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DESIGN OF AN INTELLIGENT MULTI-SENSOR DRONE DETECTION SYSTEM

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Dedication

With a deep affection I would like to dedicate this humble work to my family, my source of success and happiness.
To the one who enlighten my darkness.
My mother " Khaldia"
To the one who gave me strength and hope.
My father " Lakhdar"
My sisters Keltoum, Chahrazed, Chaimaa and my Brothers Abdelkader, Mohamed
My Dearest friends Sabra, Amina, Sara, Lylia for their endless support and positive effort.
To all those who believe in me
My teachers, colleagues, friends and those who helped me to achieve this work...

Acknowledgment

*In the Name of Allah, the Most Merciful, the Most Compassionate all praise be to Allah, the Lord of the worlds; and prayers and peace be upon Mohammed His servant and messenger. We would like to express our sincere gratitude to our thesis supervisor Professor **CHEGGAGA Nawal**, for her patience, motivation, enthusiasm, and immense knowledge, without her guidance this thesis would not have been accomplished. we appreciate her time and efforts throughout the duration of our work. Our deepest thanks also go to all the members of the jury for their acceptance to review and to enrich our work. Last but not least,our thanks to every one who,in one way or another, has helped and supported us to complete our thesis.*

Abstract

The technologies of unmanned aerial vehicles (UAVs) especially small low-altitude drone, have emerged as the preferred tool for terrorist and criminal activities, involving both civilian and military applications. Consequently, it has posed a significant challenge for researchers to ensure the safety and security of individuals, public spaces, and government institutions. Various detection technologies have been developed and enhanced, such as radar, optical, acoustic detectors, and radio frequency analyzers. However, each detector comes with its limitations, for instance, the ability of producing a low signal in low light or foggy environments, and noisy. Our thesis work focuses on the hybridization of multi-sensors for drone detection, including optic, acoustic, and magnetic field detectors, using artificial intelligence. We have developed optic and acoustic detectors based on Convolutional Neural Networks CNNs, as well as the magnetic field detector using the BBC card. Each detector autonomously makes decisions, which may align or conflict with those of other detectors. By applying a Bayesian inference (BI) approach, we enhance the decision-making process in cases of conflict among decisions made by multiple sensors. Indicators such as the ephemeris indicator (EI) and the acoustic environment indicator (AI) have been used to resolve disagreement situations. The hybrid drone detector was fully automated, with optimized conflict resolution, achieving the best performance to prevent unwanted drone interventions.

Keywords: Unmanned Aerial Vehicles (UAVs), Safety and Security, Artificial Intelligence, Bayesian Inference (BI), Multi-sensors, Optic detector, Acoustic detector, Magnetic field detector, Hybrid Drone Detector.

Résumé

Les technologies des drones sans pilote (UAVs) en particulier petit drone de basse altitude, se sont imposées comme l'outil privilégié pour les activités terroristes et criminelles, couvrant à la fois les applications civiles et militaires. En conséquence, cela a ouvert un important défi pour les chercheurs afin de garantir la sécurité et la sûreté des individus, des espaces publics et des institutions gouvernementales. Diverses technologies de détection ont été développées et améliorées, telles que le radar, les détecteurs optiques, acoustiques et les analyseurs de fréquences radio. Cependant, chaque détecteur présente des limitations distinctes, telles qu'une efficacité réduite dans des conditions de faible luminosité, de brouillard ou de bruit. Notre travail de thèse se concentre sur l'hybridation de multi-capteurs pour la détection des drones, notamment le détecteurs optique, acoustique et du champ magnétique, en utilisant l'intelligence artificielle. Nous avons développé le détecteur optique et le détecteur acoustique à base des réseaux de neurones convolutifs CNNs, ainsi que le détecteur du champ magnétique à l'aide de la carte BBC. Chaque détecteur prend des décisions de manière autonome, qui peuvent être conformes ou en conflit avec celles des autres détecteurs. En appliquant une approche d'inférence bayésienne (IB), nous améliorons le processus de prise de décision dans les cas de conflit entre les décisions prises par les multiples capteurs. Des indicateurs tels que l'indicateur d'éphéméride (IE) et l'indicateur d'ambiance acoustique (IA) ont été utilisés pour résoudre les situations de désaccord. Le détecteur hybride de drones était entièrement automatisé, avec une résolution optimisée des conflits atteignant la meilleure performance pour prévenir les interventions non désirées des drones.

Mots Clée : Véhicules aériens sans pilote UAVs, la sécurité et la sûreté, Intelligence artificielle, Inférence bayésienne BI, Multi-capteurs, Détecteur optique , Détecteur acoustique , Détecteur du champs magnétique, Détecteur hybride de drones.

ملخص

قد ظهرت تقنيات الطائرات الجوية بدون طيار (UAVs) خاصة الطائرات بدون طيار صغيرة ذات ارتفاع منخفض، كأداة مميزة للأنشطة الإرهابية والإجرامية، تغطي كل من التطبيقات المدنية والعسكرية. ونتيجة لذلك، فقد فتح ذلك تحدياً كبيراً أمام الباحثين لضمان أمان وسلامة الأفراد والمساحات العامة والمؤسسات الحكومية. تم تطوير وتحسين مجموعة متنوعة من تقنيات الكشف، مثل الرادار وأجهزة الاستشعار البصرية والصوتية ومحللات تردد الراديو. ومع ذلك، فكل جهاز استشعار يعاني من قيود متميزة، مثل نقص فعالية في ظروف الإضاءة المنخفضة أو الضباب أو الضوضاء. يركز عملنا في الاطروحة العلمية على تهجين أنظمة متعددة الاستشعار للكشف عن الطائرات بدون طيار، بما في ذلك جهاز الاستشعار البصري والصوتي والمغناطيسي، باستخدام الذكاء الاصطناعي. لقد قمنا بتطوير جهاز الاستشعار البصري وجهاز الاستشعار الصوتي بناءً على شبكات الأعصاب التابعة للتحويل (CNNs)، بالإضافة إلى جهاز الاستشعار المغناطيسي باستخدام بطاقة. (BBC) يتخذ كل جهاز استشعار قرارات بشكل مستقل، التي قد تتماشى أو تتعارض مع تلك التي اتخذها أجهزة الاستشعار الأخرى. من خلال تطبيق نهج الاستدلال البيزيان (BI)، نحسن عملية اتخاذ القرار في حالات التعارض بين القرارات التي اتخذتها أجهزة الاستشعار المتعددة. تم استخدام مؤشرات مثل مؤشر الحالة الفلكية (IE) ومؤشر البيئة الصوتية (IA) لحل حالات عدم التوافق. كان جهاز استشعار الطائرات بدون طيار الهجين متميزاً بالكامل، مع دقة محسنة في حل التعارضات محققا أفضل أداء لمنع تدخلات الطائرات بدون طيار غير المرغوب فيها.

الكلمات المفتاحية:الطائرات بدون طيار (UAVs)، الأمان والسلامة، الذكاء الاصطناعي، الاستدلال البيزيان (BI)، أنظمة متعددة الاستشعار، جهاز الاستشعار البصري، جهاز الاستشعار الصوتي، جهاز الاستشعار المغناطيسي، جهاز استشعار الطائرات بدون طيار الهجين

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GENERAL INTRODUCTION

General Introduction

Unmanned Aerial Vehicles (UAVs) or Unmanned Aerial Systems (UAS) (The terms UAVs, UAS, and drones, are increasingly becoming integrated into citizens' daily lives [1–4]. UAVs have demonstrated their autonomy and adaptability across various environments and tasks, contributing to a sustained market growth in an increasing array of practical activities. Research studies validate the global proliferation of UAV manufacturing [5]. Today, UAVs are utilized by government authorities for a multitude of tasks, including border security, search and rescue, planetary exploration, and firefighting. Simultaneously, civilians employ UAVs for various commercial purposes such as construction, photography, videography, agriculture [6, 7].

However, the rapid proliferation of UAVs is giving rise to significant security concerns. These flying robots can be exploited for nefarious and criminal purposes, including piracy, hacking personal data, invasion of privacy, and monitoring the safety of public officials such as politicians and celebrities. Furthermore, flying UAVs over facilities deemed to be of National Security interest, including military installations and state boundaries, is prohibited as these areas fall under 'no-fly zones' [8]. One notable incident took place in January 2015 when a drone crashed on the lawn in front of the White House in Washington [9]. On December 2018, a UAV was observed flying near Gatwick airport, leading to the closure of Britain's second-largest airport for 36 hours and disrupting 1000 flights and affecting approximately 140,000 passengers [10].

Facilities such as prisons, airports, sporting venues, public buildings, and other sensitive sites are under significant threat [11]. It is crucial to accurately understand the variety of challenges presented by UAVs to ensure the effective protection of critical infrastructures and citizens. In recent years, various solutions have been proposed to tackle these challenges, including Radiofrequency (RF) scanners applying passive detection technologies [12]. These scanners are designed to detect, track, and identify UAVs based on their communication characteristics. Commercial off-the-shelf FPGA-based software-defined radio systems [13] can also serve as viable solutions. Some commercial off-the-shelf radar-based drone detection devices include Kaspersky radar [14]. Acoustic detection presents another method that utilizes audio patterns emitted by drone propellers for drone localization and categorization through acoustic signature recognition [15].

The last method is Optic or Visual Detection, which uses image devices and cameras to detect and classify drones across both visible and infrared spectra [16, 17]. Electro-optical sensors can identify UAS based on their visual signature, although this detection source may not always be reliable. To detect small objects at a distance, these sensors often incorporate high zoom capabilities. However, it is important to point out that every method used has its own limitations [18]. Sensor fusion is also mentioned as an open research topic for improving detection outcomes over a single sensor, while study in this area is still limited. Surveillance radar, combining radar and audio sensors with single or multiple antennas, has the capability to simultaneously identify and track various objects, including unmanned aerial vehicles [19].

Besides, another interesting study involves multiple sensors, investing to an annotated multi-sensor database for drone detection consisting of both infrared and nominal videos as well as audio files. where the acquisition sensors are set up on a pan-tilt platform that directs the cameras to the objects of interest [20].

Artificial neural networks ANNs, or neural networks (NNs), are computing systems inspired by biological neural networks and the human brain. Deep learning, a subset of ANNs, has become increasingly prominent for its efficacy in classification, pattern recognition, and object detection. By integrating expert systems with certainty factors, artificial intelligence techniques can be utilized to create fully intelligent sensors. Multi-layer neural networks have proved success as intelligent sensors for process modeling and control in real-world scenarios. These sensors serve various purposes, including control and surveillance, automated object recognition, remote sensing, and guidance [17].

The sensors are all available for use, with priority given to the one considered most suitable. Our primary focus in the thesis is the hybridization of multiple detectors using the Bayesian inference approach for drone detection, which may include the probabilistic model. This model is founded on a combination of hardware architecture and control software, using a variety of sensors including Optical, Acoustic, magnetic field sensors, and existing measurement devices. These devices serve as indicators of ephemeris and acoustic atmosphere, enabling us to provide information skills related to drone detection model. We launch by outlining the theories, techniques, and databases associated with each detector used in our approach. The experimental work will showcase the effectiveness of combining multiple detectors, each providing a decision on the presence or absence of a drone. To overcome individual detector limitations, we've integrated three detectors: optical, acoustic, and magnetic field. Along hardware indicators for ephemeris and acoustic ambiance, Bayesian inference serves as our control software. Evaluating detector limitations with these indicators allows more accurate decisions on drone presence or absence.

We outline the thesis to underscore the principal objectives of our study that allows us to detect drones using the intelligent multi-sensory system based on the Bayesian inference approach:

1. Develop methodologies for the effective integration of data from multiple sensors, including optic, acoustic, and magnetic field detectors, enhancing the accuracy and reliability of drone detection.

2. Incorporate Indicators as ephemeris and acoustic atmosphere to overcome distinctive detector limitations, considering factors such as sensor noise and varying environmental conditions.

3. Design Bayesian inference approach that enables real-time decision-making based on probabilistic model and muti-sensor outputs allowing the system to effectively detect UAVs.

4. Conduct thorough performance evaluations and validation experiments in diverse environmental conditions to assess the effectiveness and robustness of the proposed multi-sensor drone detection system, comparing it with existing methods.

This work is divided into six chapters, an overview of each is provided below:

- Chapter 01 presents the background and fundamental concepts related to Unmanned Aerial Vehicles (UAVs), including their classification into various types, diverse applications across civilian and military purposes, and an analysis of sophisticated techniques used for UAV detection including their advantages and limitations.

- Chapter 02 offers a comprehensive overview of the state-of-the-art in machine learning-based drone detection methods, as well as a discussion on the synopsis of the Bayesian inference approach, accompanied by detailed explanation.

