (2 WiFi routers)	Numerical simulation	Yes

2.1.4 Acoustic

The acoustic detection method is based on generated sound waves from the movement and flying of the drones. The sensor of the acoustic based method detection is simple as a microphone that consider being a low cost. Moreover, the acoustic sensor can work in NLoS compared with computer vision. However, the acoustic system works poorly when operated in noisy areas or bad weather. In top of that, a database needs to be developed in order to distinguish the acoustic signature for each drone. One final disadvantage is the limited range detection for such detection technique.

2.2 RSS-based Detection of Malicious UAVs

RF UAV signal detection is challenging because the intensity of signal can vary repeatedly due to environmental attributes like topology, temperature, interaction with objects. Received Signal Strength (RSS) detector is one of the good candidate detection techniques.

This type of sensor will rely on the strength of the signal received to be able to distinguish between noise signal and drone signal. One of the advantages of RSS is being able to measure without making impractical hypothesis like having synchronization between the drone and the probe sensors or having knowledge of drone signal waveform. However, some of the serious limitations of RSS-based drone detection scheme includes a requirement for high SNR, and susceptibility to RF interference. Thus, the high level of interference due to high density of mobile devices in environments like urban can cause much degradation in the drone detection performance.

2.3 ML-based Detection Techniques

When looking at the UAV detection, most papers were previously focusing on the physical sensing as a function layer. Nevertheless, machine learning is being utilized where raw data is fed and processed for detection and classification through developed algorithms. There are different types of machine learning like deep learning which are mainly popular with Deep Neural Networks (DNN) and Convolutional Neural Networks (CNN) algorithms. DNN is a complex structure of hierarchical layers that establish powerful representations from raw data. CNN has come out as the leading architecture for computer vision tasks, such as large-scale image classification [29]. It contains an input layer, one or more hidden layers, and an output layer which are connected to each other. The main advantage of CNN is their capability to learn high level features from raw data without the need to be directly programmed. As a result, CNN became successful and heavily used as the preferred method for many pattern recognition applications, such as speech recognition, face recognition, and UAV recognition.

As stated before, RF is one of the famous techniques for UAV detection especially when combined with ML like RF fingerprint-based detection. It depends on the attribute and feature of the RF signals of the UAV controllers. Experimental investigations proved that the UAV controllers have a unique RF signature due to the circuitry design and modulation techniques employed [26]. Therefore, ML RF fingerprint analysis is very helpful in detecting and classifying UAVs. This is due to its capability to recognize patterns recognition without human intervention in a very quick manner. Some of these pattern's recognitions cannot be perceived by humans such as radio frequencies, optic, and acoustic signals since it is beyond the abilities of human sense organs [30]. In Table 3 below is a summary survey for all RF ML related works.

Table 3: Summary of works on RF ML Survey

Work	System Band	Range	Classes	Features	Classifier	Results
[31]	Wi-Fi ISM 802.11x 2.4 - 2.5 GHz		Drone vs WiFi	frequency range signal strength	Logistic Regression (LR) Artificial Neural Network (ANN)	Detection Accuracy LR 89.8 % ANN 95 %
[32]	2.4 GHz	40 m radius 20 altitudes	2 class UAV detection 4 class UAV type 10 class flight mode	PSD frequency domain	Logistic Regression (LR) k Nearest Neighbour (kNN)	100 % 99.9 % 96.4 %
[33]	2.4 GHz		2 class UAV detection 4 class UAV type 10 class flight mode	Final layer of CNN	CNN Light Gradient Boosting Machine (LightGBM) ConvLGBM	A & F1 85.46 % & .814 92.37 % & .946 95.5 % & .967
[34]			2 class UAV detection 4 class UAV type 10 class flight mode	Automatic feature extraction	CNN	99.8 % 85.8 % 59%
[35]				Darknet 53	CNN YOLOv4	
[36]	2.4 GHz		4 drones	PCA feature reduction	SVM Knearest neighbor (KNN)	100% accuracy for number of controllers Declination in classifying 4 controllers
[37]	2.4 GHz	6 feet, 9 feet, 12 feet, 15 feet	6 drones	Automatic Feature extraction	(CNN), (DNN), recurrent neural network (RNN)	98 % Test Accuracy

[38]			2 class UAV detection 4 class UAV type 10 class flight mode	Correlations of RF signal	CNN	Average detection accuracy 92.5%
[39]	2.4 GHz	7 meters	9 drones 1 WiFi signal	Frequency signatures	CNN	Classification accuracy 99% (SNR) 0 dB 5% SNR-10 dB
[40]			2 class UAV detection 4 class UAV type 10 class flight mode	Raw RF time domain input RF frequency domain input	TFMS-CNN time-frequency multiscale convolutional neural network	99.89% 98.56% 87.67%
[41]	2.4 GHz		17 drones	RF spectrograms	CNN MobileNet V2 network	Accuracy 95.24% Sensitivity 93.62%
[42]			15 drones	RF fingerprints	CNN	Classification accuracy of 97.70%.
[43]			2 class UAV detection 4 class UAV type 10 class flight mode	DFT in frequency domain.	XGBoost	99.98% 98.74% 79.25%
[44]			2 class UAV detection 4 class UAV type 10 class flight mode	Extracts the RF frequency segments	multi-channel 1-dimensional CNN XGBoost	100% 94.6% 87.4%
[45]			2 class UAV detection 4 class UAV type 10 class flight mode	PSD	1-dimensional CNN XGBoost	100% 100% 99.73%

CHAPTER 3

Performance of Energy-based Detection for Single UAV

In this chapter, the system model in this thesis and the problem formulation including the RF channel for the intruding UAV signal will be introduced and discussed. Moreover, the performance of the energy-based detector for a single intruding UAV will be investigated. Specifically, mathematical closed-form expressions of the probability of false alarm and probability of detection are derived. Then, the impact of the surrounding environment, system parameters, on the detection performance will be investigated through Monte-Carlo simulations.

3.1 Problem Statement

Because of the prevalent utilization of drone in different sectors like military, agriculture, and commercial sectors, detection and surveillance of drones has become critical and important challenging problem. Drone communication system might not be identified, either because it is a proprietary designed system or because it is malicious (unauthorized) drone. However, drone communication uses RF signal which can be used without the need to transmit any signal. RSS can be used at the detector side to detect the RF drone signal even for the unauthorized. However, there is no analytical derivation for sampling an unknown signal by an energy-detector over multipath fading channel along with numerical simulation for such detector. Moreover, in this chapter the RSS and relevant mathematical formulation and validation through Monte Carlo simulation will be presented.

3.2 System Model

The scenario for proposed RF signal received strength detection system is shown in Figure 3 in the presence of an interfering RF signal.

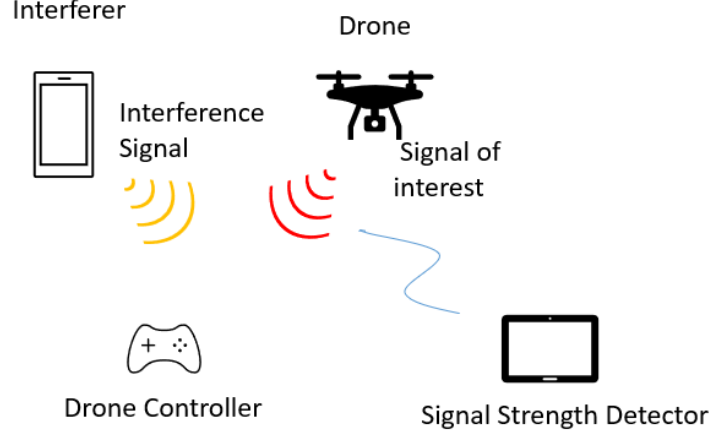


Figure 3: Example of intruding UAV with sensed RF signal in presence of interference

The received bandpass waveform UAV signal can be represented as

$$r(t) = \mathcal{R}\{[h S_{LP}(t) + n_{LP}(t)]e^{j2\pi f_c t}\} \quad (1)$$

where $\mathcal{R}\{\cdot\}$ denotes the real part function, $h = \alpha e^{j\theta}$ is a slow fading channel with amplitude α and phase θ , f_c is the carrier frequency, $S_{LP}(t) = S_c(t) + jS_s(t)$ is an equivalent lowpass representation of the unknown UAV signal with $S_c(t)$ and $S_s(t)$ denoting the in-phase (I) and quadrature (Q) components, respectively. On the other hand, the received signals at the sensing node can be represented in case of M multiple UAV signals using the same carrier frequency and experiencing statistically independent fading channels

$$r_M(t) = \mathcal{R}\left\{\left[\sum_{m=1}^M h_m S_{LP,m}(t) + n_{LP}(t)\right]e^{j2\pi f_c t}\right\}. \quad (2)$$

3.3 Air-to-Ground Channel Model

Radio signals emitted by the UAV are mainly line-of-sight (LoS) or NLoS as shown in Figure 4.

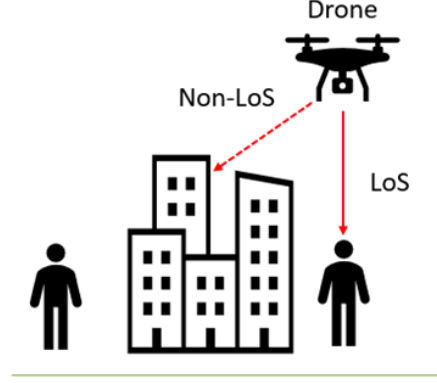


Figure 4: RF signal propagation from a flying UAV in an urban environment

The probability of having a LoS condition with the ground sensor is given by

$$P_{\text{LoS}} = \frac{1}{1 + a \exp\left(-b \left(\frac{180}{\pi} \tan^{-1}\left(\frac{h'}{r_i}\right) - a\right)\right)} \quad (3)$$

where a and b are constants that depend on the environment $r_i = \sqrt{(x_i - x_D)^2 + (y_i - y_D)^2}$ is the horizontal distance, $(x_i, y_i) \in \mathbb{R}^2$ is the location of energy-based ground sensor, and $(x_D, y_D) \in \mathbb{R}^2$ denotes projection of the UAV location in the 2D plane, h' denotes the UAV height. Moreover, the probability of NLoS is $P_{\text{NLoS}} = 1 - P_{\text{LoS}}$. As shown in Figure 5, the probability of LoS is plotted with respect to UAV elevation angle at different environments [20], [46]: Suburban (0.1, 750, 8), Urban (0.3, 500, 15), and Dense Urban (0.5, 300, 20).

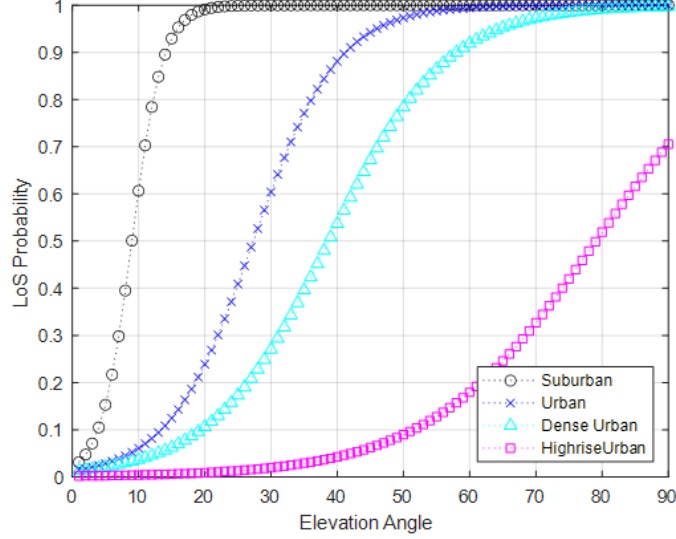


Figure 5: Line-of-sight probabilities across various environments

3.3.1 Probabilistic large-scale path loss

Because path loss and shadowing happen over comparatively large distances, this variation is often referred to as large-scale propagation effects. In addition to free space propagation loss, radio signals encounter losses due to the urban environment in the sort of shadowing and scattering. UAV as a result encounter such environment effect while communication which causes signal degradation and impact system performance [47]. The mean value of this excessive pathloss is η . Therefore, the path loss model for LoS and NLoS links in dB are respectively [48]

$$L_{\text{LoS}} = 20 \log \left(\frac{4\pi f_c d_i}{c} \right) + \eta_{\text{LoS}} \quad (4)$$

$$L_{\text{NLoS}} = 20 \log \left(\frac{4\pi f_c d_i}{c} \right) + \eta_{\text{NLoS}} \quad (5)$$

where d_i is the distance from the UAV to the ground energy-based sensor, η_{LoS} and η_{NLoS} are the excessive path losses due to LoS and NLoS conditions. In the absence of terrain knowledge, we cannot determine whether the link is in LoS or NLoS conditions. Therefore,

we consider a probabilistic mean path loss, which is averaged over the LoS and NLoS conditions as

$$L(h', r_i) = L_{\text{LoS}} P_{\text{LoS}} + L_{\text{NLoS}} P_{\text{NLoS}} \quad (6)$$

$$L(h', r_i)_{\text{dB}} = \frac{A}{1 + ae^{(-b(\frac{180}{\pi}\theta_i - a))}} + 20 \log\left(\frac{r_i}{\cos \theta_i}\right) + B \quad (7)$$

where $A = \eta_{\text{LoS}} - \eta_{\text{NLoS}}$ and $B = 20 \log\left(\frac{4\pi f_c d_i}{c}\right) + \eta_{\text{NLoS}}$, and P_{LoS} is defined in (3). In

Figure 6, the pathloss of the UAV signal varies with UAV altitude at $x_i = y_i = 0$ and $x_D = y_D = 40\text{m}$. It can be observed clearly for each environment, there is an optimal altitude with lowest pathloss. As shown in Figure 6, the suburban environment can achieve the lowest pathloss at 20m altitude. Moreover, the altitude to achieve the minimum pathloss requirement increases when the environment changes as well. To have a more intuitive meaning of the plot, the pathloss initially is high due to low altitude. As the altitude increases, the elevation angle increases as well causing the P_{LoS} increment. The increment in P_{LoS} results in a lower path loss until the optimal point at height of 20m in suburban, for example. As the altitude/elevation angle increases the P_{LoS} have already reach its maximum impact as shown in Figure 5. After that optimal point, the pathloss will increase due to the increment in the range from the ground sensor.