- Chapter 03 provides optical UAV detection using transfer learning with the pre-trained VGG-16 model, underlying principles of the selected optical detection approach, presenting experimental findings, demonstrating its effectiveness in computer vision tasks.

- Chapter 04 focuses on exploring of acoustic drone detection using sound recordings, employing techniques like FFT, TFCT, wave decomposition, spectrogram, and periodogram, involving filtering and correlation methods for signal decomposition, with preliminary results assessing accuracy, overall system performance.

- Chapter 05 showcases a modern approach of UAVs detection using magnetic field sensor with the Micro-bit Card, providing a detailed exploration of the adopted approach, covering the functionality of magnetic field sensors, integration processes, and data collection techniques, including findings related to overall system, highlighting the crucial role of these sensor in enhancing drone surveillance.

- Chapter 06 explores a novel approach for drone detection utilizing the integration of visual, acoustic, and magnetic field sensors based on Bayesian inference to address their limitations. Indicators such as the Ephemeris Indicator (EI) and the Acoustic Ambiance Indicator (AI) provided valuable support for decision-making, as well as evaluation experiments, improving accuracy in drone detection through multi-sensor integration.

Finally, this work concludes with a general conclusion, which summarizes the various studies conducted in our thesis, while highlighting the main results obtained and future perspectives.

CHAPTER 1
ADVANCED TECHNIQUES IN UAV DETECTION AND CLASSIFICATION

Chapter 1

Advanced Techniques in UAV Detection and Classification

1.1 Introduction

As the skies become increasingly populated with unmanned aerial vehicles (UAVs) due to their versatility and capabilities, they undertake a wide range of tasks, including those traditionally associated with civilian and military operations such as search and rescue, as well as personal and business applications. Chapter I delves into the fundamental context of UAV technologies, focusing on their classification and applications in both civilian and military operations. This exploration is followed by a discussion of safety concerns, challenges, and threats associated with UAV technology, as well as the cutting-edge methods employed for their detection. As we delve into the realm of UAVs, our exploration begins with a meticulous examination of their classifications based on factors such as mass, operational altitude, propulsion/wings, and autonomy, alongside their diverse applications across civilian and military sectors. From the peaceful skies of civilian applications to the strategic landscapes of military operations, the chapter navigates the breadth of UAV utility and addresses safety issues and challenges related to this technology. Furthermore, attention is given to the advancement of sensing technologies used for drone detection. Here, we unravel the types and characteristics that empower UAVs with the ability to perceive and interact with their surroundings, presenting both their advantages and limitations.

1.2 Definitions

UAV (Unmanned Aerial Vehicle): An unmanned aircraft operated remotely or autonomously, often referred to as a drone, used for various purposes including surveillance, data collection, and transportation.

Artificial Intelligence: Artificial Intelligence, often termed AI, is the quest to bestow machines with intellectual capabilities, enabling them to mimic human-like thinking, problem-solving, and adaptation. It represents the culmination of computer science's aspiration to create systems that can comprehend, reason, learn, and adapt within a myriad of contexts. AI leverages a spectrum of methods, including neural networks, to decode data, make informed judgments, and interact with the world, promising innovation, and automation across diverse domains, from smart systems to personalized healthcare.

Machine Learning: An approach to data analysis that involves training algorithms to recognize patterns and make decisions based on input data, potentially enhancing the capabilities of a multi-sensory UAV detection system.

Neural Networks: Neural networks are computational structures that emulate the intricate network of neurons in the human brain. They exhibit the remarkable ability to autonomously learn and make decisions by processing complex, interconnected data. These networks are integral to the realm of machine learning, facilitating the discovery of patterns and insights from data, with applications spanning from computer vision to natural language understanding.

Detection: The process of identifying and locating the presence of an object or phenomenon within a given environment or dataset.

UAV Detection: The act of identifying and locating the presence of unmanned aerial vehicles within a specified airspace or geographical area.

Sensor Fusion: The process of integrating data from multiple sensors into a single and more accurate modelling of the monitored environment or the target object.

Radar: A technology that uses radio waves to detect, locate, and track objects, often employed for long-range surveillance and tracking.

LiDAR (Light Detection and Ranging): A remote sensing technology that uses laser pulses to measure distances and create detailed 3D representations of the environment.

RF (Radio Frequency) Sensors: Sensors that monitor electromagnetic signals and radio waves, including those used for communication between UAVs and their operators.

Optical Sensors: Devices that capture visual information in the form of images, making use of visible light or infrared radiation to detect objects and features.

Acoustic Sensors: Sensors that detect sound waves and vibrations in the environment, suitable for acoustic signature analysis and auditory surveillance.

Multi-sensory System: A system that integrates data from multiple sensors to improve the accuracy, reliability, and robustness of information collection and decision-making.

Bayesian Inference: A probabilistic framework for updating beliefs or making predictions based on new evidence, combining prior knowledge with observed data using Bayes' theorem.

Decision Threshold: The value or condition used to determine whether a sensor reading indicates the presence of a UAV, affecting the sensitivity and specificity of the detection system.

Feature Extraction: The process of identifying and extracting relevant information or features from sensor data, such as the shape, speed, or behavior of detected objects (UAVs).

Safety and security: Safety involves the prevention of accidents and protection from unintentional harm, emphasizing risk management and hazard mitigation. Security, on the other hand, focuses on safeguarding assets and information from deliberate threats, unauthorized access, and damage to maintain their integrity and confidentiality. Both safety and security measures are crucial for ensuring well-being and asset protection in various contexts, addressing different types of risks.

1.3 UAVs: Classification and Applications

Unmanned Aerial Vehicles (UAVs), commonly known as drones, have witnessed a rapid evolution over the past few decades. To understand the context of this research, it is essential to explore the various classifications and applications of UAVs.

1.3.1 Classification of UAVs

UAVs can be classified into several categories based on their characteristics and intended use. We can further classify drones based on their mass (weight), operational altitude, type of propulsion (such as rotary-wing or fixed-wing), and autonomy (level of automation) as shown in Figure 1.1. Here's a breakdown of drones using these categories:

A/ Based on Mass:

- **Nano Drones:** These are the smallest and lightest drones, typically weighing less than 250 grams. They are often used for indoor and close quarters flying.
- **Micro Drones:** Slightly larger than nano drones, micro drones typically weigh between 250 grams and 2 kilograms. They are commonly used for recreational and educational purposes.
- **Mini Drones:** These drones have a weight range between 2 kilograms and 25 kilograms. They are popular for photography, videography, and recreational flying.
- **Small Drones:** Small drones weigh between 25 kilograms and 150 kilograms. They are commonly used for commercial and industrial applications.
- **Medium Drones:** Medium-sized drones have a mass ranging from 150 kilograms to 600 kilograms. They find applications in various industries, including agriculture and surveillance.
- **Large Drones:** Large drones weigh between 600 kilograms and several tons. They are typically used for military, cargo, or long-endurance missions.

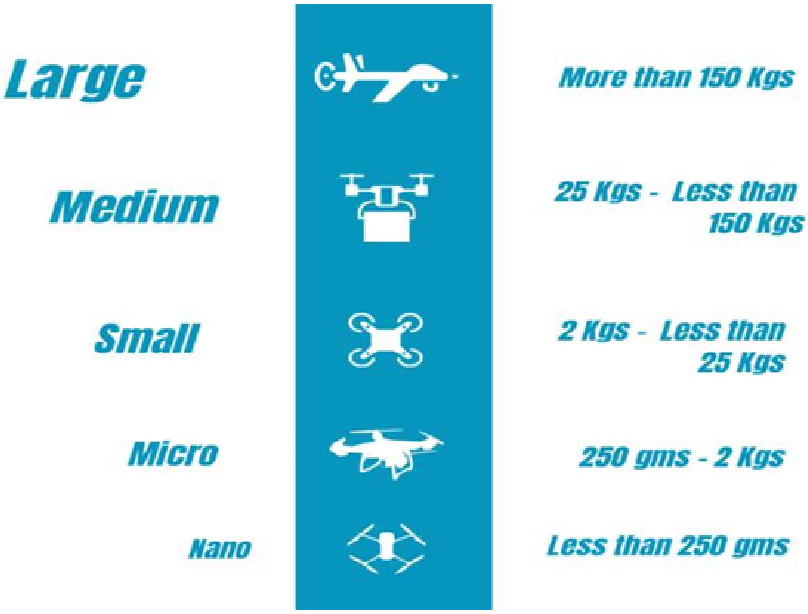

Figure 1.1: Classification of drone based on mass [21].

B/ Based on Operational Altitude:

- **Low-Altitude Drones:** These drones operate at altitudes of up to 150 meters above the ground and are often used for close-range applications like photography, surveillance, and agricultural tasks.

- **Medium-Altitude Drones:** These drones operate at altitudes between 150 meters and 10,000 meters. They are suitable for various surveillance and reconnaissance missions.

- **High-Altitude Drones:** High-altitude drones can operate at altitudes above 10,000 meters and are used for long-range surveillance and atmospheric research as presented in Figure 1.2.

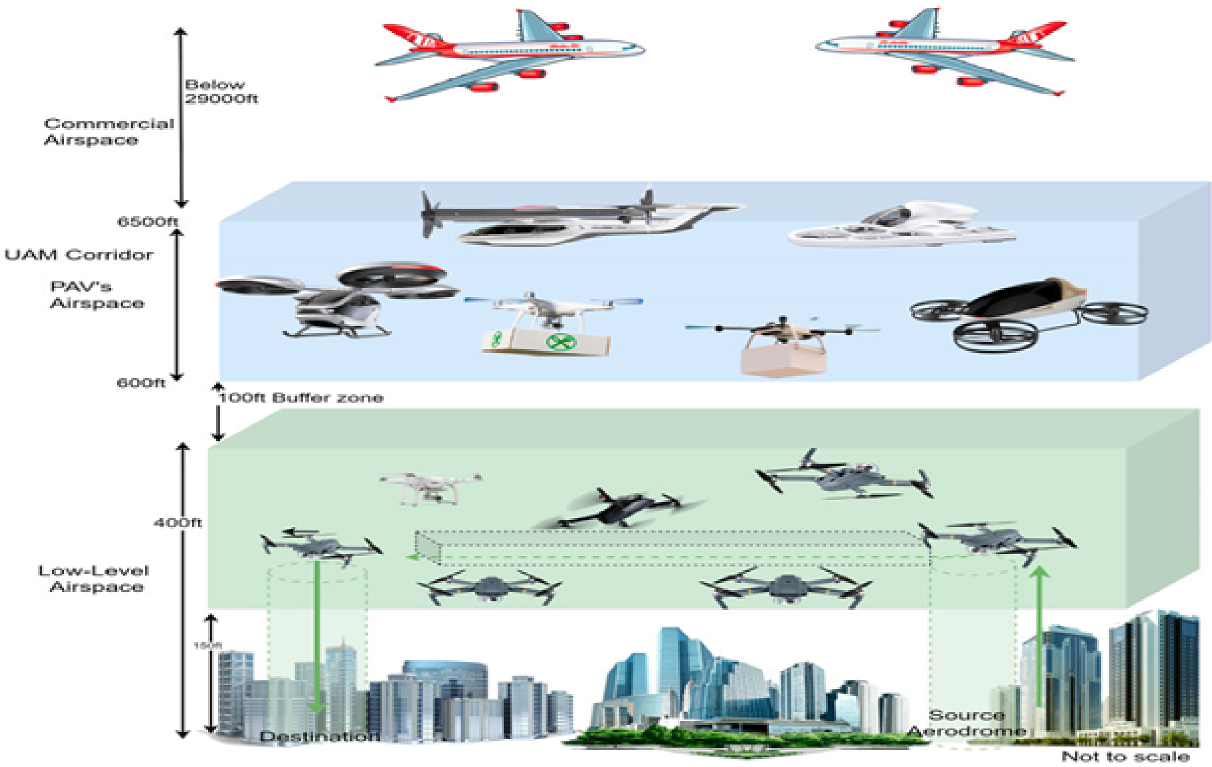

Figure 1.2: Classification of drone based on operational altitude [22].

C/ Based on Propulsion and wings:

- **Rotary-Wing Drones:** These drones use rotor blades for lift and propulsion, making them highly maneuverable. Examples include quadcopters, hexacopters, and octocopters.

- **Fixed-Wing Drones:** Fixed-wing drones have a traditional airplane-like design, using wings for lift and propulsion. They are recognized for their long-range capabilities.

- **Hybrid Drones:** Hybrid drones combine both fixed-wing and rotary-wing capabilities for vertical takeoff and landing (VTOL) and efficient, long-range flight as indicated in Figure 1.3.

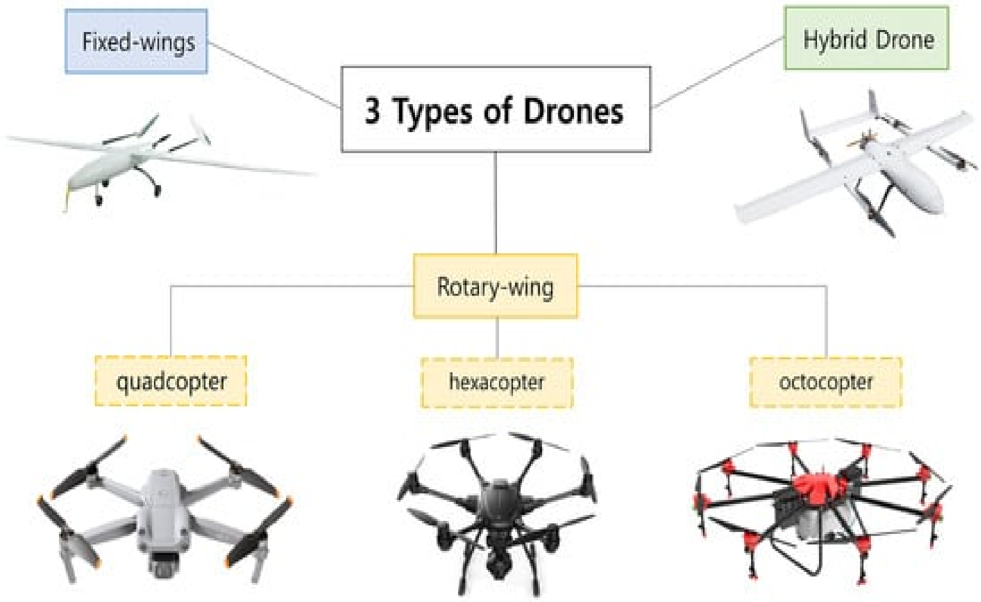

Figure 1.3: Classification of drone based on wings [23].

D/ Based on Autonomy:

- **Manual Control Drones:** These drones require human operators to control their flight and make decisions.
- **Semi-Autonomous Drones:** Semi-autonomous drones can perform certain tasks independently, such as maintaining a stable hover, following GPS waypoints, or avoiding obstacles.
- **Autonomous Drones:** Autonomous drones can operate with minimal human intervention. They can perform complex tasks like mapping, surveying, and following dynamic objects.
- **Swarm Drones:** These drones operate in coordinated groups, communicating with each other to perform tasks collectively. They may be either semi-autonomous or fully autonomous as described in Figure 1.4.

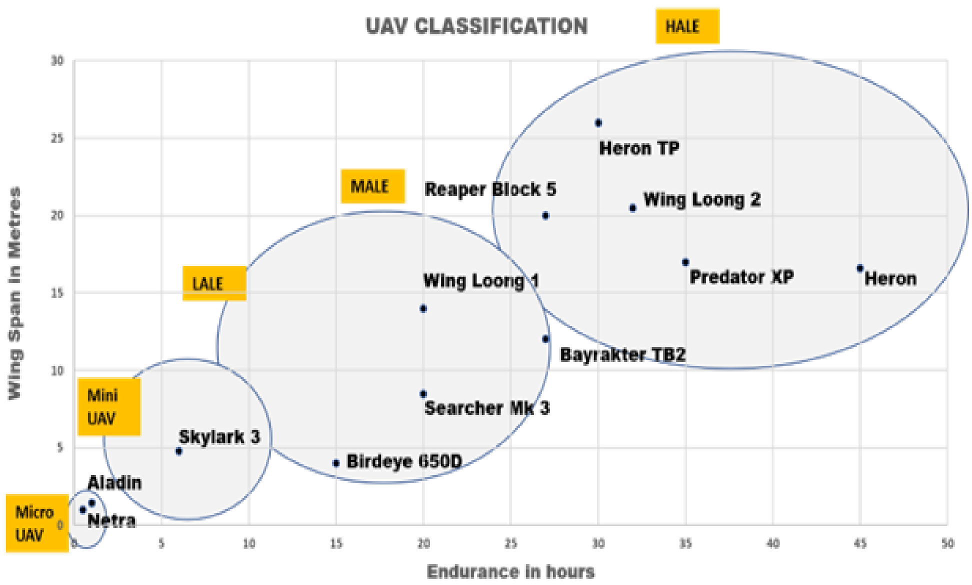

Figure 1.4: Classification of drone based on autonomy [24].

1.3.2 Applications of UAVs

UAVs have a very vast range of applications among different industries and fields.. Drone applications encompass a wide range of uses in both civilian and military activities. These unmanned aerial vehicles serve diverse purposes, from enhancing efficiency and safety in civilian sectors to providing strategic advantages in military operations:

A/ Civilian applications:

- **Agriculture:** Agricultural drones are used for crop monitoring, precision agriculture, and the application of fertilizers and pesticides. They help farmers optimize crop yields and reduce costs.

- **Infrastructure Inspection:** Drones can inspect critical infrastructure, such as bridges, pipelines, power lines, and cell towers. They reduce the need for manual inspections in dangerous or hard-to-reach locations.

- **Search and Rescue:** Drones can quickly survey disaster-stricken areas, locate missing persons, and assess the extent of damage. They provide critical data to first responders during search and rescue missions.

- **Environmental monitoring and Firefighting:** They are utilized to monitor environmental changes, track wildlife, and assess the impact of climate change on ecosystems. They can aid firefighters by providing real-time information on the fire's location and temperature, helping them plan their response.

- **Aerial Photography and Videography:** Drones equipped with high-quality cameras are used for capturing stunning aerial photos and videos for various purposes, including filmmaking, real estate marketing, tourism, and event coverage.
- **Delivery and Logistics:** Companies like Amazon and UPS are experimenting with drone delivery services to transport small packages quickly to customers, especially in remote or hard-to-reach areas.
- **Mapping and surveying:** Drones are valuable for creating detailed maps, conducting surveys, and monitoring construction sites, saving time and resources compared to traditional methods.

B/ Military applications:

- **Surveillance and reconnaissance:** Drones play a crucial role in military intelligence, providing real-time surveillance and reconnaissance without risking human lives.
- **Defense and Military:** Military drones are used for reconnaissance, surveillance, intelligence gathering, and, in some cases, combat missions. They are capable of performing in hazardous environments exposing no risk to human lives.
- **Border security:** Drones are employed for border surveillance, helping monitor and secure national borders against illegal activities.
- **Combat support:** Drones can provide support during combat situations by delivering supplies, conducting electronic warfare, and assisting communication.
- **Target identification:** UAVs are used to identify and track potential targets, enhancing the precision and accuracy of military operations.
- **Anti-Submarine warfare:** In maritime operations, drones are used for anti-submarine warfare, detecting, and tracking underwater threats.
- **Strategic strikes:** Armed drones are capable of carrying out precision strikes on enemy targets, reducing the risk to human personnel.
  All these applications are shown in Figure 1.5.

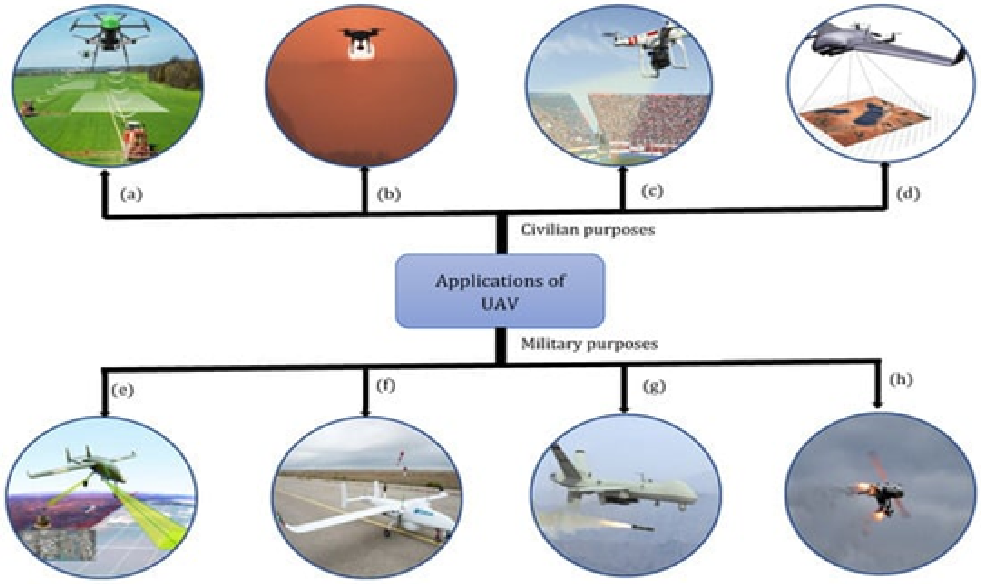

Figure 1.5: Drone applications [25].

1.4 Emerging Challenges and Threats in Drone Technology

As drones become more prevalent and their capabilities advance, several challenges and threats have emerged that need to be addressed to ensure their safe and responsible use as shown in Figure 1.6. These challenges include:

- **Privacy Concerns:** Drones equipped with cameras and other sensors can potentially invade individuals' privacy. Unauthorized surveillance or data collection can be a significant concern, raising questions about the boundaries between public and private spaces.

- **Safety Risks:** Drones can pose safety risks to people, property, and other aircraft. Collisions with manned aircraft, birds, or even other drones can lead to accidents. This is a particularly important concern as more drones share the airspace.

- **Regulatory Compliance:** Many regions have established regulations and airspace restrictions for drone use. Ensuring compliance with these rules, particularly for commercial operators and hobbyists, can be challenging and requires a good understanding of local laws.

- **Cybersecurity Vulnerabilities:** Drones are becoming increasingly connected and reliant on digital systems. As a result, they are vulnerable to cyberattacks, which can lead to unauthorized access, data breaches, and potential control of drones by malicious actors.

- **Technological Advancements:** Rapid advances in drone technology can outpace the development of regulations, making it challenging for authorities to keep up with emerging capabilities and potential threats.
- **Cross-Border Drone Operations:** Drones do not respect international borders, making it challenging for governments to regulate and manage drone operations that cross into neighboring territories.
- **Resource and Infrastructure Protection:** Drones can be used to conduct surveillance of critical infrastructure, posing risks to national security. This includes power plants, communication networks, and transportation systems.
- **Emerging Applications:** As drones find new applications in fields such as urban air mobility, delivery services, and surveillance, they bring with them specific challenges related to infrastructure, safety, and public acceptance.
- **Ethical Dilemmas:** The use of drones for surveillance, decision-making, and military purposes raises ethical questions about privacy, accountability, and the potential for autonomous action.
- **Airspace Integration:** Integrating drones into existing air traffic control systems is a complex challenge. Ensuring that drones can share the airspace safely with manned aircraft requires significant technological and regulatory efforts.
- **Espionage and Surveillance:** Drones can be used for espionage, intelligence gathering, or corporate espionage. The discreet and airborne nature of drones makes them attractive to intelligence agencies, researchers, or competitors looking to gain a competitive edge.
- **Smuggling:** Criminal organizations and individuals may find drones attractive for smuggling illegal goods, such as drugs, weapons, or contraband, over border fences or prison walls.

Figure 1.6: Drone threats and risks [26].

1.5 Sensing Technologies: Types and Characteristics

The ability to detect and track UAVs relies heavily on sensor technologies. A variety of sensors can be employed for this purpose, each with its own advantages and limitations. In this section, we explore some common sensor types and their characteristics.

1.5.1 Diverse Sensor Types in Drone Detection

1. **Radar Sensors:** Radar (Radio Detection and Ranging) is a well-established technology for detecting and tracking objects in the air. Radar sensors emit radio waves and measure the time it takes for the waves to bounce back after hitting an object. Radar is known for its long-range capabilities and all-weather operation. It can detect UAVs, even those with low radar cross-sections, making it suitable for surveillance and defense applications.

2. **Optical and Infrared Sensors:** Optical and infrared sensors rely on visible light and heat signatures to detect objects. Cameras, whether visible light or infrared, provide high-resolution images and are useful for identifying and tracking UAVs during daylight hours. However, they may be limited in low-light or adverse weather conditions.

3. **Acoustic sensors:** 2Acoustic sensors detect sound waves generated by UAVs. They are useful for detecting UAVs in scenarios where sound is a distinguishing factor.

Acoustic sensors can be effective in urban environments or during night operations when visual or radar detection may be challenging.

4. **RF Sensors:** Radio Frequency (RF) sensors monitor electromagnetic signals emitted by UAVs. RF sensors can detect the communications signals between the UAV and its operator, aiding in the identification of the UAV's location and type.

5. **multi-Sensors:** Multisensors refers to the use of multiple sensors or sensing modalities to collect information from various sources or perspectives. In the context of drone detection, multisensors integration involves combining data from different types of sensors, such as optical, acoustic detectors, to enhance the overall accuracy and reliability of the detection system. This approach leverages the strengths of each sensor while compensating for their individual limitations, resulting in a more comprehensive and robust detection capability.