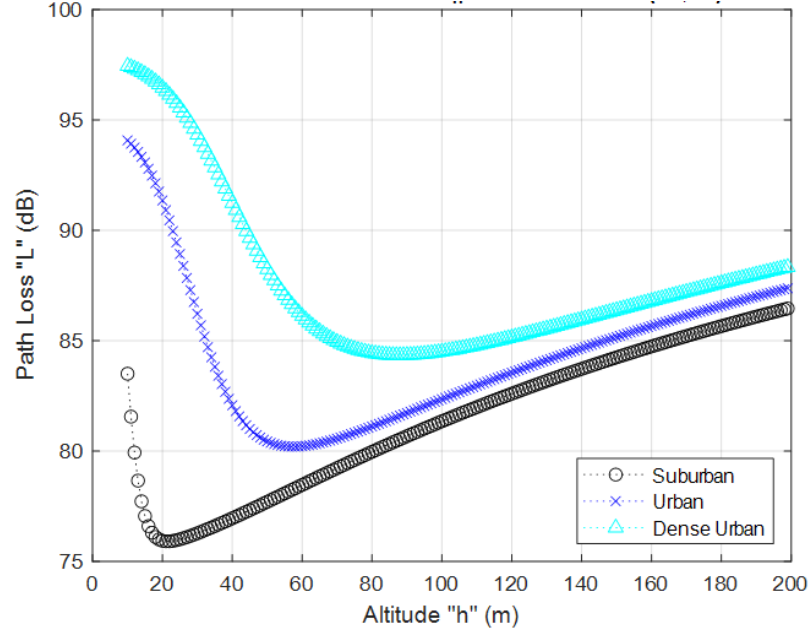


Figure 6: Path loss in dB versus the intruding UAV altitude

3.3.2 Small-scale Multipath Fading

The change in the phase of received signal will cause a constructive and destructive addition of different paths. This can happen over very short distances travelled by the UAV, on the order of the signal wavelength. So, these variations are often called small-scale propagation effects or multipath fading [49]. Small scale fading can be statistically described by well-known distribution like Nakagami, Rician, Rayleigh, Weibull, and Gaussian distributions [50].

Distributions have been assumed and selected based on the environment and conducted measurements campaigns and experimental data and the best fit computations. The author in [51] has selected log-logistic distribution as best distribution that fit foliage environment. By using the log-likelihood (LL), the author in [52] selected log-logistic distribution as well for hilly environment. Other paper for over lake environment, the author in [47] used

Kolmogorov–Smirnov (KS) test to evaluate the best fit similarity between the empirical CDF and the measured one; and found that Weibull distribution is the best fit for that environment. Usually, the Rayleigh distribution is modeled for NLoS while Rician is modeled for LoS conditions. In this work, we will consider the small variations in the received signal strength due to multipath propagation. As it will be seen in the subsequent section, the multipath fading channel will be taken into consideration in testing the performance of the detection and associated analytical derivations.

3.4 Results and Discussion

For a given transmit power, P_T , the received power in dB at the sensing node from the intruding UAV depends on the path loss encountered by its communication link, and can be expressed as

$$P_R = P_T - L(h', r_i)_{\text{dB}} \quad (8)$$

where $L(h', r_i)_{\text{dB}}$ is the path loss in dB for a signal sensed from an intruding UAV at an altitude h' given in (7). The received bandpass signal, similar to the approach in [53], at the sensing node as function of the transmitted power and the path losses will be

$$r_{\text{BP}}(t) = \mathcal{R} \left\{ \sqrt{\frac{P_t}{L(h', r_i)}} [h S_{LP}(t) + n_{LP}(t)] e^{j2\pi f_c t} \right\} \quad (9)$$

where $h = \alpha e^{j\theta}$ is the multipath fading channel with an amplitude α and phase θ , $S_{LP}(t)$ is the equivalent lowpass of the unknown received signal, $n_{LP}(t)$ is the equivalent lowpass of the AWGN random process, and f_c is the carrier frequency. Energy detection is one of the simplest techniques which can be used for UAV signal detection due to its low computational complexity. The received signal is first prefiltered by an ideal bandpass

filter. Then, the output of this filter is squared and integrated over a time interval T to finally produce a measure of the energy of the received waveform. This energy detection technique can be represented in the block diagram shown in Figure 7.

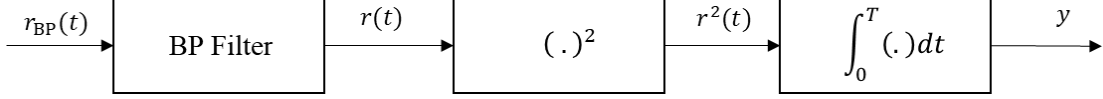


Figure 7: Energy Detection Technique Block

The output of the integrator is denoted by y , a sample depending on the random process $r(t)$ and result in the random variable Y ; and it is given by:

$$y = \frac{1}{N_0} \int_0^T r^2(t) dt$$

$$\approx \frac{P_t}{N_0 W L(h', r_i)} \left[\sum_{i=1}^{\frac{N}{2}} (\alpha_c S_{ci} - \alpha_s S_{si} + n_{ci})^2 + \sum_{i=1}^{\frac{N}{2}} (\alpha_c S_{si} - \alpha_s S_{ci} + n_{si})^2 \right] \quad (10)$$

The number of samples per in-phase or quadrature is $\frac{N}{2}$, α_c and α_s are the amplitudes of the fading channel, and S_x and n_x are the signal and noise components, respectively, upon sampling. Both random variables n_{ci} and n_{si} are zero mean Gaussian with same variance σ_n^2 , and after normalization then $\frac{n_{ci}}{\sigma_n}$ and $\frac{n_{si}}{\sigma_n}$ are Gaussian random variables with common variance of $\sigma^2 = 1$. The noncentral Chi-square random variables in (10) are

$\sum_{i=1}^{\frac{N}{2}} \left(\frac{\alpha_c S_{ci} - \alpha_s S_{si}}{\sigma_n} + \frac{n_{ci}}{\sigma_n} \right)^2$ and $\sum_{j=1}^{\frac{N}{2}} \left(\frac{\alpha_c S_{sj} + \alpha_s S_{cj}}{\sigma_n} + \frac{n_{sj}}{\sigma_n} \right)^2$ with different means, i.e.

$$m_i = \frac{\alpha_c S_{ci} - \alpha_s S_{si}}{\sigma_n} \quad (11)$$

and

$$m_j = \frac{\alpha_c S_{sj} + \alpha_s S_{cj}}{\sigma_n} \quad (12)$$

using mathematical manipulations after making $n_{ci} = 0$ in $\frac{\sigma_n^2}{N_0 W} \sum_{i=1}^{\frac{N}{2}} \left(\frac{\alpha_c S_{ci} - \alpha_s S_{si}}{\sigma_n} + \frac{n_{ci}}{\sigma_n} \right)^2$ to find the noncentrally parameter, i.e.

$$\frac{\sigma_n^2}{N_0 W} \frac{P_t}{L(h', r_i)} \sum_{i=1}^{\frac{N}{2}} \left(\frac{\alpha_c S_{ci} - \alpha_s S_{si}}{\sigma_n} \right)^2 = \frac{2\sigma_n^2}{N_0} \frac{1}{2W} \frac{P_t}{L(h', r_i)} \sum_{i=1}^{\frac{N}{2}} \left(\frac{\alpha_c S_{ci} - \alpha_s S_{si}}{\sigma_n} \right)^2 \quad (13)$$

$$= \frac{2}{N_0} \frac{1}{2W} \frac{P_t}{L(h', r_i)} \sum_{i=1}^{\frac{N}{2}} (\alpha_c S_{ci} - \alpha_s S_{si})^2 \quad (14)$$

$$\approx \frac{2}{N_0} \frac{\alpha^2}{2W} \frac{P_t}{L(h', r_i)} \sum_{i=1}^{\frac{N}{2}} (\cos^2 \theta S_{ci}^2 + \sin^2 \theta S_{si}^2) \quad (15)$$

This is after substituting $\alpha_c = \alpha \cos \theta$, $\alpha_s = \alpha \sin \theta$. Similarly,

$$\frac{\sigma_n^2}{N_0 W} \frac{P_t}{L(h', r_i)} \sum_{j=1}^{\frac{N}{2}} \left(\frac{\alpha_c S_{sj} + \alpha_s S_{cj}}{\sigma_n} \right)^2 \approx \frac{2}{N_0} \frac{\alpha^2}{2W} \frac{P_t}{L(h', r_i)} \sum_{j=1}^{\frac{N}{2}} (\cos^2 \theta S_{sj}^2 + \sin^2 \theta S_{cj}^2) \quad (16)$$

Then, let $L = L(h', r_i)$, the noncentrally parameter is

$$s^2 = \frac{2}{N_0} \frac{\alpha^2}{2W} \frac{P_t}{L} \sum_{i=1}^{\frac{N}{2}} (\cos^2 \theta S_{ci}^2 + \sin^2 \theta S_{si}^2) + \frac{2}{N_0} \frac{\alpha^2 P_t}{2WL} \sum_{j=1}^{\frac{N}{2}} (\cos^2 \theta S_{sj}^2 + \sin^2 \theta S_{cj}^2) \quad (17)$$

$$= \frac{2\alpha^2}{N_0} \frac{1}{2W} \frac{P_t}{L} \sum_{i=1}^{\frac{N}{2}} (\cos^2 \theta S_{ci}^2 + \sin^2 \theta S_{ci}^2 + \sin^2 \theta S_{si}^2 + \cos^2 \theta S_{si}^2) \quad (18)$$

$$= \frac{2\alpha^2}{N_0} \frac{1}{2W} \frac{P_t}{L} \sum_{i=1}^{\frac{N}{2}} ((\cos^2 \theta + \sin^2 \theta) S_{ci}^2 + (\cos^2 \theta + \sin^2 \theta) S_{si}^2) \quad (19)$$

$$= \frac{2\alpha^2}{N_0} \frac{1}{2W} \frac{P_t}{L} \sum_{i=1}^{\frac{N}{2}} (S_{ci}^2 + S_{si}^2) = \frac{2\alpha^2 E_s}{N_0} \frac{1}{L} = \frac{2\gamma}{L} \quad (20)$$

Here, $\gamma = \frac{\alpha^2 E_s}{N_0}$ and

$$E_s \cong \frac{P_t}{2W} \sum_{i=1}^{\frac{N}{2}} (S_{ci}^2 + S_{si}^2) \quad (21)$$

Now, the mean and variance of Y are given by (See Appendices A and B for parameter definitions and the derivation details):

$$E[Y] = n\sigma^2 + s^2 = n + \frac{2\gamma}{L} \quad (22)$$

$$= n + 2\gamma \frac{1}{L} = N + \lambda \frac{1}{L} \quad (23)$$

while

$$\text{var}[Y] = 2n\sigma^4 + 4\sigma^2 S^2 = 2n + 8\gamma \frac{1}{L} \quad (24)$$

$$= 2 \left(n + 4\gamma \frac{1}{L} \right) = 2 \left(N + 2\lambda \frac{1}{L} \right) \quad (25)$$

where $\frac{N}{2}$ is the number of samples per either I or Q components (we finally have terms to sum over), $\sigma^2 = 1$, $\alpha_c = \alpha \cos \theta$ and $\alpha_s = \alpha \sin \theta$ generally x_{ci} and x_{si} , respectively, denote the i th samples of $x_c(t)$ and $x_s(t)$, i.e., I and Q components. It then follows that Y has a noncentral Chi-square distribution with variance $\sigma^2 = 1$.