1.5.2 Advantages and Limitations of Different Sensors

All the sensor types currently employed in drone detection exhibit specific advantages and limitations. Consequently, a system of this nature must integrate a diverse array of sensors to enhance the overall detection rate. A brief overview of each sensor category is provided below, and the distinct pros and cons for each category are summarized in Table 1.1

Type	Pros	CONS
Acoustic Sensor	• Covers the spectrum of 20Hz-20kHz. • Acoustic signature library could be updates easily from flight to flight. • Lightweight and can be easily associated with other types of sensors.	• Limited range. • Vulnerable to ambient noise. • Susceptible to decoys.
Optic sensor	• Covers all of the visible and IR spectrum (3MHz-300GHz). • IR cameras could operate in cloudy weather and in day or night. • Could be assisted by computer-vision technologies.	• Provides 2D images. • Limited performances by weather conditions and background temperature. • Dependent of georeferenced data. • LoS is required
Radar	• Bandwidth used: 3MHz-30GHz. • Could operate in all weather and day/night conditions. • Offers information regarding the velocity of the target. • Can recognize micro-Doppler signatures (MDS). • Offers high coverage . • Good accuracy. • Compact and high mobile, required for tactical applications. • High reliability.	• Large radar across-section is desired. • Difficult to differentiate UAVs from birds. • Limited performance for low altitudes and speeds (death cone). • Could interfere easily with small objects, especially birds. • LoS is required. • High cost.
RF Analyser	• Captured the communication spectrum and signals UAV and operators. • Low complexity and easy to implement. • Could operate in all weather and day/night conditionst. • Easier to improve due to modular implementation of receivers and digital signal processing units used in implementation. • Possibility to localize the pilot.	• Knowledge regarding UAV communication specification (e.g. frequency bands,modulations,etc.)is required. • Difficult to accurately determine AoA. • Vulnerable to malicious or illegal modified RF that will exceed receiver capabilities. • Difficult to use in urban areas due to fading and multipath phenomena.
Multi-sensors	• Integrating the advantages of multiple methods, demonstrating superior performance. • Higher accuracy. • Long-range detection capabilities. • Robust under different scenarios and environmental conditions.	• Involving higher costs and computational complexity compared to single-sensor systems.

Table 1.1: Pros and Cons of different sensors used in drone detection

1.6 Conclusion

This chapter highlights the significant role of Unmanned Aerial Vehicles (UAVs), delving into their classification based on various factors such as mass, operational altitude, propulsion/wings, and autonomy. This exploration emphasizes the extensive applications of UAVs across both civilian and military sectors. Subsequently, attention is drawn to safety concerns and challenges associated with this technology, acknowledging the importance of addressing these issues for widespread approval and integration into various industries. Furthermore, the chapter proceeds to analyze diverse sensor types used in the detection of UAVs, uncovering their relevant advantages and limitations. This comprehensive review provides insights into the capabilities and constraints of sensor technologies, underscoring the complexity and adaptability of UAV detection systems. In essence, while UAVs offer exceptional opportunities and advantages in modern society, it is crucial to address safety concerns and optimize sensor technology to enhance their abilities across diverse objectives. Careful consideration of these factors is necessary for harnessing the potential of UAVs and ensuring their safe and effective integration into the technological realm.

CHAPTER 2
STATE OF ART DRONE DETECTION METHODS

Chapter 2

State of Art drone detection methods

2.1 Introduction

From the foundational backgrounds of UAVs to the sophisticated sensing technologies employing Machine Learning, this chapter offers a comprehensive exploration of state-of-the-art drone detection methods. It delves into the cutting-edge advancements in Machine Learning (ML)-based drone detection, detailing ML-based drone classification methodologies using radars, visual data, acoustic signals, and radio frequency analysis. These techniques represent the forefront of technology, showcasing the adaptability of ML algorithms in addressing the challenges posed by the dynamic nature of UAVs. The chapter provides a comprehensive overview of available approaches for detecting drones. The primary objective is to gain insight into the design landscape of drone detection techniques and highlight any inherent or situational limitations associated with each approach. Additionally, it explores various factors crucial for selecting a drone detection method, such as cost, power consumption, accuracy, and environmental variables that may impact the system's performance. In the pursuit of enhancing UAV detection capabilities, this section introduces a cutting-edge approach multi-sensory integration. Drawing inspiration from Bayesian inference, it explores how combining information from multiple sensing modalities can lead to a more robust and accurate detection system. By providing a comprehensive perspective, the aim is to enhance the efficiency and reliability of UAV detection in complex and dynamic environments.

2.2 State of art of ML based drone detection

In our survey, we initially focus on different radar-based approaches, as they stand out as one of the most promising methods in terms of accuracy. However, it's crucial to note that their cost and deployment requirements may render radars unsuitable for certain use cases. Continuing our exploration of drone detection techniques, we turn our attention to off-the-shelf acoustic sensors, offering a cost-effective albeit less precise alternative to radars in specific deployment scenarios. Subsequently, we investigate methods reliant on the RF transmission of the drone, followed by visual and optical sensor detection techniques. Concluding our survey, we engage in a discussion of multi-modal and sensor-fusion approaches. These innovative methods harness multiple sensors in tandem or sequence to enhance detection accuracy. By doing so, we aim to provide a comprehensive and insightful overview of the diverse landscape of drone detection methods.

2.2.1 Ml-Based Drone Classification By Radars

Researchers who utilized machine learning techniques on radar signals pursued one of the following aims:

1. Detecting Drones: This takes place when texts are manually tagged with two classes: drone and no-drone.

2. Drone vs. Bird Classification with Radar: The classification in this case is very basic since it employs only two labels, robot or drone as against bird or avian.

3. Drone vs. Drone Classification with Radar: This is so where the number of labels applied correlates with the diversity of the studied drones' types.

4. Drone Characterization and Classification : The data is labelled depending on the unique characteristics of drones such as the payload or number of rotors.

5. Detecting Multiple Drones: Data has been grouped by the researchers according to the number of drones in the operation.

2.2.1.1 Detecting Drones

Jahangir and Baker highlighted the significance of machine learning in radar detection, employing a high-end 3-D holographic radar for drone detection at a 1km range [27]. By adjusting amplitude thresholds and considering lower Dopplers, they enhanced drone detection but observed more false positives due to heightened radar sensitivity. Through training a binary decision tree model, they improved drone prediction probability and reduced false alarm rates, showcasing the efficacy of machine learning in radar-based drone detection [28, 29].

2.2.1.2 Drone vs. Bird Classification with Radar

Torvik et al. addressed the challenge of distinguishing between drones and birds, especially considering the low Radar Cross Section of both [30]. They identified common features like insignificant Micro Doppler Signature (MDS) and low RCS modulation in gliding birds and plastic-rotor UAVs. They proposed the utilization of polarimetric features as a solution for more accurate drone detection [31]. The study demonstrated significant success, achieving nearly 100% classification accuracy. The results were obtained using real data collected from BirdRAD, a specialized radar system designed for avian monitoring and drone detection.

Fuhrmann et al. focused on distinguishing drones from birds by analyzing three Micro Doppler Signature (MDS) characteristics: mean spectrogram, the first left singular vector of Singular Value Decomposition (SVD), and mean Cadence Velocity Diagram (CVD) [32]. Experimental setups involved six drones placed two meters from the radar, following varied paths in outdoor and controlled lab settings. The optical range of the drones was not specified. Using the same Continuous-Wave (CW) radar setup employed for drone data collection, they simulated bird sight data. Post-training, the Support Vector Machine (SVM) classifier achieved an exceptional 100% classification accuracy.

Mohajerin et al. utilized radar tracks for the differentiation of manned aircraft, birds, and Unmanned Aerial Vehicles (UAVs) [33]. Their thirty-layered artificial neural network achieved a remarkable 100% accuracy in classifying UAV tracks. However, concerns were raised regarding the assumption of long-range drone tracks and the impracticality of the 20-kilometer range, which deviates from published figures.

2.2.1.3 Drone vs. Drone Classification with Radar

Molchanov et al. conducted feature extraction using Eigenvectors and Eigenvalues of the Micro Doppler Signature (MDS) [34]. They employed Naive Bayes, non-linear SVM, and linear SVM classifiers for training, flying eleven items for 30 seconds each, including fixed-wing, helicopters, quad-rotor, artificial bird, and stationary rotors. Data collected through Continuous Wave (CW) radar achieved a 95% average classification accuracy in 10-fold cross-validation. In subsequent tests, the classifier accurately categorized drones into fixed-wing, stationary rotor, or helicopter groups with an accuracy range of 87% to 100%, even after excluding specific models from training.

Mendis et al. extracted the Spectral Correlation Function (SCF) extracted from the Micro Doppler Signature (MDS) [35, 36] to train a deep belief network for accurate drone classification. The study involved generating 70 SCF images representing four distinct drone classes, and to enhance data diversity, Gaussian noise was introduced. The resulting classification accuracy of the system surpassed an impressive 90%

Zhang et al. suggested the use of a dual-band Continuous Wave (CW) radar, operating in the K-band and X-band, for the classification of three drones (helicopter, hexa-copter, and quadcopter) [37]. Using the Short-Time Fourier Transform (STFT), time-frequency spectrograms and Principal Component Analysis (PCA), their approach demonstrated superiority over a single radar setup, with a marginal 1.2% average reduction in classification accuracy compared to using the K-band radar alone. The experiments were conducted in a controlled lab setting, featuring stationary drones.

Kim et al. applied a pre-trained Convolutional Neural Network (CNN) for the classification of two drones, utilizing a Ku-band Frequency Modulated Continuous Wave (FMCW) radar [38]. The CNN demonstrated exceptional accuracy of 100% in outdoor measurements. However, its performance was comparatively lower in anechoic chambers, indicating potential environmental influence on the classification outcomes.

Brooks et al. developed a comprehensive two-dimensional drone model involving scattering points and ground clutter simulation [39]. They conducted experiments on three distinct drone types and utilized three classifiers: Fully Convolutional Networks (FCNs), Recurrent Neural Networks (RNNs), and Multilayer Perceptron (MLP). The MLP classifier demonstrated an accuracy range of 70%-85%, while the RNN and FCN classifiers achieved a remarkable 100% accuracy in their assessments. These findings provide insights into the effectiveness of different classifiers for drone detection within the simulated environment.

2.2.1.4 Drone Characterization and Classification

Fioranelli et al. employed machine learning techniques to distinguish between three drone payloads (zero, 200, and 500 grams) [40] using the NetRAD multi-static radar system [41]. They extracted centroid and bandwidth features from the radar data recorded by three receivers while a drone hovered at a 60-meter distance for 30 seconds. Training and testing were conducted using Naive Bayes and discriminant analysis. The authors extended their approach by extracting the Singular Value Decomposition (SVD) and centroid of the Minimum Detectable Signal (MDS). Additionally, they introduced the random forest classifier to the set of experimented classifiers [42]. The majority voting model demonstrated the highest accuracy, with discriminant analysis proving superior to Naive Bayes. The study revealed that increasing drone payload led to a more uniform and straighter Minimum Detectable Signal (MDS), contributing to improved classification results.

2.2.1.5 Detecting Multiple Drones

Zhang et al. explored the feasibility of employing a K-band Continuous Wave (CW) radar for the simultaneous detection of drones [43]. They focused on the cadence frequency spectrum (CFS) and converted it into a Cadence Vector Diagram (CVD), which served as training data for a K-means classifier. Lab tests involved using a helicopter, hexacopter, and quadcopter to collect data for scenarios involving one, two, and all three UAVs. The study revealed classification accuracy results of 96.64% for a single drone, 90.49% for two drones, and 97.8% for three drones, highlighting the radar's effectiveness in multiple drone detection scenarios as demonstrated in Table 2.1.

Work	**Radar system**	**Classes**	**Data**	**Features**	**Classifier**	**Results**
[27]	L-band Holo-graphic radar	2 classes: Drone(hex-acopter), Non-drone	5-min flight	Height, max-height, Doppler, ac-celeration, jerk	Decision tree	Detection probability: 88%
[30]	S-band Bir-dRad	4 classes: two birds and two drones (3D solo and DJI Phantom II)	8000 trail samples	9 polarimetric features	Nearest-neighbor classifier	Classification accu-racy:100% accuracy
[32]	Ka-band CW radar	2 classes: UAVs vs sim-ulated bird data	30 10-second trials per drone, sim-ulated bird MDS	Mean spectro-gram, SVD, CVD	SVM	Classification accu-racy:96% to 100%.
[33]	S-band pulsed radar	2 classes: UAV tracks vs bird track	Bird tracks real. UAV tracks by simulation	20 features extracted from track	ANN with 30 hidden layers	Classification accuracy: up to 100%.
[34]	X-band CW radar	11 classes: 11 drones	30 seconds recording for each drone	Eigenvector and eigenvalue of MDS	Naïve Bayes, lin-ear and Non-linear SVM	Classification accuracy: approx. 95%
[35,36]	S-band CW	4 classes: 3drones and non-drone classes	280 images	Spectral corre-lation function (SCF) of MDS	Deep belief Network (DBN)	Classification accuracy: above 90% when SNR>=0
[37]	K-band and X-band CW radar	3 classes: Quad-copter,Heli-copter,Hexa-copter.	720 sam-ples each radar/drone	PCA based features	SVM	Classification accuracy: up to 94.7%
[38]	Ku-band FMCW radar	2 classes: in-spire 1 and F820	50000/10000 images in-door/outdoor	Contatendated MDS and CVD	CNN	Classification accuracy: 94.7%

[39]	Pulsed	2 classes: Phantom 2 and S1000+	Own database	Virtual scattering point's images	MLP, RNN, FCN	Classification accuracy: from 70% to 100%
[40]	S-band pulsed radar (NetRaAD)	3 classes: no payload, 200 g payload, 500g payload	45 samples per class	Centroid and band width of MDS	Naïve Bayes and Discriminant analysis	Classification accuracy: 90-100%
[42]	S-band pulsed radar (NetRaAD)	5 classes: no payload, 200g,300g,400g, 500g	45 samples per class	SVD and centroid of MDS	Naïve Bayes and Discriminant analysis and random forest	Classification accuracy: 95-96%
[43]	CW K-band radar	Quadcopter,Helicopter,Hexacopter	140segments with 0.375s for each segment	Cadence frequency spectrum (CFS) features	k-means classifier	Classification accuracy: up to 96.64%, 90.49% and 97.8% for single, two and three drones respectively.

Table 2.1: Summary of related works on radar methods based on machine learning for drone detection and tracking

2.2.2 Ml-Based Drone Classification By Visual Data

Although radar technology has proven effective in target identification and tracking, it relies on trained personnel for decision-making. Recognizing this limitation, researchers are now turning to advancements in computer vision to explore drone detection and classification using visual data. This shift towards leveraging computer vision indicates a growing interest in developing automated systems that can enhance the efficiency of drone monitoring and recognition without the dependency on specialized human expertise.

Rozantsev et al. introduced two techniques for identifying airborne drones by employing 3-dimensional Histograms of Gradients (HoG3D) and a Convolutional Neural Network (CNN) model [44]. The approach involves segmenting video frames into overlapping temporal slices, creating spatiotemporal cubes (st-cubes), and implementing a motion compensation algorithm through regression. Two boosted tree regressors predict translation, while two distinct CNNs handle regression tasks. The system's effectiveness was assessed using publicly accessible datasets featuring UAVs and aircraft. Notably, the regressors are trained to adapt to various image scales.

Yoshihashi et al. applied a deep learning methodology named Recurrent Correlational Networks (RCN) designed for the detection and tracking of small Unmanned Aerial Vehicles (UAVs) [45]. The architecture comprises four key networks, including convolutional, ConvLSTM, cross-correlation, and fully connected layers. The authors employed a tuning approach and assessed the system's performance on two datasets, one featuring UAVs and the other birds. The evaluation demonstrated superior results, particularly evident in Receiver Operating Characteristic (ROC) curves.

Aker et al. created YOLOv2, a single-shot object detector, through fine-tuning for Unmanned Aerial Vehicle (UAV) detection [46]. Their approach resulted in equal precision and recall values of 0.9 on an artificial dataset.

Saqib et al. conducted a study focusing on pre-trained Convolutional Neural Network (CNN) models [47], specifically examining Zeiler and Fergus, as well as VGG16 in conjunction with Faster R-CNN, for the purpose of drone detection from video data. They applied transfer learning using VGG16 and ZF, training the models on a Bird-Vs-Drone dataset. The training process involved a learning rate of 0.0001 and batch sizes of 64.

Peng et al. applied the Physically Based Rendering Toolkit to produce photorealistic images of Unmanned Aerial Vehicles (UAVs) [48]. These images were subsequently utilized to enhance the performance of a Faster R-CNN network designed for UAV detection. The refined model demonstrated a notable performance, achieving an average precision of 80.69%.

Lee et al. designed a system for drone detection utilizing a camera mounted on a separate drone [49]. The system integrated a Haar feature cascade classifier along with a Convolutional Neural Network (CNN) network. Training was conducted using the Adam optimizer and a dataset consisting of 7000 drone images. The model demonstrated robust performance with an 89% detection accuracy and an impressive 91.6% identification accuracy as described in Table 2.2.

Work	Drone	Dataset	Features	Detection method	Results
[44]	UAVs and Aircraft	UAV database and Aircraft database	HoG3D, Learned features	Boosted trees, CNN	Average precision is 0.849, 0.864 for the UAV and Aircraft databases respectively
[45]	Small UAVs	UAV database and video-based bird database	Ilearned features	Recurrent correlational Networks (RCN)	ROC curves demonstrate the superiority of the system
[46]	NS	Artificial dataset	Learned features	Fine tuning CNN (YOLOv2)	Precision and recall values of approximately 0.9
[47]	NS	Drone VS Bird database	Learned features	Fine tuning CNN (VGG and ZF)	Mean average precision 0.66
[48]	NS	Synthetic database for drone detection	Learned features	Fine tuning Faster R-CNN with ResNet 101	Mean average precision 80.69%
[49]	NS	10013 images collected from google	Haar and learned features	Haar cascaded classifier, CNN	Detection and Identification accuracies are 89% and 91.6% respectively
[50]	NS	NS	Geographical distributed data points	Intelligent Probabilistic Model	Results show good performance but needs more investigation and improvements
[51]	NS	**1340 images for drones and birds**	Generic Fourier Descriptor (GFD)	Neural Network	Classification accuracy is: 85.3%

Table 2.2: Summary of related work on visual methods for drone detection

2.2.3 Ml-Based Drone Classification By Acoustic Data

Acoustic drone detection captures humming sounds with sensors, employing correlation methods or machine learning for accurate identification based on unique audio fingerprints. This technology enhances adaptability and precision in recognizing drones.

Nijim and Mantrawadi conducted a feasibility study on drone detection, employing the Hidden Markov Model specifically for DJI Phantom 3 and FPV 250 drones [50] . Jeon et al. used Gaussian Mixture Model (GMM), CNN, and RNN classification to detect drone presence in 150 meters [51]. They built datasets by augmented drone sounds and found RNN classifiers performed best, followed by GMM and Performance decreases with unseen data as indicated in Table 2.3.

Bernardini et al [52] proposed a multi-class Support Vector Machine (SVM) classifier to distinguish drone sounds from ambient noises in crowds and daytime nature. They gathered 70 minutes of web audio data containing drone sounds, segmented it into 5-second and 20-millisecond sub-frames, and trained the classifier on features extracted from the pre-processed signals. The classifier achieved an impressive accuracy of 96.4%.

Kim et al. employed spectrum images, correlations, and KNN classifier methods for DJI Phantom 1 and 2 detections [53], achieving 83% accuracy with image correlation and 61% with the KNN classifier. They achieved an 83% accuracy using image correlation and 61% with the KNN classifier, analyzing various sound sources such as indoor, outdoor, and YouTube videos.

Yue et al. created a distributed system [54] for detecting and approximating drone presence, utilizing an acoustic wireless sensor network (WSN) coupled with machine learning. The study revealed distinctions in the power spectrum density (PSD) of drone sounds compared to natural sounds. The system utilized Fast Fourier Transform (FFT) and a low-pass filter to eliminate noise, training a Support Vector Machine (SVM) classifier to identify drone sounds amidst rain and natural background.

Seo et al. used normalized Short-Time Fourier Transform (STFT) [55] to generate 2D images from acoustic signals of DJI Phantom 3 and Phantom 4 drones. The dataset comprised 68,931 sound frames, achieving a high detection rate of 98.97% and a low false alarm rate of 1.28% when training a Convolutional Neural Network (CNN) with 100-epoch low Signal-to-Noise Ratio (SNR). Matson et al. adressed Mel-Frequency Cepstral Coefficients (MFCCs) and Short-Time Fourier Transform (STFT) features [56] extracted from an optimized multiple acoustic nodes system. These features were employed to train Support Vector Machine (SVM) and Convolutional Neural Network (CNN) supervised classifiers. the audio signal was represented as 2D images, and the dataset included two cases: drone flying and environmental noise recording, outperforming of STFT and SVM.

Work	Drone	Dataset	Features	Detection method	Results
[50]	DJI Phantom 3 and FPV 250	NS	NS	HMM	Very preliminary results that show the feasibility of detection
[51]	DJI Phantom 3 and 4, DJI Inspire, 3RD Solo	9556-sec augmented sound (training), 151 sec (testing), 1557 sec (unseen data)	MFCCs	Binary classification: GMM, CNN, RNN	Best accuracy with RNN (80%) followed by GMM (68%) followed by CNN (58%). Low performance with unseen data.
[52]	NS	Five 70-min sounds from the classes	Short-time energy, temporal centroid, ZCR, spectral centroid, roll-off, MFCCs	Multi-class SVM	Classification accuracy of 96.4%.
[53]	DJI Phantom 1 and Phantom 2	NS	Spectrum image and FFT amplitude spectrum	Correlation and KNN classifier	83% accuracy in image correlation 61% in KNN classification.
[54]	/	2000 tuples sampled for drone and non-drone sounds divided 50%, 30% and 20%	PSD	SVM classifier	Best TPR and FNR when SIR is greater than 10dB.
[55]	DJI Phantom 3 and Phantom 4	68931 sound frames for drones and 41958 sound frames for non-drone's others	Normalized STFT	CNN	DR is 98.97% and FAR is 1.28 with 100-epoch and low SNR environment.
[56]	Parrot AR Drone 2.0	Drone and environment noise audio signals	MFCCs, STFT	SVM classifier, CNN model	BSTFT-SVM show best detection accuracy in terms of color map.

Table 2.3: Summary of related work on acoustic methods for drone detection

2.2.4 Ml-Based Drone Classification By Radio Frequency

Unmanned Aerial Vehicles (UAVs) are equipped with onboard transmitters that utilize Radio Frequency (RF) signals for control and operation. This characteristic enables the detection and localization of UAVs from a considerable distance, offering the added capability of identifying the controller responsible for sending the RF signal.

Shi et al. designed a system utilizing Hash Fingerprint features for the detection of slow, small unmanned aerial vehicles (LSSUAVs) operating at a frequency of 2.4 GHz [57] . While effective in detecting and recognizing signals in an indoor environment, the system's performance diminishes when subjected to the addition of white Gaussian noise.

Nguyen et al. developed a system using algorithms to detect drones by analyzing their physical attributes [58], including body shifting, vibration from spinning propellers, and navigation patterns. Tested on Parrot Bebop and DJI Phantom drones, the system demonstrated an accuracy of 84.9%, precision of 81.5%, and recall of 90.3%

Ezuma et al. designed a system converting raw RF signals into wavelet domain frames for preprocessing, employing a Markov model for UAV presence description and a naive Bayes classifier for detection [59]. Classification involved the energy transient signal, with extracted statistical features such as skewness, variance, entropy, and kurtosis. Robust feature selection was performed using Neighborhood Component Analysis (NCA). The system achieved an average detection accuracy of 96.3%, with performance varying based on the signal-to-noise ratio (SNR) as outlined in Table 2.4.

Work	**Drone**	**Dataset**	**Features**	**Detection method**	**Results**
[57]	LSSUAVs	NS	Hash fingerprint	SVDD	Successful detection in indoor environment in 2.4 Ghz band without noise
[58]	Parrot Bebop, and DJI Phantom	NS	Body shifting, body vibration	Wavelet analysis and maximum PSD	Accuracy of 96.5%, precision of 95.9% and recall of 97% for 10m distance
[59]	Controller for different UAVs	100 RF signals from 14 UAV controllers	Skewness, variance, entropy and kurtosis with NCA	SVM, DA, ANN and KNN classifiers	96.3% detection accuracy with KNN classifier and good SNR value.