Now, the probability density function (PDF) of Y , under the hypothesis of detection of UAV, can be expressed as

$$f_Y(y) = \frac{1}{2\sigma^2} \left(\frac{y}{s^2} \right)^{\frac{N-2}{4}} e^{-\frac{s^2+y}{2\sigma^2}} I_{\frac{N}{2}-1} \left(\frac{\sqrt{s^2 y}}{\sigma^2} \right) \quad (26)$$

where $s^2 = \frac{2\gamma}{L(h, r_i)}$ is the non-centrality parameter for Y which is a non-central Chi-square random variable with N degrees of freedom and common variance σ^2 , and $I_x(\cdot)$ is the x th-order modified Bessel function of the first kind. The probability of false alarm and probability of detection will be based on the cumulative distribution function (CDF) of Y , under null hypothesis H_0 and no presence of the intruding UAV, is given by

$$\begin{aligned} P_f &= P(Y > \lambda \mid H_0) \\ &= \int_{\lambda}^{\infty} f_Y(y) dy = \int_{\lambda}^{\infty} \frac{1}{\sigma^N 2^{\frac{N}{2}} \Gamma\left(\frac{N}{2}\right)} y^{\frac{N}{2}-1} e^{-\frac{y}{2\sigma^2}} dy = \frac{\Gamma\left(\frac{N}{2}, \frac{\lambda}{2\sigma^2}\right)}{\Gamma\left(\frac{N}{2}\right)} \end{aligned} \quad (27)$$

where $\Gamma(\cdot, \cdot)$ is the incomplete Gamma function. The probability of detection in the presence of the intruding UAV is

$$\begin{aligned}
P_D &= P(Y > \lambda | H_1) \\
&= \int_{\lambda}^{\infty} f_Y(y) dy = \int_{\lambda}^{\infty} \frac{1}{2\sigma^2} \left(\frac{y}{\frac{2\gamma}{L}} \right)^{\frac{N-2}{4}} e^{-\frac{\frac{2\gamma}{L} + y}{2\sigma^2}} I_{\frac{N}{2}-1} \left(\frac{\sqrt{\frac{2\gamma y}{L}}}{\sigma^2} \right) dy \\
&= Q_{\frac{N}{2}} \left(\sqrt{\frac{2\gamma}{\sigma^2 L(h', r_i)}}, \sqrt{\frac{\lambda}{\sigma^2}} \right)
\end{aligned} \tag{28}$$

and $Q_{\frac{N}{2}}(a, b)$ is the generalized Marcum Q -function defined as

$$Q_v(a, b) = \frac{1}{a^{v-1}} \int_b^{\infty} x^v e^{-\left(\frac{x^2+a^2}{2}\right)} I_{v-1}(ax) dx \tag{29}$$

We can rewrite the probability of false alarm expression to find λ in terms of P_f using the regularized incomplete Gamma function

$$Q_R(x, a) = \frac{\Gamma(a, x)}{\Gamma(a)} = \frac{1}{\Gamma(a)} \int_x^{\infty} t^{a-1} e^{-t} dt \tag{30}$$

So, after some mathematical manipulations, the threshold is given by

$$\lambda = 2\sigma^2 Q_R^{-1} \left(P_f, \frac{N}{2} \right), \tag{31}$$

Substituting the derived expression in (28), the probability of detection in terms of the probability of false alarm is

$$P_D = Q_{\frac{N}{2}} \left(\sqrt{\frac{2\gamma}{\sigma^2 L(h', r_i)}}, \sqrt{2Q_R^{-1} \left(P_f, \frac{N}{2} \right)} \right). \tag{32}$$

The horizontal distance between the UAV and the RF sensor can be approximated by Rayleigh distribution [54]. In Figure 8, the ROC curves for Rayleigh channel are plotted over different transmitted power, P_t , considering a suburban area, noise power level of -80dBm at sensor, and a single UAV detection. It can be seen that the derived expressions for the probability of detection are validated through Monte Carlo simulation and we have exact match for high samples N . As the received power from the intruding UAV increases

in the suburban environment, the probability of detection increases. This is also observed if the UAV moves to an altitude with higher chance of LoS and therefore an increase in received power at the RF sensor, which increases the SNR and eventually enhances the probability of detection.

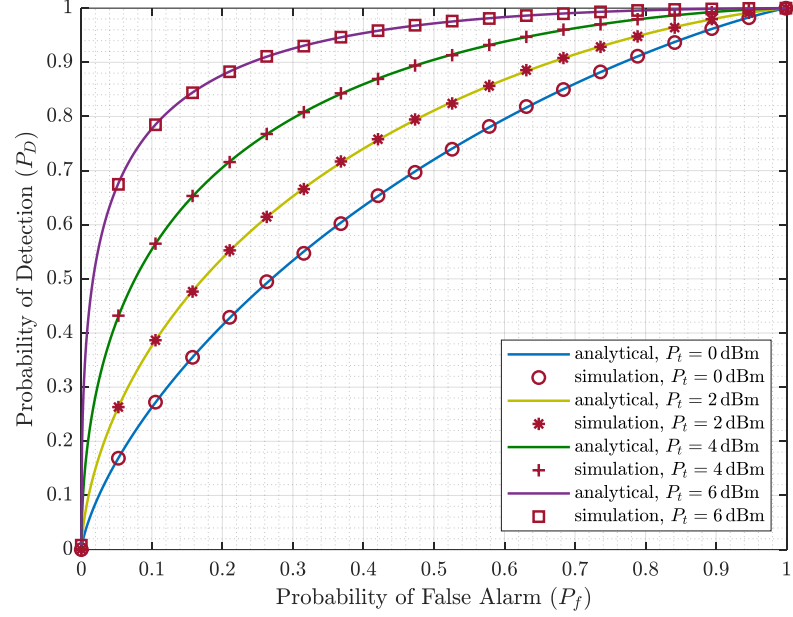


Figure 8: ROC curves for a Rayleigh channel in suburban area with UAV located at $x_D = y_D = 40\text{m}$ and at an altitude $h' = 15\text{m}$

In Figure 9, we consider the ROC curves for Rayleigh channel in an urban environment where the UAV is at $x_D = y_D = 40\text{m}$ and flying at an altitude $h' = 15\text{m}$ for different transmitted power, P_t . It can be seen that the derived expressions for the probability of detection are validated through Monte Carlo simulation and we have exact match for high samples $N > 30$. As the received power from the intruding UAV increases in the suburban environment, the probability of detection increases however at a lower rate compared to the suburban. This has also been observed if the UAV at a higher altitude and better LoS conditions with an increase in received power at the RF sensor. This increases the average

received SNR and enhances the probability of detection but requires much higher P_t , e.g. reaching 24 dBm.

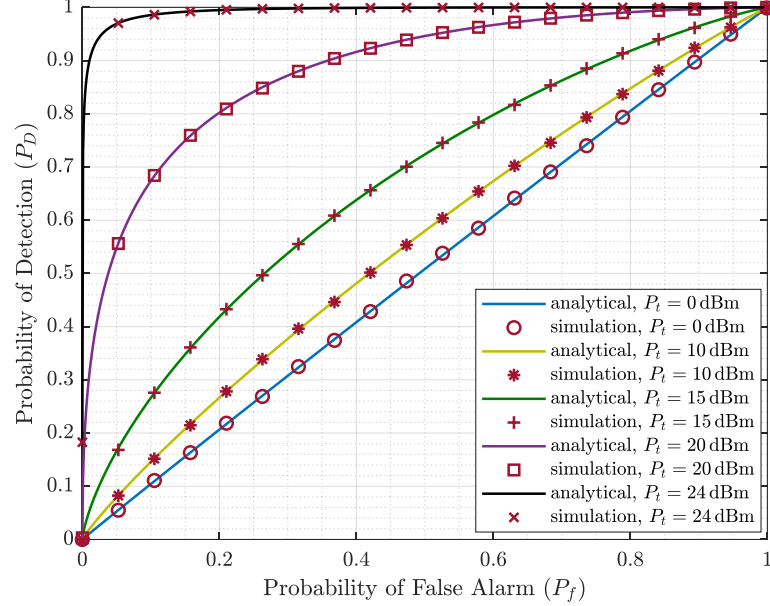


Figure 9: ROC curves for a Rayleigh channel in urban area with UAV located at $x_D = y_D = 40\text{m}$ and at an altitude $h' = 15\text{m}$

Comparing Figures 8 and 9, the density of buildings and surrounding environment have an impact on the probability of detection as it increases. Consequently, the probability of detection in suburban is better than urban areas with higher chances of LoS conditions.

We specifically compare them in Figure 10 at a fixed transmit power of $P_t = 4\text{ dBm}$ and observe the detector performance after varying the intruding UAV altitude from 15m to 20m. There is a slight improvement in the probability of detection in the urban environment at such relatively low transmit power; however, in suburban environment, we can see much enhancement in the probability of detection. Referring to Figure 6, the enhancement going from 15m to 20m is due to the lower path loss encountered by the intercepted UAV signal.

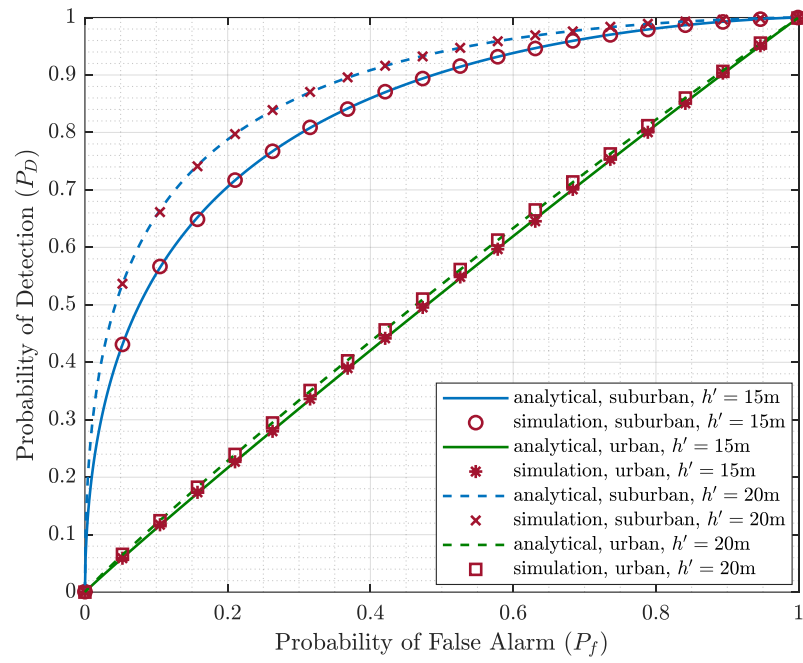


Figure 10: ROC curves for a Rayleigh channel comparing the performance in suburban and urban areas with $P_t = 4$ dBm, UAV at $x_D = y_D = 40\text{m}$

CHAPTER 4

Detection and Classification of Multiple UAVs using Spiking Neural Networks

The results presented in Chapter 3 for the energy-based detector considering a single intruding UAV are extended to the case of multiple UAVs. This is a more challenging problem as there will be multiple RF signals received at the same time. Therefore, a novel machine learning technique has been proposed based on the Spiking Neural Networks (SNN) and is tested on real RF data measurements using the DroneRF dataset [55]. This dataset has been used widely in the literature for the detection and classification of multiple drones. This multi-intruding-UAVs detection is assisted with multiple low-cost ground energy-based sensors.

This chapter begins with a brief background and introduction on SNN, and the literature review on their adoption and applications. Then, the proposed SNN model architecture is discussed along with the pre-processing on dataset, and obtained results and observations.

4.1 Spiking Neural Networks

Artificial neural networks (ANN) are well-known in the machine learning domain for their exceptional ability to learn complex nonlinear transformations [56]. The idea of employing a distributed network composed of neurons that can change their connection weight during training came to reality and was inspired by the human brain [57]. Nowadays, an increasing number of real-world problems are being solved effectively by using Spiking Neural Networks (SNNs) [58].