Table 2.4: Summary of related work on RF methods for drone detection

2.3 Multisensory Integration for Drone Detection: A Bayesian Inference Approach

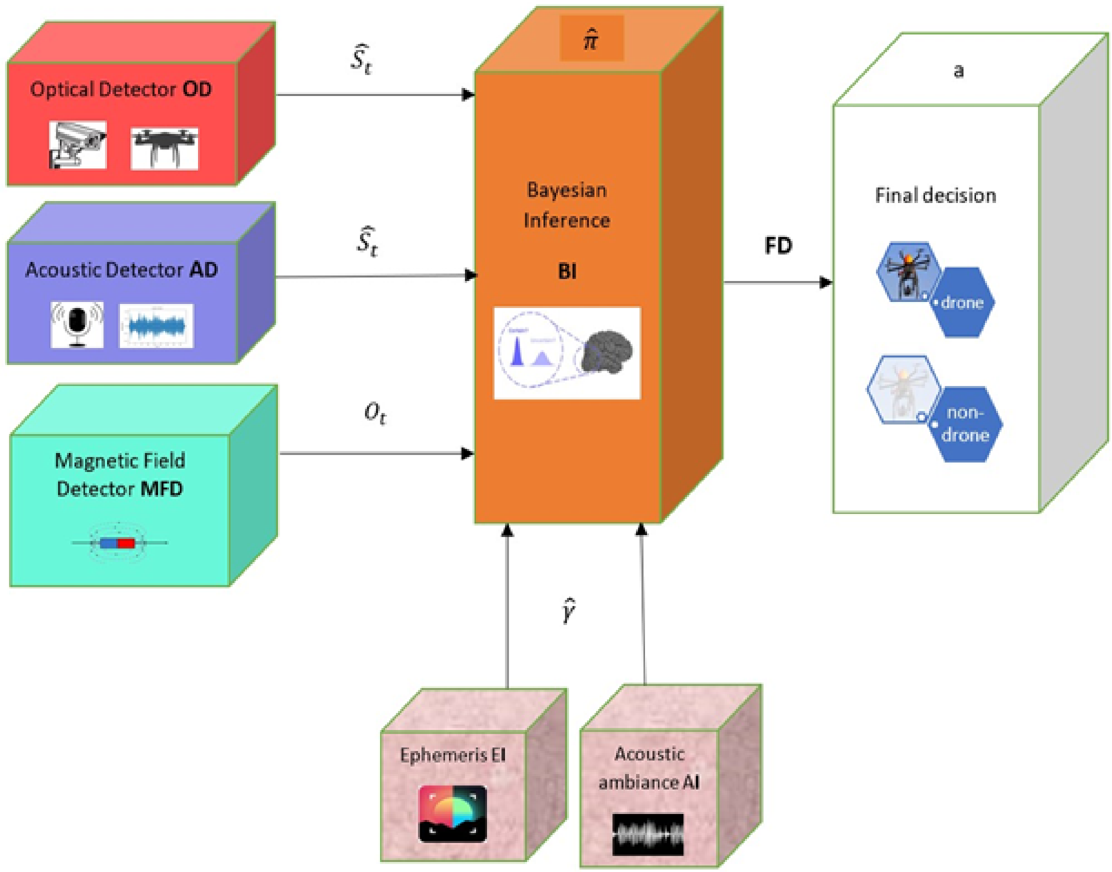

Figure 2.1: Synoptic of Intelligent Multi-Detectors using Bayesian Inference BI model where OD is Optical Detector, AD is Acoustic Detector, MFD is Magnetic Field Detector, EI is Ephemeris Indicator, and AI is Acoustic Ambiance Indicator

- **Explication**

The Probabilistic model presented in this paper leverages Bayesian inference, utilizing a combination of imagery, acoustic ambiance, and magnetic field detectors to capture the high temporal variability of drone detection. This approach is chosen for its ability to analyze multiple variables and address challenges in designing patterns and detecting behaviors. For anomaly detection and correct identification of the root causes meaningful, optical, acoustic and magnetic field detectors, perceptual data ephemeris, acoustic ambiance indicators and accurate modeling must be selected and used. The Bayesian network model in Figure 2.1 demonstrates the integration of these components in our proposed approach. Locating a drone based on a combination of sight, sound, and magnetic field signals falls under the general class of multisensory integration problems, where perceptual systems triangulate different sensory signals to determine the drone's location. Each detector processes signals separately but combining them yields a more accurate result. Utilizing Bayesian inference in our proposed approach allows effective integration of signals from different detectors, resulting in a more accurate and reliable drone detection system [60].

The Bayesian model of multisensory integration assumes that perceptual systems combine different signals based on their reliability or uncertainty. Our approach considers signals from visual, acoustic, and magnetic field detectors, along with ephemeris and acoustic ambiance indicators providing information about the environment. Environmental conditions impact detector reliability, and our approach evaluates ephemeris and acoustic ambiance indicators to eliminate the final decision of one detector. For instance, optic detector may not function very well during low light conditions while, acoustic detector may not function very well during noisy conditions. Considering these factors promotes a detector relative to others, ensuring accuracy and reliability under varying environmental conditions. Experimental work demonstrates that when agents share beliefs and confidence, collective decisions become more reliable. Integrating this confidence information suits indicators used for greater precision in multisensory combination, enhancing the final decision-making process [60].

2.4 Conclusion

The anticipated growth in the drone market and the subsequent rise in drone numbers present a challenge to traditional methods, raising questions about the efficiency of human-centered solutions. This review underscores the pivotal role that machine learning can play in addressing this challenge. The digital processing of various modalities has rendered machine learning applicable in nearly every detection system, contingent upon the system operator's willingness to attend to data. While challenges related to the quantity and quality of data in machine learning are widely acknowledged, they become particularly urgent in the context of drone detection and classification. Collaborative efforts to construct publicly available datasets are essential to assist researchers and developers in creating robust classification models for drones around all modalities. The risk associated with drone operations significantly depends on the drone's location and its distance from critical areas during flight, making ranging a crucial objective. However, the reviewed literature mostly emphasizes detection performance, with limited information on the drone's detected distance. As highlighted in this chapter, no single modality is optimal for both drone detection and classification. Addressing this limitation, various authors have proposed bi-modal and multi-modal systems, showing promising outcomes. Nevertheless, current solutions often assume a statically located detection system, which proves restrictive in modern cities where obstacles, such as buildings, can hinder detection by obstructing views, RF, and radar signals. Additionally, elevated noise levels pose challenges for acoustic detection. Recognizing these issues, the implementation of distributed and collaborative detection systems, utilizing wide-area solutions or city-wide surveillance sensors, could present an effective strategy to navigate the complexities of drone detection and classification. Moreover, we launch a pioneering technique called multi-sensory integration. Inspired by Bayesian inference, it delves into the final decision-making from diverse sensing modalities to enhance the robustness and accuracy of the detection system.

CHAPTER 3
OPTIC DETECTION WITH CONVOLUTIONAL NEURAL NETWORKS (CNNS)

Chapter 3

Optic Detection with Convolutional Neural Networks (CNNs)

3.1 Introduction

A new contender takes flight—the Unmanned Aerial Vehicle (UAV), whether facilitating package deliveries, capturing mesmerizing aerial footage, or conducting surveillance missions, have become an integral part of our modern world. But how do we keep track of these elusive aviators? Detecting drones poses a substantial challenge due to limitations in existing radar systems designed for larger aircraft, which depend on the object's dimensions surpassing the emitted radio signal's wavelength. However, the similarity in size between drones and birds complicates matters, requiring solutions that can distinguish between aircraft and wildlife. Moreover, the lower flight altitudes of UAVs contribute to radar clutter as signals bounce off the ground and surrounding obstacles. Addressing these complexities is essential for effective drone detection [61]. In recent years, Deep Convolutional Neural Networks (DCNNs) have emerged as a pivotal technology for advancing visual systems dedicated to object detection and tracking. These methods harness learning principles to extract feature maps from input images, facilitating the development of probabilistic distributions for different categories or variables [62, 63].

Recent advancements in neural networks and deep learning algorithms have highlighted the value of optical data for UAV detection systems. Research in this area has been influenced by the success of deep learning in image classification tasks, notably demonstrated in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) contest in 2012 [64]. Numerous studies employing deep neural networks (DNNs) for UAV detection adopt a generic object detection architecture, integrating a robust DNN as a classification model customized for UAV identification [65, 66].

The ImageNet project aims to build a vast database of annotated images, including pretrained models like VGG-16 and VGG-19, which are developed from scratch and trained on millions of images spanning numerous categories. Due to its extensive training, the model has acquired a good representation of low-level features like spatial, edges, rotation, lighting, shapes. These features can be shared across different computer vision tasks, enabling knowledge transfer, and serving as effective feature extractors for new images [67]. In this chapter, we explore the potential of transfer learning by using the pretrained VGG-16 model to classify drone vs non-drone (such as birds. . . etc.). This study includes interpreting the underlying principles of the chosen optical detection approach, presenting experimental results, aiming to contribute valuable insights to the field of optical detection, demonstrating its effectiveness in tackling diverse computer vision challenges.

3.2 Exploring Deep Learning Mechanisms: A Comprehensive Overview

Deep learning is a branch of artificial intelligence that stems from machine learning, enabling machines to learn autonomously. This stands in contrast to traditional programming, where machines strictly follow predetermined rules. Its operation entails computers employing artificial neural networks that emulate the structure of the human brain to handle vast volumes of data. Whenever new information is encountered, existing connections between neurons undergo alteration and expansion. Its objective is to empower the system to learn autonomously without manual intervention, while enhancing its performance, decision-making capabilities, and predictive accuracy.

3.2.1 Fundamentals of Convolutional Neural Networks (CNNs)

An artificial neural network, known as a multilayer perceptron (MLP), comprises an input neural layer, one or more hidden layers, and an output layer, all utilized for information processing Incoming data, or the input vector, is received by the input layer. Subsequently, it is transmitted to the hidden layer through artificial neurons, where they are assigned "weights". Eventually, a specific pattern is adopted upon reaching the output layer. The greater the number of layers within an artificial neural network, the greater the complexity of tasks artificial intelligence can address. One of the most effective algorithms in deep learning is Convolutional Neural Networks (CNNs). The program is constructed on the foundation of deep learning convolutional neural networks (CNNs) and transfer learning. Nonetheless, to boost CNN performance, it's imperative to integrate specific methods, including dropout regularization and data augmentation. Convolutional Neural Networks (CNNs) are a specialized type of multilayer neural networks, with a design inspired by the architecture of the visual cortex in mammals. These neural networks can classify information ranging from simple to complex. They comprise multiple layers of neurons and employ various mathematical functions with adjustable parameters, enabling them to preprocess a limited amount of information. CNNs are distinguished by their initial convolutional layer, typically consisting of one to three layers. As the name implies, the convolutional layer operates based on the mathematical concept of convolution, aiming to detect patterns within data, such as signals or images. In the case of images, the initial convolutional layer is adept at identifying object contours, like circles. Following this, the second convolutional layer can translate these contours into recognizable objects, such as wheels. Subsequent layers, while not strictly convolutions, leverage these features to discern between details pertaining to cars and motorcycles [68]. The process of teaching the network to recognize known objects entails optimizing parameters through exposure to vast datasets, including thousands of images depicting dogs, cars, or sports. A key challenge lies in efficiently and swiftly adjusting these parameters. Convolutional neural networks find extensive applications in image recognition, video processing, and natural language processing [69].

3.2.1.1 The layers of a Convolutional Neural Network

To execute a convolutional neural network, we require four types of layers: convolutional layer, pooling layer, ReLU activation layer, and fully connected layer.

- **Convolutional Layer:** Convolution is the fundamental operation in convolutional neural networks (CNNs), initiated as a mathematical formula commonly used for image manipulation. It allows the extraction of features such as vertical, horizontal, and diagonal lines, as well as image blur, texture smoothing, and color inversion. These features are achieved through the application of filters to images. In essence, convolution takes an image and a filter as input, performs calculations, and produces a new image, typically smaller in size. There are several types of convolutions, although the basic one is commonly used. It can be useful to be aware of the tools at our disposal. Types of convolutions include:

1. **Classic convolution:** The standard convolution operation involves applying a filter to an input image to extract features. It contains three parameters: the kernel, or filter, is applied to the input data to extract features, with the stride determining the spatial movement of the kernel. Padding, which involves adding additional pixels around the input data, ensures that the spatial dimensions of the output feature map match the input dimensions, helping to preserve spatial information.

2. **Dilated convolution:** Dilated convolution involves introducing gaps or dilations between filter elements to increase the receptive field without increasing the number of parameters.

3. **Transposed convolution:** Also known as deconvolution, it is used for up sampling or increasing the spatial resolution of feature maps.

4. **Separable Convolution:** Separable convolution decomposes the standard convolution operation into depthwise and pointwise convolutions, reducing computational cost while preserving accuracy. Depthwise convolution applies a separate filter for each input channel, followed by a pointwise convolution to combine the results. It is commonly used in lightweight neural network architectures like MobileNet.

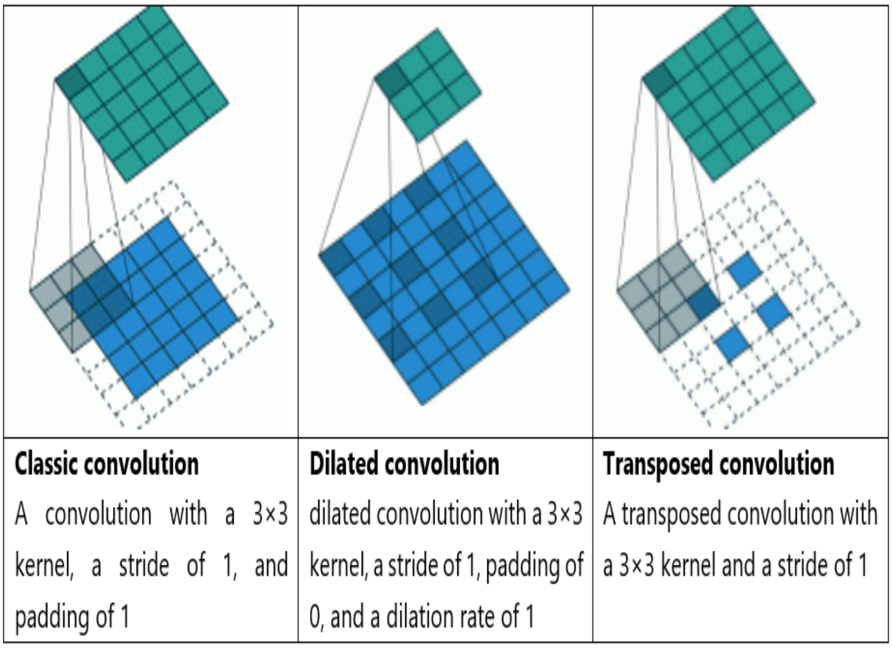

Figure 3.1: Different Types of convolutions [70]

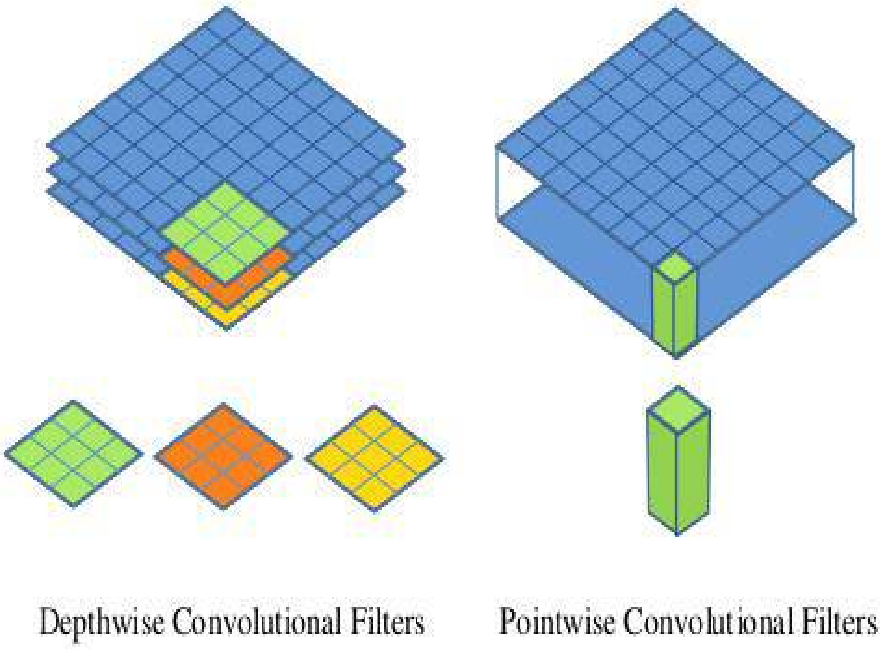

Figure 3.2: Two Techniques of Separable Convolution [71]

• **The Rectified Linear Unit Layer:** The Rectified Linear Unit (ReLU) activation function, widely used in Deep Learning, particularly after convolutional layers in convolutional neural networks, is preferred for several reasons: it accelerates computations by eliminating negative values, enhances important features in images by widening the gap between features, and preserves positive values without altering the traits highlighted by convolution. A popular variant of ReLU is the Leaky ReLU, which retains data non-linearity to a lesser extent.

• **The Pooling Layer:** Pooling is an operation that simplifies an image by replacing a square of pixels with a single value (typically 2×2 or 3×3), reducing the size and complexity of the image. To apply pooling, a square of pixels of size 2×2 (for example) is first selected, and then the value to replace this square is calculated. The square is then shifted to the right (or downwards) based on the stride (step). There are several types of pooling, including "max pooling" which takes the maximum value of the selection, "mean pooling" which takes the average of the pixels, and "sum pooling" which calculates the sum of the values.

• **the fully connected layer:** The fully connected layer (FC) applies to inputs that have been previously flattened, where each input is connected to all neurons. These layers typically appear at the end of the CNN architecture and are used to optimize specific objectives, such as course grades.

Flattening: Or flattening out, is the final step in the "information extraction" phase, involving concatenating all the images (matrices) to form a long vector. This entails retrieving pixels row by row and adding them to the final vector, thereby converting the images into arrays of numbers.

3.2.1.2 VGG-16 Model

The VGG-16 model is a convolutional neural network architecture proposed by the Visual Geometry Group at the University of Oxford. This is made up of 16 layers such as 13 convolutional and 3 fully connected. The network is known for its simplicity and uniform architecture, where the convolutional layers primarily use 3 × 3 filters with a stride of 1 and padding to maintain spatial dimensions. VGG-16 achieves high accuracy on image classification tasks by stacking multiple convolutional layers followed by max-pooling layers to gradually reduce spatial dimensions while increasing the number of filters. The final layers are fully connected layers followed by a SoftMax layer for classification [72, 73].

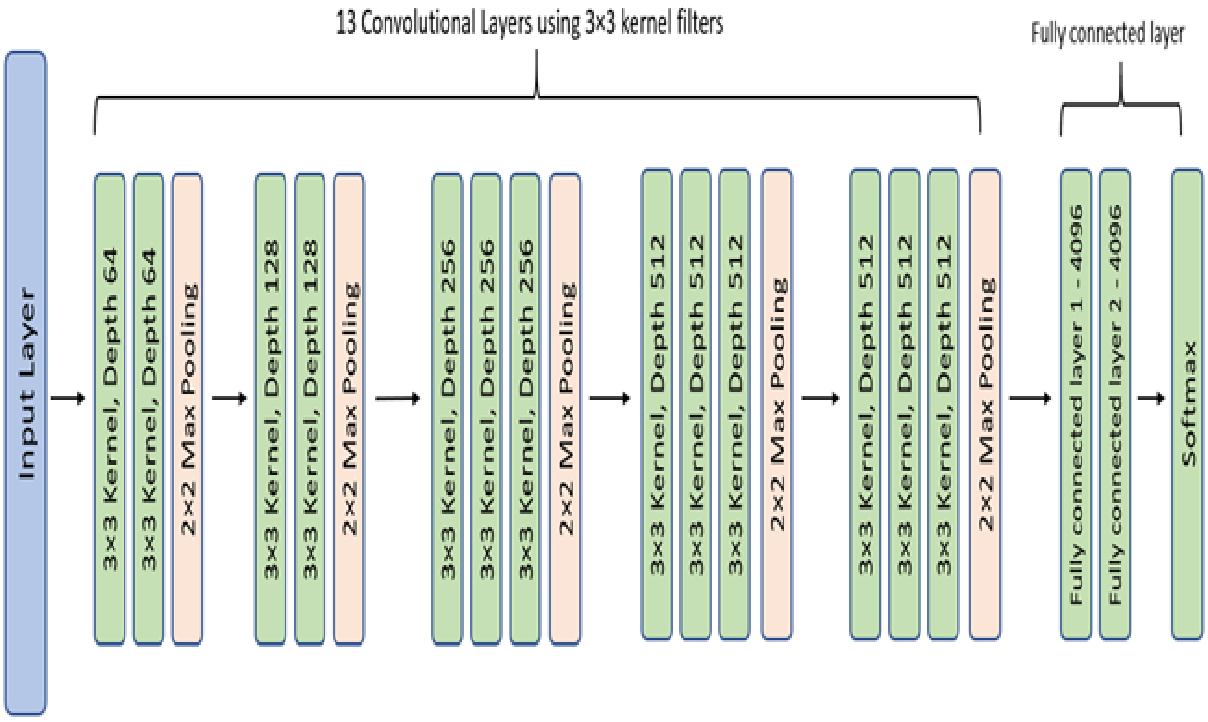

Figure 3.3: The architecture of VGG-16 model [72]

3.3 Optic detection methodology

In this section, we describe a framework of the recent technology of Deep Convolutional Neural Networks CNNs. It was to provide a system that integrates tracking algorithms with deep learning classification structures and protocols and evaluate its effectiveness. It is dedicated to collecting data, then pre-processing images. The current approach technique used imaging systems and cameras with visual spectrum to detect and classify drones. Not typically a primary detection source, electrooptical sensors use a visual signature to detect UAS. Typically, they come with a high zoom capability for viewing small objects far away.

3.3.1 dataset collection

Aiming to select and analyze the datasets, the data images of the UAVs were randomly taken from a website selected for all forms of drones Mini/Micro which have been divided into three main sets assigned to the training, testing, and validation. Next, we create two files for each sampling unit, one for drones and the other for non-drones: Selecting non-drone images as flying objects, raptor birds, UFOs, flying plastic bags, as well as balloons, kites, and parachutes distant. Further, we should avoid duplicate images using Duplicate Media Finder to enhance the desired number of images and modify the images by removing all handwriting and faces, and even objects similar to drones so that our program could easily distinguish the UAVs. This study emphasizes the critical role of dataset analysis in developing a precise and robust object detection model.

The COCO (Common Objects in Context) dataset was chosen for training and evaluation due to its comprehensive representation of diverse object classes in real-world scenarios. Through meticulous analysis, key dataset attributes such as object distribution, image quality, and annotation accuracy were examined. The insights gained from this analysis informed decisions related to model architecture selection, hyperparameter tuning, and evaluation metric design. By tailoring the object detection approach to the intricacies of real-world scenes uncovered in the dataset, the study aims to create a versatile model capable of accurately detecting objects across various contexts [73].

The main idea behind the machine learning algorithm is that we first need to learn our algorithm using some RGB images called training data. After that, to calculate the performance of our model, we need to use some new RGB images called test data that have not been used for training. So, we can assess the effectiveness of the selected model using the testing data. We splitted 1767 images into training testing and validation sets. We used 20% images for testing, 70% images for training, 10% images for validation.

Table 3.1 shows our data splitting.

Classes	Training	Test	Validation
DRONE (0)	1002	286	143
NON-DRONE (1)	235	67	34
TOTAL	1237	353	177

Table 3.1: Database Collection and Utilization for Model Processing

According to the drone's identification, we needed to do image pre-processing which is a crucial task for achieving a better result. Alternative techniques had been evolved so far for enhancing UAV images in which they were not cleared. For this reason, we utilized LabelImg for its enhancement. Primarily, Since the images in the dataset have different resolutions, all of them were resized to $(224 \times 224 \times 3)$. Finally, for each image, we performed normalization. The databases must undertake a pre-processing to be adapted to the inputs and the outputs of the neuronal network which consists of carrying out appropriate standardization, accounting for the amplitude of values accepted by the neuronal network.

Technically, we prepared CNNs input data and created a new drone database by labeling data for detection and identification activities for distinct CNN models wherever it utilizes a data label for drone detection. This label denotes the dataset specifications. Furthermore, the CNNs model has learned in the earlier layers more generic features, that could be useful in other tasks. After the pre-processing and labeling of datasets, the next step sheds light on the overall methodology to assess the algorithm's capability in extracting drone images, including pre-processing, feature extraction, and object classification, as described.

The UAV images were analyzed on a personal computer with a MacOs Catalina i7 CPU 2.8 GHz, 16 GB RAM, Intel HD Graphics 6301536 MB, and Python 3.7 TensorFlow 2.3 Keras 2.3.1. To detect, categorize, and estimate drones, computational analysis for the overall program execution from image processing is used.

3.3.2 Description of neuronal network and its training

After performing image pre-processing, a novel deep Convolutional Neural Network (CNN) model was created to extract the most discriminant features from the photos. Following feature extraction, the extracted features were pre-processed before being fed into various well-known machine learning algorithms. The choice of neural networks depends on the specific task and the characteristics of the data. In this case, a fully convolutional neural model was trained. This model consists of an input layer, hidden layers, and an output layer as depicted in Figure 3.4. The input layer receives the preprocessed image data, and the hidden layers perform intricate computations to learn relevant patterns and features. Finally, the output layer provides the classification or prediction results based on the trained model.