SNNs can be trained on real data, like other neural networks, but only for a certain field. This has spurred a body of research on the creation and application of SNN architectures for novel computing paradigms. A way to use these networks to more practical problems became necessary as this discipline developed [59]. Biologically inspired SNNs offer an extremely effective way to handle signal processing issues. As the brain encodes the spikes, spiking neurons link using discrete spikes and the target neuron records a synaptic current trace in response to a spike.

Neurons, inside the human brain, interconnect and form a massive network of other neurons. The ideal spiking neuron consists of dendrites (or the input device), soma (working as a central processing unit), and the axon, which is the output device. Dendrites collect signals from nearby neurons and send them to the soma; whereas, the soma, a central cell body, performs a non-linear processing function based on the threshold and total input generated/received. Then, the axon and its endings transmit the signal to other neurons [60]. If any of these neurons gives a spike, all downstream neurons might get affected. Figure 9 shows synapses are mostly formed in the junction between axons and dendrites of the next neuron(s).

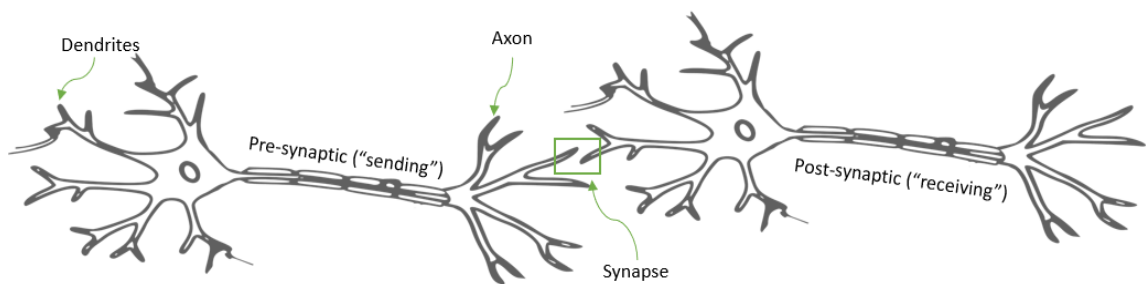


Figure 11: Neurons and the junction between neurons through the synapse

Input spikes can either excite or inhibit a neuron's ability to fire. If neurons are sufficiently excited, it will emit its own spike down its axon to the interconnected and downstream neurons.

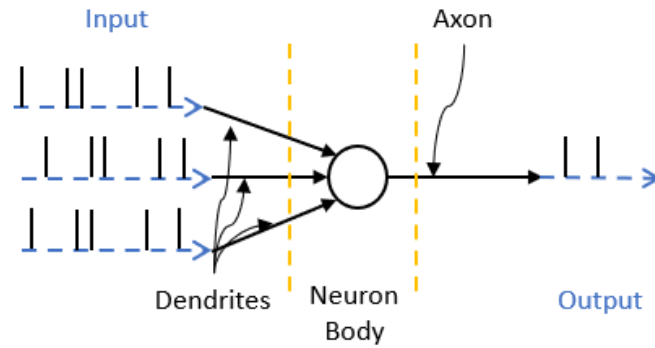


Figure 12: Spikes from 3 neurons processed in the soma and output is delivered through the axon

The action potential (or spike), which occurs at the output as shown in Figure 10, is typically a short voltage pulse with an amplitude that can reach 100mV in a short duration of 1-2 ms. The transmission of signals from presynaptic neuron to a postsynaptic neuron is through synapse. For a chain of action potentials from a single neuron, the shape of spike is not critical; moreover, the events causing the spikes can occur at regular or irregular intervals. The minimal distance between two spikes defines the absolute refractory period of a neuron followed by a relative refractoriness phase.

4.2 Literature Review

SNNs have been attracting the attention of researchers as an efficient and promising deep learning model [58]-[67]. Their structure inherits asynchronous and sparseness of spike trains, which make them energy-efficient while maintaining a relatively good performance [62]. Although the study of neurons dates back to the 1900s and works of Santiago Ramòn

Cajal, a pioneer in neuroscience, there are number of neuron mathematical models in the literature. Examples of such early models include a simple spiking model introduced by Izhikevich in [61], Mcculloch-Pitts model [71] using propositional logic, and well-known Spiking Response Model (SRM) by Gerstner and Kistler [60], sometimes referred to as SRM0. One of the common SNN implementations is based on the Leaky Integrate and Fire (LIF) concept. This was observed due to the resemblance nerve membranes with electric circuitry, where it can be approximated by a capacitor with a leakage. If the membrane potential exceeds this threshold, then a voltage spike will be generated and rested [72].

SNNs dynamics were initially explored based on deterministic models. For instance, in [61] Izhikevich proposed a simple model to represent the spiking behavior using the biological Hodgkin-Huxley dynamics combined with an integrate-and-fire model. The proposed model is rich in covering spiking, bursting, post-inhibitory spikes/burst, among others. More recently, with the GPU accelerated tensor computation gradient-based learning with SNNs can be implemented with snnTorch, which is a Python package. It extends the capabilities of PyTorch, taking advantage of its GPU applying it to networks of spiking neurons where each spiking neuron is an activation in a sequence of layers.

Probabilistic SNN model had been discussed by Jang et al. [73] and compared to the ANN models. In probabilistic SNN, the outputs of all spiking neurons are following a probabilistic model, typically a binary random process. Such distribution is differentiable in the synaptic weights. They can well approximate the performance of ANN with a general tradeoff between accuracy, which is sacrificed for an improved energy and lower delay [74].

Computational power in deep learning models rely on high amount of power to achieve exceptional performance [58]. This directed more researchers towards the neuromorphic computing, or in another words brain-inspired computing for machine intelligence [75]. Such neuromorphic hardware implementation can face some challenges in the presence of external noise as depicted by the FPGA-based SNNs proposed by Guo et al. [76].

To the best of our knowledge there is no prior research works on SNNs for the RF-based UAV detection reported in the literature. However, for vision-based UAV detection Kirkland et al. in [77] proposed a combination of dynamic vision sensor (DVS) and SNN. Such a system propagates a minimal amount of information through the network while training using 43,000 images. The achieved overall accuracy was 91% with lower computation due to the sparse nature of SNN compared to the traditional CNNs.

Recently, Robertson et al. [78] demonstrated the combination of neuromorphic photonic hardware and software SNN to have an efficient learning and ultrafast operations. This is based on a single layer optical SNN for the detection and tracking application at high rates. Furthermore, SNNs had been applied for an efficient content-based image retrieval (CBIR) [79] which is one example of wide-range of SNNs recent applications. Lapicque [72] concluded that a spiking neuron resembles a low-pass filter circuit consisting of a resistor R and a capacitor C , later dubbed the leaky integrate-and-fire (LIF) neuron as shown in Figure 11. The dynamics of the passive membrane modeled using an RC circuit can be represented as:

$$\tau \frac{dU_{mem}(t)}{dt} = -U_{mem}(t) + I_{in}(t)R \quad (33)$$

$$U_{mem}(t + \Delta t) = U_{mem}(t) + \frac{\Delta t}{\tau} (- U_{mem}(t) + RI_{in}(t)) \quad (34)$$

where $\beta = e^{-\frac{1}{\tau}}$ denotes the decay rate (or “inverse time constant RC”) of $U_{mem}(t)$. When the membrane potential exceeds a threshold θ , a spike is generated.

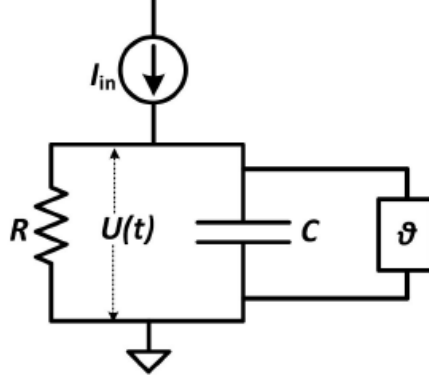


Figure 13: LIF RC circuit [72]

4.3 Model Architecture

In this section, the considered model architecture for the detection of multiple UAVs based on the sensed and measured RF signals is discussed, the RF dataset followed by the preprocessing and hyperparameters. Finally, the results and observations are illustrated and presented.

4.3.1 System Model

The system model under consideration for detecting and classifying multiple UAVs is shown in Figure 12. It consists of a Universal Software Radio Peripheral (USRP) device to record the emitted RF signals or the communication signals between the drone and remote controllers, or background noise in the case of no drones appearing in the scene. After recording and measuring the RF signals, it stores the measured data and sends it to a

computing unit for feature extraction, concatenating the signal, and filtering. After that, the extracted filtered data is fed to our proposed SNN model.

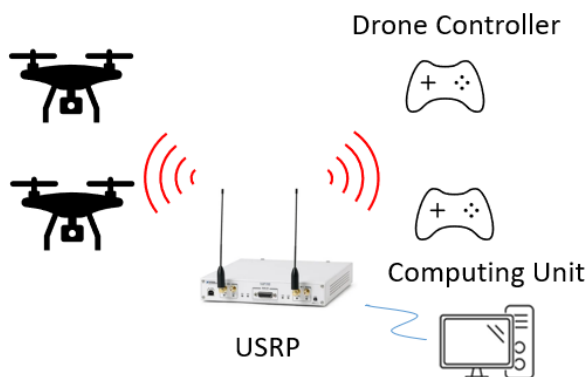


Figure 14: System model for the experiment setup

4.3.2 Dataset

The DroneRF database used in this thesis is a publicly available database in [7]. It is raw RF measured signals for three different types of drones: Parrot Bebop, Parrot AR Drone and DJI Phantom 3 shown in Figure 15.



Figure 15: (a) Parrot Bebop [80], (b) Parrot AR [81], (c) DJI Phantom 3 [82]

Moreover, background noise with no drone is included as well and available in the dataset. The communication signals emitted from drones are captured through two RF receivers. One dedicated for the low side of bandwidth, i.e. from 0 to 40 MHz while the other one is for high side of bandwidth up to 80 MHz. The RF receiver records 10.25 seconds of

background activity and 5.25 seconds of RF drone communication in different modes of the three drones. The total segments of this database are 277 segments. Each segment consists of 10 million samples where each sample represents the amplitude of the signal in time domain. Originally, this database meant for three task experiment as follow:

- Drone Detection: binary hypothesis testing problem which involves detecting the presence of drone. It is binary classification problem because it has two possibilities: “Drone” or “No Drone”.
- Drone Identification: 4 class problem which involves identifying 3 types of drones and background activities.
- Drone Mode Identification: 10 class problem which involves distinguishing between the type and mode of operation of drones and background activities.

Table 4 shows the data distributions for the two experiments, drone detection and drone identification. It shows the number of segments, number of samples, and ratio across the classes considered for the intended experiment as well.

Table 4: Data Distribution Ratio

Experiment	Class	Segments	Sample Number	Ratio (%)
Drone Detection	No Drone	41	820	18.06%
	Drone	186	3720	81.94%
Drone Identification	No Drone	41	820	18.06%
	Bebop	84	1680	37%
	AR	81	1620	35.68%
	Phantom	21	420	9.26%

4.4 Preprocessing

In this section, the preprocessing of the RF data measured resulting from the multiple UAVs is explained. This includes the feature extraction, appropriate filtering, and correction for the classes’ imbalance.

4.4.1 Feature Extraction

One essential step before training our proposed model is to conduct proper preprocessing for the raw RF signal, e.g. selecting a feature extraction technique. Utilizing the time domain, the signals can be analyzed over time. On the other hand, the frequency domain analysis will show the signal frequency content located in a specific frequency bandwidth. This generates a unique spectra of frequency amplitude and gives more robustness feature against noise unlike time domain. Hence, frequency domain is used for more simplicity and better performance in the RF signal classification. To proceed forward, a Discrete Fourier Transform (DFT) is applied to the raw RF time series data to extract frequency domain features with a frequency bin of 2048. After that, the low and high bands are concatenated by scaling the high spectrum and appending it to the end of the low spectrum. Moreover, the mean and median were calculated for each signal and added as a feature to enhance the accuracy of the classification. It was observed that this feature enhances accuracy by 2 %.

4.4.2 Filtering

By analyzing all signal spectrum segments, it is obvious that some segments have no active RF communication signal even though it is labeled as a drone as shown in Figure 16.

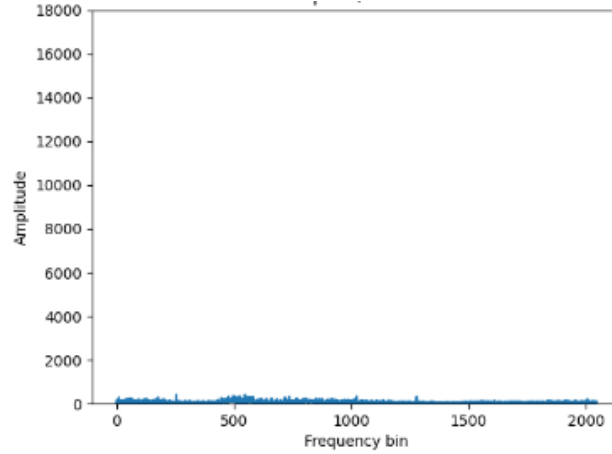


Figure 16: UAV segment with no active amplitude RF signal

Feeding such a segment to the classification model might not be the best option and may result in misclassification. This explains the limited and low accuracies in the first classification problems. To overcome this issue, we propose a filtering mechanism to filter out all segments labeled as drones, but with no actual RF communication signal. First, we determine the maximum amplitude of signal under the no drone assumption. Then, consider this amplitude as a threshold to filter out other drone segments from feeding it to the model during the training phase.

4.4.3 Class Imbalance

The DroneRF dataset has an unbalanced distribution of classes. Looking at the 4-class classification problem, the distributions are 41, 84, 81, and 21 respectively. This unbalanced distribution can lead to low performance classification. Hence, there is a requirement to overcome this issue either by resampling, eliminating some of sample, or regenerating more sample data. In this thesis, we have generated sample data by oversampling between each two segments of the same class label as provided in Table 5.

Table 5: Balancing segments across the four classes in the dataset

Drone Experiment	Class	Segments
Before	No Drone	4100
	Bebop	1596
	AR	1652
	Phantom	1392
After	No Drone	1392
	Bebop	1392
	AR	1392
	Phantom	1392

4.5 Hyperparameters

To conduct these experiments, we have fine-tuned the hyperparameters to find the proper hyperparameters that will achieve the optimal performance of the proposed SNN models based on numerous and extensive experiments. Table 6 represents the best parameters for each of these experiments. Please note the principle of these hyperparameters are already explained in section 4.2.

Table 6: Hyperparameters

Drone Experiment	Epoch	Beta	Learning rate	Threshold
Drone Detection	14	0.2	5×10^{-4}	0.2
Drone Identification	30	0.2	5×10^{-4}	0.2

4.6 Experimental Results

The performance of the proposed SNN architecture for multiple UAV detection has been evaluated using the accuracy metric. It is a common metric score used to calculate how

many correct predictions result from the classification generated by the algorithm. The accuracy metric is given by

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (35)$$

where TP, TN, FN, and FP represent the number of true positives, true negatives, false negatives, and false positives, respectively.

4.6.1 Binary classification

The model was trained with segments being filtered. In this experiment, the main target is to detect the presence of drones. As shown in Figure 17, the model achieved 100% accuracy, based on the RF dataset, which indicates the high capability and accuracy of the proposed model to detect any drone with no wrong prediction. At the 10th epoch, there was a drop in the accuracy which indicates the model is still learning from the error weight. However, the model was able to achieve 100% steady accuracy after that.

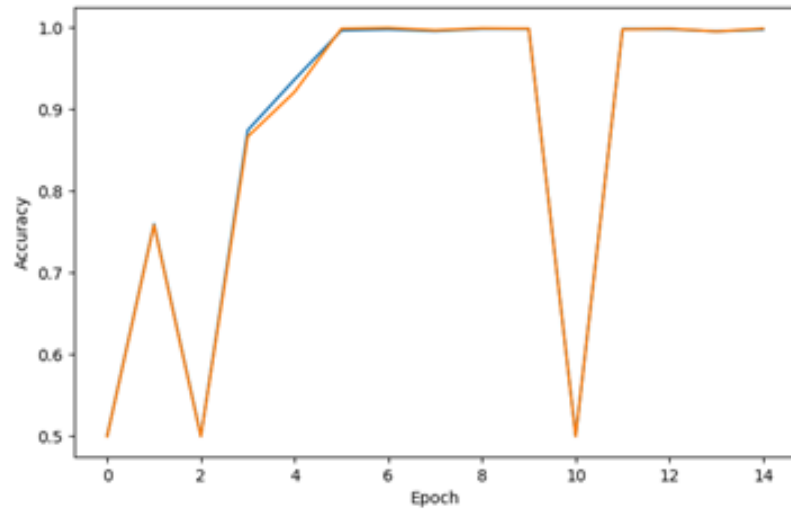


Figure 17: Accuracy in detection Vs Epoch (Binary)

In Figure 18, the confusion matrix is plotted with almost no wrong prediction. The model was clearly able to identify the drone RF signal from background noise.

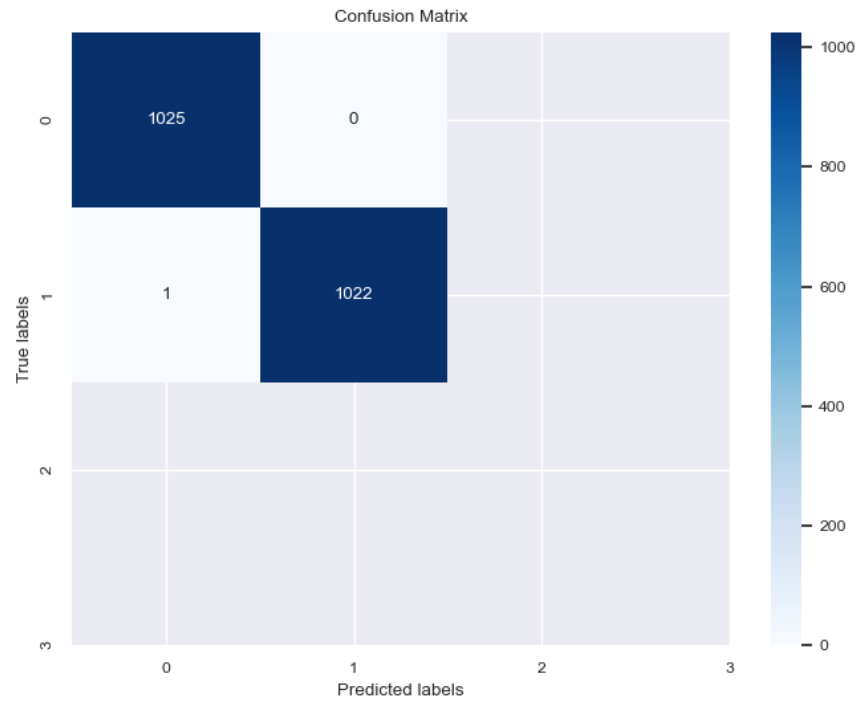


Figure 18: Confusion Matrix (Binary)

4.6.2 Multiclassification

First, we have trained the model without applying the filter and Figure 19 shows the accuracy of the model with 30 epoch which reached 38% in its maximum, while fluctuations occur between epoch 15 and 30 below 40%.

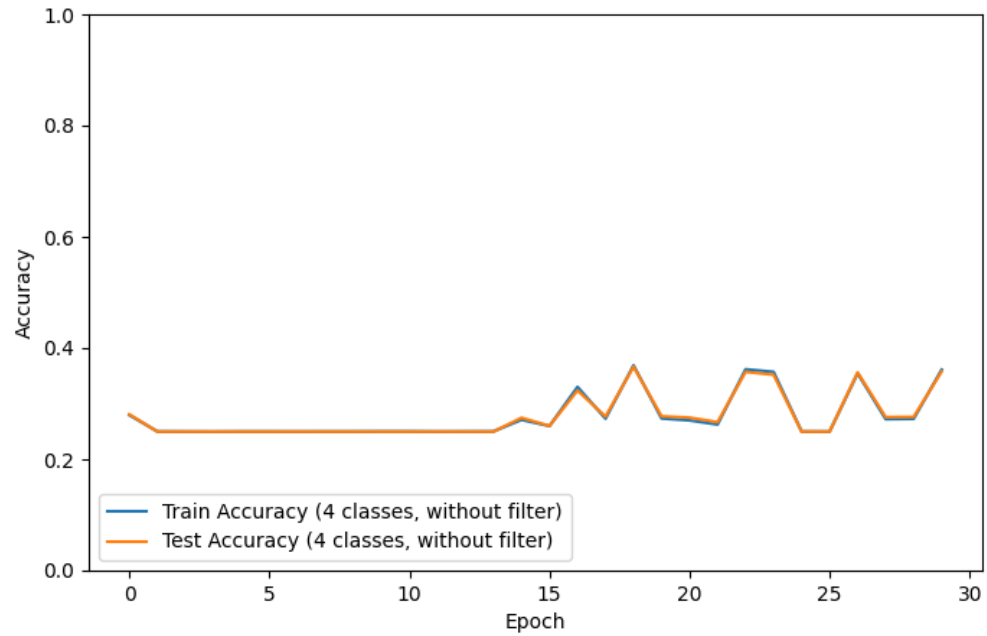


Figure 19: Accuracy vs epoch considering four classes and without filter

It can be observed from Figure 19 that the model is trained with certain issues in the labeled data causing confusion in the learned new weights and patterns each time/epoch. This has caused difficulties in the learned features and results in lower performance in classification and below expectations in terms of the accuracy.

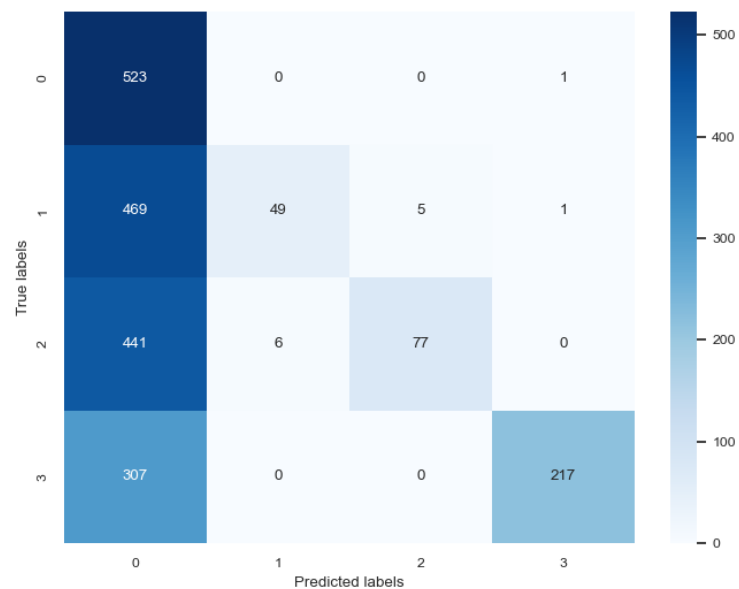


Figure 20: Confusion matrix considering four classes and without filter

The confusion matrix in Figure 20 depicts that most of errors are in predicting there is no drone label/class. This is mainly because the segments from class with drones have no distinguishable amplitudes.

On the other hand, the proposed SNN model for multiple UAV detection has been trained with segments after applying an appropriate filter. As shown in Figure 21, the accuracy has improved substantially reaching 97% in its maximum and slight fluctuations around 95%, with an excellent error reduction in both the train and test data.

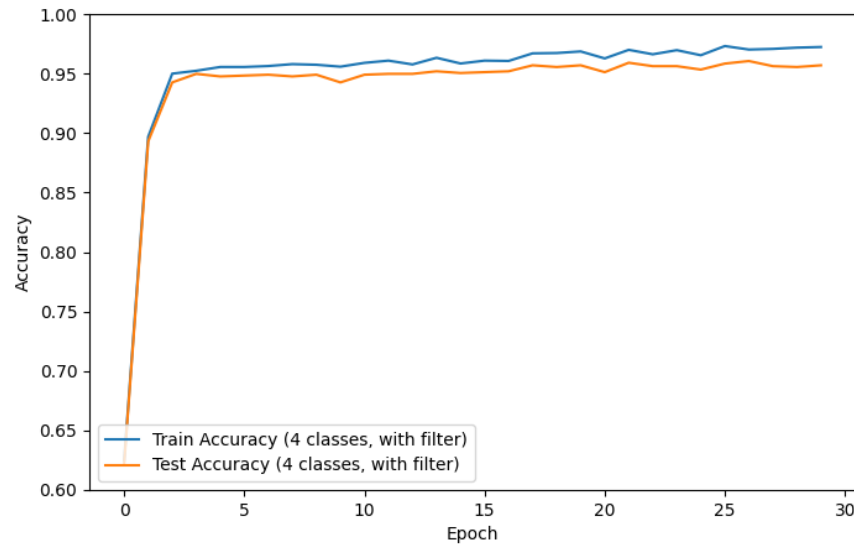


Figure 21: Accuracy vs epoch considering four classes and with filter

Comparing the confusion matrix in Figure 20 with Figure 22, it can be seen that the issue of misprediction with no drone has been eliminated. Most of test data in class 0, i.e. “no drone”, and class 3 “Phantom” have very minor misprediction. On the other hand, class 1 “Bebop” and class 2 “AR” have relatively higher misprediction. This is because both drone models are manufactured by the same company with similar technology making it more challenging to the proposed SNN classifier to make firm distinction.