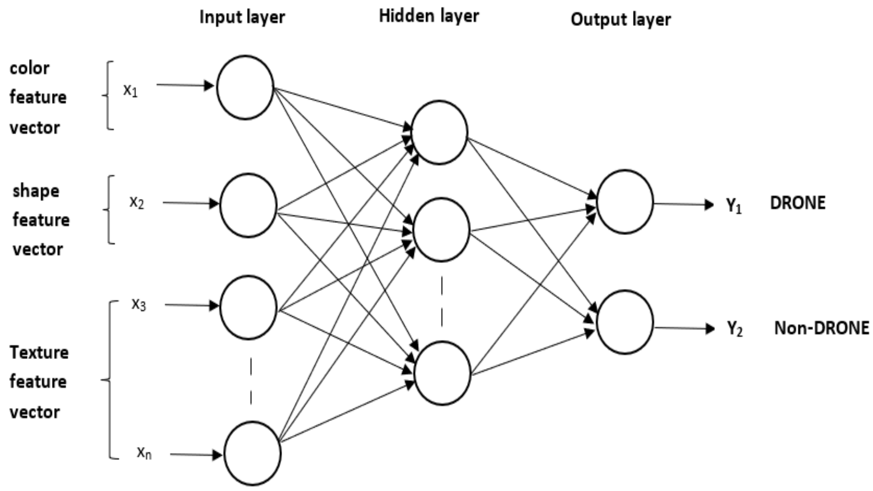

Figure 3.4: Artificial neural network

The proposed CNN technique focused on the VGG 16 model: Visual Geometry Group that contains thirteen learned convolutional Layers using 3×3 kernel filters. Except for the final convolutional layer, each convolutional layer is followed by a parametric Rectified Linear Unit (ReLU) activation layer that learns the parameters of the rectifiers. RGB photos of size $128 \times 128 \times 3$ are accepted by the network. The output of the final convolutional layer is sent into a Softmax layer, which generates a distribution over the drone and non-drone classes. Since it has been shown to improve classification results, Maxpooling layers are used after the second, fourth, seventh, tenth, and thirteenth convolutional layers, with the goal of reducing the spatial size of their input and the number of parameters contributing to overfitting control, while a response normalization layer is used after the first pooling layer to aid generalization like Figure 3.5.

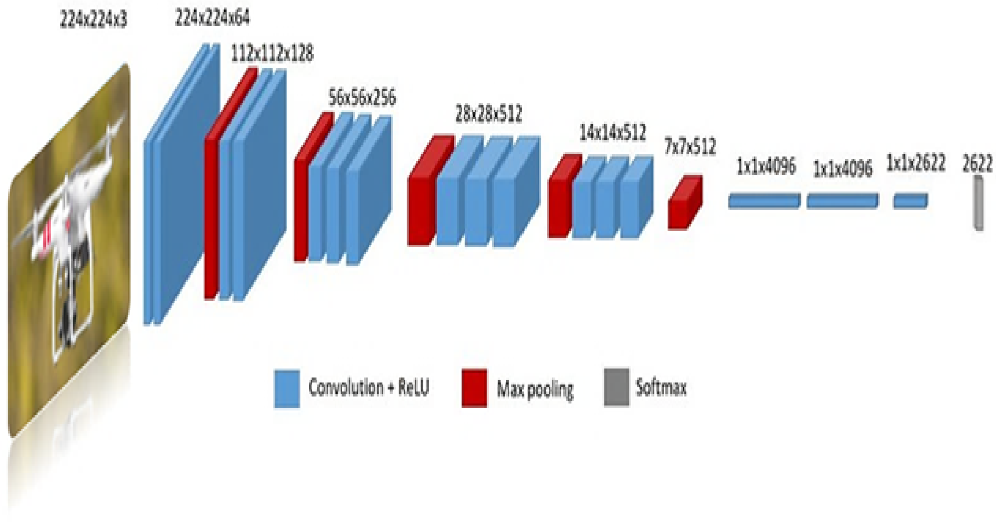

Figure 3.5: Convolutional Neural Network

Max-pooling layers follow the convolutional layers, while the ReLU non-linearity formula is $(f(x) = max(0; x)$ except for the two last fully connected layers (denoted as FC). The two classes of ImageNet are represented by the output of the FC layer as a probabilistic distribution. The softmax loss is used during the training. Specifically, we launch the parameters by sampling weights from the pre-trained VGG-16 network on ImageNet. Despite having three branches, the implemented network has around 75% of the VGG-16 network. VGGNet adds 3×3 convolutions to form a deeper architecture. Most of the research propositions use VGG as a structure and create a better component at each phase (split by stride) [73]. Eventually, we used this ensemble method to improve the overall performance of these algorithms.

We crafted a CNN model using the Python programming language. The selected choice of framework was TensorFlow, a popular open-source software library renowned for its application in machine learning, particularly neural networks. To streamline the model development, we harnessed Keras as a high-level neural network library, leveraging its capabilities as a TensorFlow wrapper. The entire development process took place within the Jupyter notebook environment. In the initial stages, we are adopting a Convolutional Neural Network (CNN) approach. This involves forwarding input images through a sequence of distinct layers: starting with convolutional and pooling layers, followed by flattening and fully connected layers. This sequential processing culminates in the generation of CNN outputs, which play a pivotal role in image classification. The procedure of progression begins with the creation of CNN models from scratch. Subsequently, we embark on enhancing these models by integrating image augmentation techniques. This strategic augmentation seeks to diversify the dataset and augment its robustness.

In general, a classification task in computer science and related fields applies a computational model inspired by the central nervous system to tackle non-linear issues corresponding to noisy or complex data, such as image analysis. We handle a pre-trained CNN model, trained on large datasets referred to the two classes, Drone and Non-Drone, such as ImageNet.

3.3.3 Object classification with machine learning

Classification task imposes a computational model inspired by the central nervous system in computer science and related fields to solve non-linear problems corresponding to noisy or complex data, including image analysis. We pre-trained CNN model on large datasets referred to the two classes, Drone and Non- Drone, such as ImageNet, then replace the classification layer with a new one that represents the labels of a specific dataset and is initialized indiscriminately and retrain the network on the specific dataset. This approach serves as baseline against the proposed model. The classification algorithm using machine learning is needed to remove the true positive detection of the drone to identify it as a non-drone. Therefore, by using classification algorithm, this indirectly enhances the performance of algorithm to correctly discriminate the drone's images and hence makes it useful during counting process. Specific architecture of hidden layers depends on the proposed classifiers architecture [72].

3.3.4 Feature extraction and Performance evaluation

Feature extraction using image processing techniques can be error-prone and time-consuming. The adopted CNN architecture consisted of thirteen convolutional layers, followed by batch normalization and max-pooling layers. Through training, the model learned the parameters necessary for drone classification. The performance of the model was evaluated based on its separation capacity, detection rate, and learning time. We compared the performance of drone image classification with manual and machine classifiers. In the realm of machine learning model development, feature extraction stands as a pivotal step to distill essential information from raw data. We highlight the application of Principal Component Analysis (PCA) and convolutional neural networks (CNNs) for effective feature extraction.

The interplay between feature extraction and accuracy-based performance evaluation is explored within the context of a meticulously partitioned dataset, separating training and testing subsets. The significance of precision, and recall in supplementing accuracy is emphasized, particularly in addressing imbalanced datasets. Through this comprehensive evaluation approach, a balanced view of model capabilities is attained. The incorporation of feature extraction and performance evaluation, with accuracy at its core, culminates in an iterative model refinement process, enhancing real-world applicability and robustness [73].

3.4 Results And Discussion Of Optical Detection model

The evaluation of model performance is crucial to validate its efficacy. The accuracy is a key metric that quantifies the correctness of predictions relative to the total instances. The performances of the drone's images were compared with manual and machine classifier count. Evaluation regarding classification accuracy, loss and precision was assessed as in Eqs. 3.1, 3.2, 3.3, 3.4.. The terms are defined as True Positive (TP) is correctly classified positive cases of true drone's detection, True Negative (TN) is correctly classified negative cases of incorrect drone's detection, False Positive (FP) is incorrectly classified negative cases and False Negative (FN) is incorrectly classified the drones as the positive cases. Accuracy and precision describe how many classified drones are relevant, and the probability of the classification is correctly performed. Loss is defined as a quantitative measure of how well a model's predictions match the true values in the dataset. It is typically calculated using a loss function, which quantifies the discrepancy between the predicted values and the actual values.

$$Sensitivity = \frac{TP}{TP + FN} \tag{3.1}$$

$$Specificity = \frac{TN}{TN + FN} \tag{3.2}$$

$$Specificity = \frac{TP}{TP + FP} \tag{3.3}$$

$$Specificity = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.4}$$

Inspired by the provided results, we can notice a performance decrease with a capacity increase but also a similar case of over-adjustment occurring more and more early in the race. Thus, we have explored three different progresses of the basic model as VGG3 with

DROPOUT, VGG3 with progress of data and Transfer Learning VGG16. The results of progressing were considered as follows in the Table 3.2:

Different Progress	Accuracy%
VGG3 + DROPOUT	77.143%
PROGRESS OF DATA + VGG3	78.286%
Transfer Learning VGG16	97.600%

Table 3.2: The Results Of Progressing Of Model CNN

Considering these findings, as depicted in Figure 3.6, a curve illustrating a linear graph for loss and another for model accuracy has been generated. The 'blue curve' represents the performance on the learning first database, while the 'orange curve' represents the results on the test database. By examining the transfer learning VGG16 curves, we find that the model quickly adapts to all the data, it does not show significant over-adjustment although the results suggest that additional capacity of the classifier and/or the use of the regularization could be useful. Therefore, we finalize that configuration and save the transfer learning VGG16 approach as a final model.

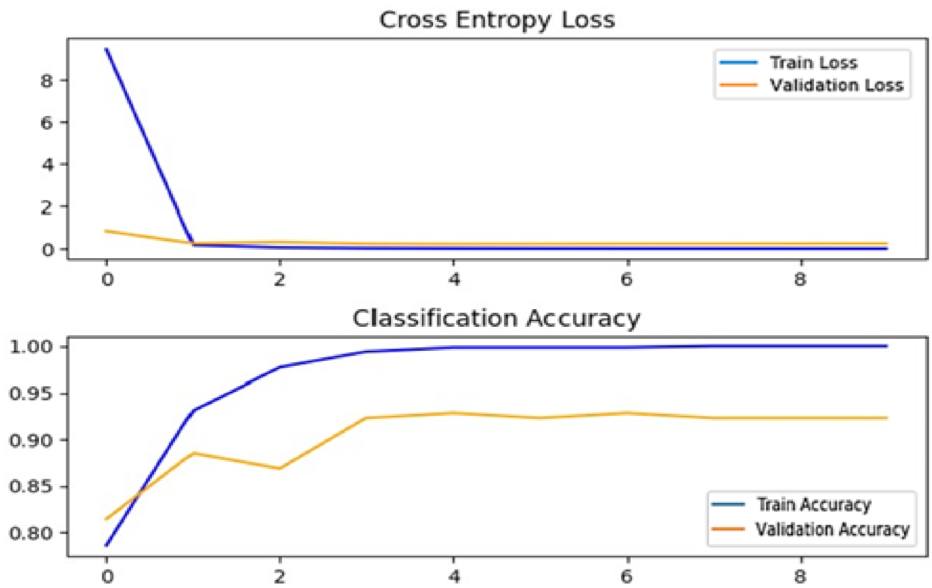

Figure 3.6: Convolutional Neural Network

For the execution of the last architecture of transfer learning VGG16, we need more data as it shows very good results. In the report of the Robustness Test of our final model, we have used three different quantities of databases. First database is shown in Table 3.1. Table 3.3 and Table 3.4 show the data splitting 2, 3 respectively:

Classes	Training	Test	Validation
DRONE (0)	3327	449	1003
NON-DRONE (1)	1149	162	351
TOTAL	4476	611	1354

Table 3.3: 2nd Datasets Splitting Into Training, Testing And Validation

Classes	Training	Test	Validation
DRONE (0)	7000	1000	2000
NON-DRONE (1)	2338	333	666
TOTAL	9338	1333	2666

Table 3.4: 3rd Datasets Splitting Into Training, Testing And Validation

In Table 3.5, we present the experimental results obtained from Transfer Learning based on VGG16 using different quantities of data. We observe that the model adapts quickly to all the data without significant over-adjustment, confirming the previous findings. To improve the final detection, we employed a soft ensemble-based approach. The robustness of the proposed model was evaluated using a confusion matrix, which allowed us to assess accuracy, precision, and loss, shows validation accuracy for different databases with the pretrained model (VGG-16) trained on huge dataset of images.

1st test	2nd test	3rd test
97.6 %	94.205 %	94.570 %

Table 3.5: Robustness and Test Results

Considering these findings, as depicted in Figure 3.7 and Figure 3.8, a curve illustrating a linear graph for loss and another for model accuracy has been generated where They represent the performance on the learning and testing of second and third database respectively.