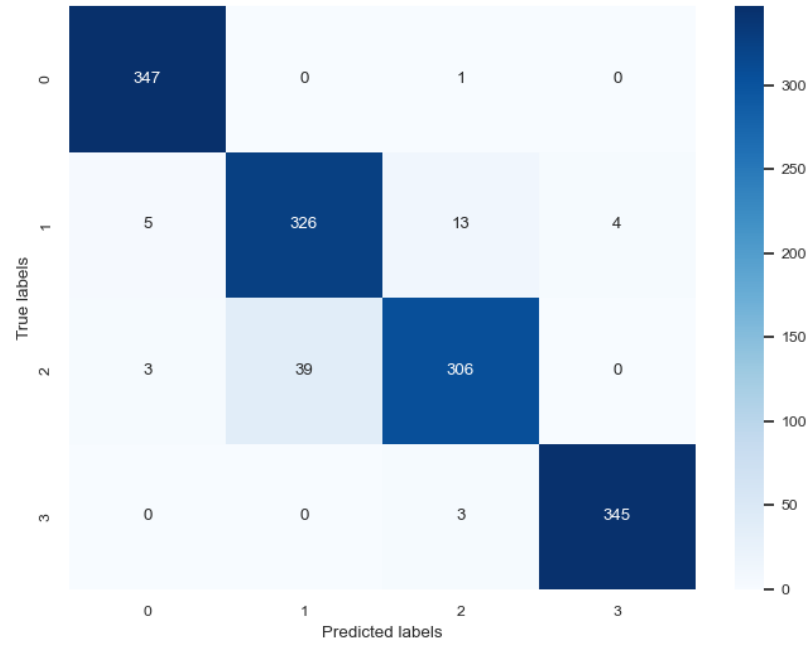


Figure 22: Confusion matrix considering four classes and with filter

The proposed SNN has proven its capability to achieve high accuracy with RF drone signal. To show the comparative of our proposal, we have conducted another experiment by training a CNN on this dataset. The model was trained with segments being filtered. As shown in Figure 23, the accuracy reaches 97% in its maximum with an excellent error reduction. Although this performance is comparable to the proposed SNN based model, in terms of energy consumption and hardware implementation, it is well-known in the literature the power consumption required for the CNN and complexity which is the motivation for selecting the SNN model.

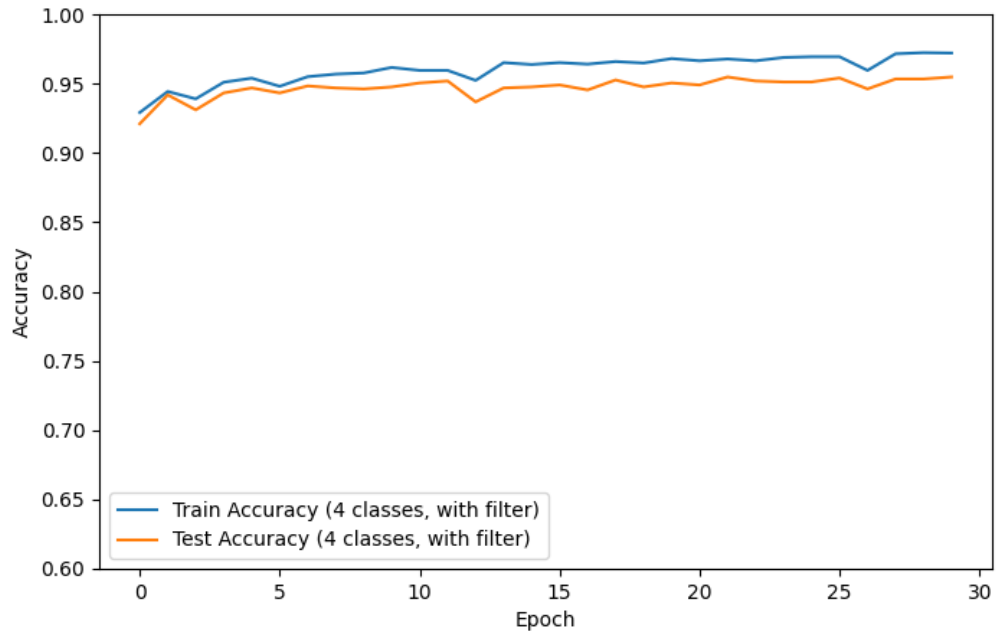


Figure 23: Accuracy vs epoch considering CNN, four classes, and with filter

Figure 24 shows the confusion matrix for the CNN of 4 classes after applying filter to signal. Clearly, similar performance is achieved to our proposed SNN model.

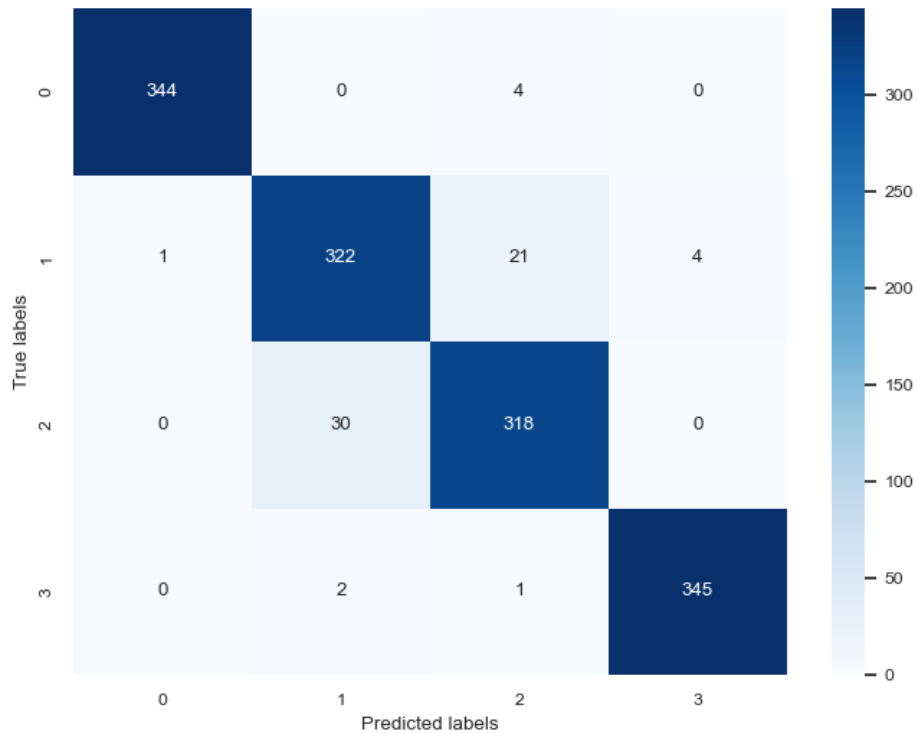


Figure 24: Confusion matrix for CNN, four classes, and with filter

CHAPTER 5

Conclusions and Future Work

This thesis provided a comprehensive literature review on drone detection techniques with a focus on the RF-based UAV detection methods. First, an accurate probabilistic channel model for the RF sensed signal emitted from the intruding UAV was proposed, which includes the air-to-ground propagation, large-scale path loss, and small-scale multipath fading. Such formulation proper sampling of the unknown sensed signal, unknown line-of-sight or non-line-of-sight conditions, and some practical system parameters of energy-based detectors. We have derived closed-form expressions of the probability of detection and false alarm under different environmental conditions, and the received operating characteristics was investigated as well.

Furthermore, we have conducted in this thesis a thorough survey in the literature on machine learning adoption for detection of intruding UAV. We proposed a novel SNN model for detecting and classifying multiple UAVs based on the RF dataset. In the proposed model, a filtering and class balancing approach for the data were applied to enhance the quality in the preprocessing phase. Before feeding the data to the SNN model, DFT was used for feature extraction in the frequency domain. The result of this model was benchmarked with CNN to show the accuracy and detection performance. We have used DroneRF database to conduct two experiments for model training and testing. Accuracy and loss metric function were used to evaluate the performance of our model. In the future, we plan to extend the results and apply this model to UAV mode identification, a 10-classification problem to achieve higher accuracy and testing it in real-time under challenging conditions.

References

- [1] H. Kang, J. Joung, J. Kim, J. Kang, and Y. S. Cho, "Protect your sky: A survey of counter unmanned aerial vehicle systems," *IEEE Access*, vol. 8, pp. 168671–168710, 2020, doi: 10.1109/ACCESS.2020.3023473.
- [2] P. Tokekar, J. Vander Hook, D. Mulla, and V. Isler, "Sensor planning for a symbiotic UAV and UGV system for precision agriculture," *IEEE International Conference on Intelligent Robots and Systems*, pp. 5321–5326, 2013, doi: 10.1109/IROS.2013.6697126.
- [3] H. Shakhathreh *et al.*, "Unmanned Aerial Vehicles (UAVs): A Survey on Civil Applications and Key Research Challenges," *IEEE Access*, vol. 7, pp. 48572–48634, 2019, doi: 10.1109/ACCESS.2019.2909530.
- [4] "Russia says Ukraine's Kremlin drone strike was an attack on Vladimir Putin - The Washington Post." Accessed: May 28, 2024. [Online]. Available: <https://www.washingtonpost.com/world/2023/05/03/vladimir-putin-attack-drones-kremlin/>
- [5] Y. N. Jurn, S. A. Mahmood, and J. A. Aldhaibani, "Anti-Drone System Based Different Technologies: Architecture, Threats and Challenges," *Proceedings - 2021 11th IEEE International Conference on Control System, Computing and Engineering, ICCSCE 2021*, pp. 114–119, Aug. 2021, doi: 10.1109/ICCSCE52189.2021.9530992.
- [6] J. Drozdowicz *et al.*, "35 GHz FMCW drone detection system," *Proceedings International Radar Symposium*, vol. 2016-June, Jun. 2016, doi: 10.1109/IRS.2016.7497351.
- [7] D. H. Shin, D. H. Jung, D. C. Kim, J. W. Ham, and S. O. Park, "A Distributed FMCW Radar System Based on Fiber-Optic Links for Small Drone Detection," *IEEE Trans Instrum Meas*, vol. 66, no. 2, pp. 340–347, Feb. 2017, doi: 10.1109/TIM.2016.2626038.
- [8] S. Zulkifli and A. Balleri, "Design and Development of K-Band FMCW Radar for Nano-Drone Detection," *IEEE National Radar Conference - Proceedings*, vol. 2020-September, Sep. 2020, doi: 10.1109/RADARCONF2043947.2020.9266538.
- [9] M. Jian, Z. Lu, and V. C. Chen, "Drone detection and tracking based on phase-interferometric Doppler radar," *2018 IEEE Radar Conference, RadarConf 2018*, pp. 1146–1149, Jun. 2018, doi: 10.1109/RADAR.2018.8378723.
- [10] T. Yang, A. De Maio, J. Zheng, T. Su, V. Carotenuto, and A. Aubry, "An Adaptive Radar Signal Processor for UAVs Detection with Super-Resolution Capabilities," *IEEE Sens J*, vol. 21, no. 18, pp. 20778–20787, Sep. 2021, doi: 10.1109/JSEN.2021.3093779.
- [11] J. Ochodnický, Z. Matousek, M. Babjak, and J. Kurty, "Drone detection by Ku-band battlefield radar," *ICMT 2017 - 6th International Conference on Military Technologies*, pp. 613–616, Jul. 2017, doi: 10.1109/MILTECHS.2017.7988830.
- [12] J. Zheng, T. Yang, H. Liu, T. Su, and L. Wan, "Accurate Detection and Localization of Unmanned Aerial Vehicle Swarms-Enabled Mobile Edge Computing System," *IEEE Trans Industr Inform*, vol. 17, no. 7, pp. 5059–5067, Jul. 2021, doi: 10.1109/TII.2020.3015730.

- [13] J. Zheng *et al.*, “An Efficient Strategy for Accurate Detection and Localization of UAV Swarms,” *IEEE Internet Things J*, vol. 8, no. 20, pp. 15372–15381, Oct. 2021, doi: 10.1109/JIOT.2021.3064376.
- [14] S. Rahman and D. A. Robertson, “Classification of drones and birds using convolutional neural networks applied to radar micro-Doppler spectrogram images,” *IET Radar, Sonar and Navigation*, vol. 14, no. 5, pp. 653–661, May 2020, doi: 10.1049/IET-RSN.2019.0493.
- [15] G. J. Mendis, T. Randeny, J. Wei, and A. Madanayake, “Deep learning based doppler radar for micro UAS detection and classification,” *Proceedings - IEEE Military Communications Conference MILCOM*, pp. 924–929, Dec. 2016, doi: 10.1109/MILCOM.2016.7795448.
- [16] M. Jahangir, C. J. Baker, and G. A. Oswald, “Doppler characteristics of micro-drones with L-Band multibeam staring radar,” *2017 IEEE Radar Conference, RadarConf 2017*, pp. 1052–1057, Jun. 2017, doi: 10.1109/RADAR.2017.7944360.
- [17] P. Sinha, I. Guvenc, and M. Cenk Gursoy, “Fundamental Limits on Detection of UAVs by Existing Terrestrial RF Networks,” *IEEE Open Journal of the Communications Society*, vol. 2, pp. 2111–2130, 2021, doi: 10.1109/OJCOMS.2021.3109105.
- [18] I. Guvenc, F. Koohifar, S. Singh, M. L. Sichitiu, and D. Matolak, “Detection, Tracking, and Interdiction for Amateur Drones,” *IEEE Communications Magazine*, vol. 56, no. 4, pp. 75–81, Nov. 2018, doi: 10.1109/MCOM.2018.1700455.
- [19] Y. Awad and S. I. Al-Dharrab, “Malicious UAV Detection Over Rician Fading Channel: Performance Analysis,” *IEEE Access*, vol. 12, pp. 34681–34690, 2024, doi: 10.1109/ACCESS.2024.3373309.
- [20] S. Al-Dharrab, “Detection Performance of Malicious UAV using Massive IoT Networks,” in *2023 IEEE 97th Vehicular Technology Conference (VTC2023-Spring)*, 2023, pp. 1–5. doi: 10.1109/VTC2023-Spring57618.2023.10200462.
- [21] W. Nie, Z. C. Han, M. Zhou, L. B. Xie, and Q. Jiang, “UAV Detection and Identification Based on WiFi Signal and RF Fingerprint,” *IEEE Sens J*, vol. 21, no. 12, pp. 13540–13550, Jun. 2021, doi: 10.1109/JSEN.2021.3068444.
- [22] C. Xu, B. Chen, Y. Liu, F. He, and H. Song, “RF Fingerprint Measurement for Detecting Multiple Amateur Drones Based on STFT and Feature Reduction,” *Integrated Communications, Navigation and Surveillance Conference, ICNS*, vol. 2020-September, Sep. 2020, doi: 10.1109/ICNS50378.2020.9223013.
- [23] H. Zhang, C. Cao, L. Xu, and T. A. Gulliver, “A UAV Detection Algorithm Based on an Artificial Neural Network,” *IEEE Access*, vol. 6, pp. 24720–24728, Apr. 2018, doi: 10.1109/ACCESS.2018.2831911.
- [24] S. Al-Emadi and F. Al-Senaid, “Drone Detection Approach Based on Radio-Frequency Using Convolutional Neural Network,” *2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies, ICIOT 2020*, pp. 29–34, Feb. 2020, doi: 10.1109/ICIOT48696.2020.9089489.
- [25] M. Ezuma, F. Erden, C. Kumar Anjinappa, O. Ozdemir, and I. Guvenc, “Detection and Classification of UAVs Using RF Fingerprints in the Presence of Wi-Fi and Bluetooth Interference,” *IEEE Open Journal of the Communications Society*, vol. 1, pp. 60–76, Nov. 2019, doi: 10.1109/OJCOMS.2019.2955889.

- [26] M. Ezuma, F. Erden, C. K. Anjinappa, O. Ozdemir, and I. Guvenc, "Micro-UAV Detection and Classification from RF Fingerprints Using Machine Learning Techniques," *IEEE Aerospace Conference Proceedings*, vol. 2019-March, Mar. 2019, doi: 10.1109/AERO.2019.8741970.
- [27] N. Soltani, G. Reus-Muns, B. Salehi, J. Dy, S. Ioannidis, and K. Chowdhury, "RF Fingerprinting Unmanned Aerial Vehicles with Non-Standard Transmitter Waveforms," *IEEE Trans Veh Technol*, vol. 69, no. 12, pp. 15518–15531, Dec. 2020, doi: 10.1109/TVT.2020.3042128.
- [28] F. Hoffmann, M. Ritchie, F. Fioranelli, A. Charlish, and H. Griffiths, "Micro-Doppler based detection and tracking of UAVs with multistatic radar," *2016 IEEE Radar Conference, RadarConf 2016*, Jun. 2016, doi: 10.1109/RADAR.2016.7485236.
- [29] G. Plastiras, M. Terzi, C. Kyrkou, and T. Theocharides, "Edge Intelligence: Challenges and Opportunities of Near-Sensor Machine Learning Applications," *Proceedings of the International Conference on Application-Specific Systems, Architectures and Processors*, vol. 2018-July, Aug. 2018, doi: 10.1109/ASAP.2018.8445118.
- [30] B. Taha and A. Shoufan, "Machine Learning-Based Drone Detection and Classification: State-of-the-Art in Research," *IEEE Access*, vol. 7, pp. 138669–138682, 2019, doi: 10.1109/ACCESS.2019.2942944.
- [31] Y. J. J. Teoh and C. K. Seow, "RF and Network Signature-based Machine Learning on Detection of Wireless Controlled Drone," *Progress in Electromagnetics Research Symposium*, vol. 2019-June, pp. 408–417, Jun. 2019, doi: 10.1109/PIERS-SPRING46901.2019.9017231.
- [32] C. J. Swinney and J. C. Woods, "RF Detection and Classification of Unmanned Aerial Vehicles in Environments with Wireless Interference," *2021 International Conference on Unmanned Aircraft Systems, ICUAS 2021*, pp. 1494–1498, Jun. 2021, doi: 10.1109/ICUAS51884.2021.9476867.
- [33] K. Raina, T. Alladi, V. Chamola, and F. R. Yu, "Detecting UAV Presence Using Convolution Feature Vectors in Light Gradient Boosting Machine," *IEEE Trans Veh Technol*, vol. 72, no. 4, pp. 4332–4341, Apr. 2023, doi: 10.1109/TVT.2022.3227192.
- [34] S. Al-Emadi and F. Al-Senaid, "Drone Detection Approach Based on Radio-Frequency Using Convolutional Neural Network," *2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies, ICIoT 2020*, pp. 29–34, Feb. 2020, doi: 10.1109/ICIOT48696.2020.9089489.
- [35] R. Jadhav, R. Patil, A. Diwan, S. M. Rathod, and A. Sharma, "Drone Based Object Detection using AI," *2022 International Conference on Signal and Information Processing, IConSIP 2022*, 2022, doi: 10.1109/ICONSIP49665.2022.10007476.
- [36] C. Xu, B. Chen, Y. Liu, F. He, and H. Song, "RF Fingerprint Measurement for Detecting Multiple Amateur Drones Based on STFT and Feature Reduction," *Integrated Communications, Navigation and Surveillance Conference, ICNS*, vol. 2020-September, Sep. 2020, doi: 10.1109/ICNS50378.2020.9223013.
- [37] H. Jafari, E. Blasch, K. Pham, and G. Chen, "Signature-Aware RF Exploitation (SNARE) Fingerprinting using Deep Learning to identify UAVs," *IEEE Aerospace*

- Conference Proceedings*, vol. 2022-March, 2022, doi: 10.1109/AERO53065.2022.9843479.
- [38] R. Akter, V. S. Doan, G. B. Tunze, J. M. Lee, and D. S. Kim, "RF-Based UAV Surveillance System: A Sequential Convolution Neural Networks Approach," *International Conference on ICT Convergence*, vol. 2020-October, pp. 555–558, Oct. 2020, doi: 10.1109/ICTC49870.2020.9289281.
 - [39] S. Basak, S. Rajendran, S. Pollin, and B. Scheers, "Drone classification from RF fingerprints using deep residual nets," *2021 International Conference on COMMunication Systems and NETworkS, COMSNETS 2021*, pp. 548–555, Jan. 2021, doi: 10.1109/COMSNETS51098.2021.9352891.
 - [40] S. Mandal and U. Satija, "Time-Frequency Multiscale Convolutional Neural Network for RF-Based Drone Detection and Identification," *IEEE Sens Lett*, vol. 7, no. 7, Jul. 2023, doi: 10.1109/LSSENS.2023.3289145.
 - [41] R. Akter, M. Golam, A. Zainudin, V. S. Doan, and D. S. Kim, "RF Signal-Based Multipurpose UAV Surveillance System Using Deep Neural Network," *International Conference on ICT Convergence*, vol. 2022-October, pp. 555–559, 2022, doi: 10.1109/ICTC55196.2022.9952604.
 - [42] K. Bremnes, R. Moen, S. R. Yeduri, R. R. Yakkati, and L. R. Cenkeramaddi, "Classification of UAVs Utilizing Fixed Boundary Empirical Wavelet Sub-Bands of RF Fingerprints and Deep Convolutional Neural Network," *IEEE Sens J*, vol. 22, no. 21, pp. 21248–21256, Nov. 2022, doi: 10.1109/JSEN.2022.3208518.
 - [43] Y. Zhang, "RF-based drone detection using machine learning," *Proceedings - 2021 2nd International Conference on Computing and Data Science, CDS 2021*, pp. 425–428, Jan. 2021, doi: 10.1109/CDS52072.2021.00079.
 - [44] M. S. Allahham, T. Khattab, and A. Mohamed, "Deep Learning for RF-Based Drone Detection and Identification: A Multi-Channel 1-D Convolutional Neural Networks Approach," *2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies, ICIOT 2020*, pp. 112–117, Feb. 2020, doi: 10.1109/ICIOT48696.2020.9089657.
 - [45] K. N. Inani, K. S. Sangwan, and Dhiraj, "Machine Learning based framework for Drone Detection and Identification using RF signals," *2023 International Conference on Innovative Trends in Information Technology, ICITIIT 2023*, 2023, doi: 10.1109/ICITIIT57246.2023.10068637.
 - [46] J. Holis and P. Pechac, "Elevation dependent shadowing model for mobile communications via high altitude platforms in built-up areas," *IEEE Trans Antennas Propag*, vol. 56, no. 4, pp. 1078–1084, Apr. 2008, doi: 10.1109/TAP.2008.919209.
 - [47] D. L. Leite *et al.*, "Unmanned Aerial Vehicle Propagation Channel over Vegetation and Lake Areas: First- and Second-Order Statistical Analysis," *Sensors 2022, Vol. 22, Page 65*, vol. 22, no. 1, p. 65, Dec. 2021, doi: 10.3390/S22010065.
 - [48] A. Al-Hourani, S. Kandeepan, and S. Lardner, "Optimal LAP altitude for maximum coverage," *IEEE Wireless Communications Letters*, vol. 3, no. 6, pp. 569–572, Dec. 2014, doi: 10.1109/LWC.2014.2342736.
 - [49] A. Goldsmith, *Wireless Communications*. Cambridge, U.K: Cambridge Univ. Press, 2005.
 - [50] R. Chen, T. Shi, X. Lv, and Q. Wang, "Small-scale fading characterization for railway wireless channels," *2016 IEEE Antennas and Propagation Society*

- International Symposium, APSURSI 2016 - Proceedings*, pp. 1701–1702, Oct. 2016, doi: 10.1109/APS.2016.7696557.
- [51] J. Liang and Q. Liang, “Outdoor propagation channel modeling in foliage environment,” *IEEE Trans Veh Technol*, vol. 59, no. 5, pp. 2243–2252, Jun. 2010, doi: 10.1109/TVT.2010.2043697.
 - [52] Z. Cui, C. Briso-Rodriguez, K. Guan, and Z. Zhong, “Ultra-Wideband Air-to-Ground Channel Measurements and Modeling in Hilly Environment,” *IEEE International Conference on Communications*, vol. 2020-June, Jun. 2020, doi: 10.1109/ICC40277.2020.9148768.
 - [53] F. F. Digham, M. S. Alouini, and M. K. Simon, “On the energy detection of unknown signals over fading channels,” *IEEE Transactions on Communications*, vol. 55, no. 1, pp. 21–24, Jan. 2007, doi: 10.1109/TCOMM.2006.887483.
 - [54] “An Introduction to the Theory of Random Signals and Noise | IEEE eBooks | IEEE Xplore.” Accessed: May 17, 2024. [Online]. Available: <https://ieeexplore.ieee.org/book/5265617>
 - [55] 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 Brief*, vol. 26, p. 104313, Oct. 2019, doi: 10.1016/J.DIB.2019.104313.
 - [56] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” vol. 521, pp. 436–444, May 2015.
 - [57] D. Rumelhart and J. McClelland, *Parallel Distributed Processing: Explorations in the Microstructure of Cognition. Foundations*, vol. 1. Cambridge, MA, USA: MIT Press, 1986.
 - [58] J. K. Eshraghian *et al.*, “Training Spiking Neural Networks Using Lessons from Deep Learning,” *Proceedings of the IEEE*, vol. 111, no. 9, pp. 1016–1054, Sep. 2023, doi: 10.1109/JPROC.2023.3308088.
 - [59] E. O. Neftci, H. Mostafa, and F. Zenke, “Surrogate Gradient Learning in Spiking Neural Networks: Bringing the Power of Gradient-based optimization to spiking neural networks,” *IEEE Signal Process Mag*, vol. 36, no. 6, pp. 51–63, Nov. 2019, doi: 10.1109/MSP.2019.2931595.
 - [60] W. Gerstner and W. M. Kistler, *Spiking Neuron Models: Single Neurons, Populations, Plasticity*. Cambridge: Cambridge University Press, 2002. doi: DOI: 10.1017/CBO9780511815706.
 - [61] E. M. Izhikevich, “Simple model of spiking neurons,” *IEEE Trans Neural Netw*, vol. 14, no. 6, pp. 1569–1572, Nov. 2003, doi: 10.1109/TNN.2003.820440.
 - [62] J. D. Nunes, M. Carvalho, D. Carneiro, and J. S. Cardoso, “Spiking Neural Networks: A Survey,” *IEEE Access*, vol. 10, pp. 60738–60764, 2022, doi: 10.1109/ACCESS.2022.3179968.
 - [63] Y. Wang, H. Liu, M. Zhang, X. Luo, and H. Qu, “A Universal ANN-to-SNN Framework for Achieving High Accuracy and Low Latency Deep Spiking Neural Networks,” *Neural Networks*, vol. 174, p. 106244, Jun. 2024, doi: 10.1016/J.NEUNET.2024.106244.
 - [64] R. Brette *et al.*, “Simulation of networks of spiking neurons: A review of tools and strategies,” *J Comput Neurosci*, vol. 23, no. 3, pp. 349–398, Jul. 2007, doi: 10.1007/S10827-007-0038-6/METRICS.

- [65] S. Ghosh-Dastidar and H. Adeli, "Spiking Neural Networks," *Int J Neural Syst*, vol. 19, no. 04, pp. 295–308, Aug. 2009, doi: 10.1142/S0129065709002002.
- [66] A. Tavanaei, M. Ghodrati, S. R. Kheradpisheh, T. Masquelier, and A. Maida, "Deep Learning in Spiking Neural Networks," *Neural Networks*, vol. 111, pp. 47–63, Mar. 2019, doi: 10.1016/J.NEUNET.2018.12.002.
- [67] H. Mostafa, "Supervised learning based on temporal coding in spiking neural networks," *IEEE Trans Neural Netw Learn Syst*, vol. 29, no. 7, pp. 3227–3235, Jul. 2018, doi: 10.1109/TNNLS.2017.2726060.
- [68] S. B. Furber *et al.*, "Overview of the SpiNNaker system architecture," *IEEE Transactions on Computers*, vol. 62, no. 12, pp. 2454–2467, 2013, doi: 10.1109/TC.2012.142.
- [69] P. U. Diehl, D. Neil, J. Binas, M. Cook, S. C. Liu, and M. Pfeiffer, "Fast-classifying, high-accuracy spiking deep networks through weight and threshold balancing," *Proceedings of the International Joint Conference on Neural Networks*, vol. 2015-September, Sep. 2015, doi: 10.1109/IJCNN.2015.7280696.
- [70] R. Benosman, C. Clercq, X. Lagorce, S. H. Ieng, and C. Bartolozzi, "Event-based Visual Flow," *IEEE Trans Neural Netw Learn Syst*, vol. 25, no. 2, pp. 407–417, Feb. 2014, doi: 10.1109/TNNLS.2013.2273537.
- [71] W. S. McCulloch and W. Pitts, "A logical calculus of the ideas immanent in nervous activity," *Bull Math Biophys*, vol. 5, no. 4, pp. 115–133, 1943, doi: 10.1007/BF02478259.
- [72] J. K. Eshraghian *et al.*, "Training Spiking Neural Networks Using Lessons from Deep Learning," *Proceedings of the IEEE*, vol. 111, no. 9, pp. 1016–1054, Sep. 2023, doi: 10.1109/JPROC.2023.3308088.
- [73] H. Jang, O. Simeone, B. Gardner, and A. Gruning, "An Introduction to Probabilistic Spiking Neural Networks: Probabilistic Models, Learning Rules, and Applications," *IEEE Signal Process Mag*, vol. 36, no. 6, pp. 64–77, Nov. 2019, doi: 10.1109/MSP.2019.2935234.
- [74] E. O. Neftci, H. Mostafa, and F. Zenke, "Surrogate Gradient Learning in Spiking Neural Networks: Bringing the Power of Gradient-based optimization to spiking neural networks," *IEEE Signal Process Mag*, vol. 36, no. 6, pp. 51–63, Nov. 2019, doi: 10.1109/MSP.2019.2931595.
- [75] K. Roy, A. Jaiswal, and P. Panda, "Towards spike-based machine intelligence with neuromorphic computing," *Nature* 2019 575:7784, vol. 575, no. 7784, pp. 607–617, Nov. 2019, doi: 10.1038/s41586-019-1677-2.
- [76] L. Guo, Y. Liu, Y. Wu, and G. Xu, "FPGA-based Small-world Spiking Neural Network With Anti-interference Ability Under External Noise," *Neural Comput Appl*, pp. 1–23, Apr. 2024, doi: 10.1007/S00521-024-09667-1/METRICS.
- [77] P. Kirkland, G. Di Caterina, J. Soraghan, Y. Andreopoulos, and G. Matich, "UAV Detection: A STDP Trained Deep Convolutional Spiking Neural Network Retina-Neuromorphic Approach," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11727 LNCS, pp. 724–736, 2019, doi: 10.1007/978-3-030-30487-4_56.
- [78] J. Robertson, P. Kirkland, G. Di Caterina, and A. Hurtado, "VCSEL-based photonic spiking neural networks for ultrafast detection and tracking," *Neuromorphic*

Computing and Engineering , vol. 4, no. 1, p. 014010, Mar. 2024, doi: 10.1088/2634-4386/AD2D5C.

- [79] Ambuj and R. Machavaram, “Neuromorphic Computing Spiking Neural Network Edge Detection Model for Content Based Image Retrieval,” *Network: Computation in Neural Systems*, May 2024, doi: 10.1080/0954898X.2024.2348018.
- [80] “Parrot Bebop Drone 1, red - Drones - Photopoint.” Accessed: May 17, 2024. [Online]. Available: https://www.photopoint.ee/en/drones/363208-parrot-bebop-drone-1-red%3Fship_to%3DQA
- [81] “Amazon.com: Parrot AR.Drone 2.0 Elite Edition Quadcopter - Snow : Toys & Games.” Accessed: May 17, 2024. [Online]. Available: <https://www.amazon.com/Parrot-AR-Drone-%202-0-Elite-Quadcopter/dp/B00FS7SU7K>
- [82] “Support for Phantom 3 Standard - DJI.” Accessed: May 17, 2024. [Online]. Available: <https://www.dji.com/global/support/product/phantom-3-standard>

APPENDIX A

The mean of Y in (10) is $E[Y]$ while the variance is denoted by $var[Y]$. Below is the derivation for a general case of k degrees of freedom. Let us define a non-zero mean with unit variance Gaussian random variable, X_i , and Y is the sum k of them squared, i.e.

$$X_i = N(\mu, 1) \quad (36)$$

$$Y = \sum_{i=0}^k X_i^2 \quad (37)$$

So, we will have

$$Y \sim \chi^2(k, \gamma) \quad (38)$$

where the parameter for the Chi-square random variable is

$$\gamma = \sum_{i=0}^k \mu^2 \quad (39)$$

In general,

$$var[X] = E[X^2] - E[X]^2 \quad (40)$$

$$E[X^2] = var[X] + E[X]^2 \quad (41)$$

So,

$$\begin{aligned} E[Y] &= \sum_{i=0}^k E[X_i^2] \\ &= \sum_{i=0}^k var[X] + E[X]^2 \end{aligned} \quad (42)$$

$$= \sum_{i=0}^k (1 + \mu^2) = k + \gamma \quad (43)$$

APPENDIX B

The mean of a noncentral Chi-square random variable Y can be shown as follows

$$E[Y] = \int_0^\infty y f_Y(y) dy = \int_0^\infty y \frac{1}{2} e^{-\frac{\lambda+y}{2}} \left(\frac{y}{\lambda}\right)^{\frac{N-2}{4}} I_{\frac{N}{2}-1}(\sqrt{\lambda y}) dy \quad (44)$$

$$= \int_0^\infty y \frac{1}{2} e^{-\frac{\lambda+y}{2}} \left(\frac{y}{\lambda}\right)^{\frac{N-2}{4}} \left(\frac{\lambda y^{\frac{1}{2}}}{2}\right)^{\frac{N}{2}-1} \sum_{i=0}^k \frac{\left(\frac{\lambda y}{4}\right)^i}{i! \Gamma\left(\frac{N}{2} - 1 + i + 1\right)} dy \quad (45)$$

$$= \frac{1}{2} e^{-\frac{\lambda}{2}} \left(\frac{1}{2}\right)^{\frac{N-2}{2}} \sum_{i=0}^k \frac{\left(\frac{\lambda}{4}\right)^i}{i! \Gamma\left(\frac{N}{2} + i\right)} \int_0^\infty y(y)^{\frac{N-2}{4}} (y)^{\frac{N-2}{4}} e^{-\frac{y}{2}} (y)^i dy \quad (46)$$

$$= \frac{1}{2} e^{-\frac{\lambda}{2}} \left(\frac{1}{2}\right)^{\frac{N-2}{2}} \sum_{i=0}^k \frac{\left(\frac{\lambda}{4}\right)^i}{i! \Gamma\left(\frac{N}{2} + i\right)} \int_0^\infty y^{\frac{2N+4i}{4}} e^{-\frac{y}{2}} dy \quad (47)$$

After some mathematical manipulation and evaluating the integral, we have

$$E[Y] = \frac{1}{2} e^{-\frac{\lambda}{2}} \left(\frac{1}{2}\right)^{\frac{N-2}{2}} \sum_{i=0}^k \frac{\left(\frac{\lambda}{4}\right)^i}{i! \Gamma\left(\frac{N}{2} + i\right)} \frac{\Gamma\left(\frac{N}{2} + i + 1\right)}{\left(\frac{1}{2}\right)^{\frac{N}{2}+i+1}} \quad (48)$$

$$= 2e^{-\frac{\lambda}{2}} \sum_{i=0}^k \frac{(\lambda)^i \left(\frac{N}{2} + i\right)}{i! \left(\frac{1}{2}\right)^i} \left(\frac{1}{4}\right)^i \quad (49)$$

$$= 2e^{-\frac{\lambda}{2}} \left(N e^{\frac{\lambda}{2}} + \sum_{i=0}^k \frac{i \left(\frac{\lambda}{2}\right)^i}{i!} \right) = N + \lambda \quad (50)$$

Vitae

Name : Abdullah Salem Alshammari
Nationality : Saudi
Date of Birth : 13/02/1990
Email : abo.salem6@gmail.com
Address : PO Box 8142, Jubail, 31951, Saudi Arabia
Academic Background : Electrical and Telecommunications Engineering

Education : (2010) Associate's degree in Instrumentation and control Engineering Technology at Jubail Industrial college
: (2015) Bachelor's degree of Electrical Engineering at University of Dayton
: (2015) Bachelor's degree of Science in Engineering Technology at University of Dayton

Career History : (2010 – 2012) Instrument Technician at SABIC
: (2016) Field Engineer at Schlumberger
: (2016 – 2018) Instrument Supervisor at SWCC
: (2018 – current) Instrument Engineer at SABIC

Technical Certifications : (2024) Radiation Safety Officer
: (2023) Functional Safety Engineer
: (2023) PHA Leader
: (2022) Certified Maintenance Reliability Professional

Projects : (2024) Radiation Source Replacement
: (2022) Drying Column Upgradations
: (2023) Control Valves Upgradations
: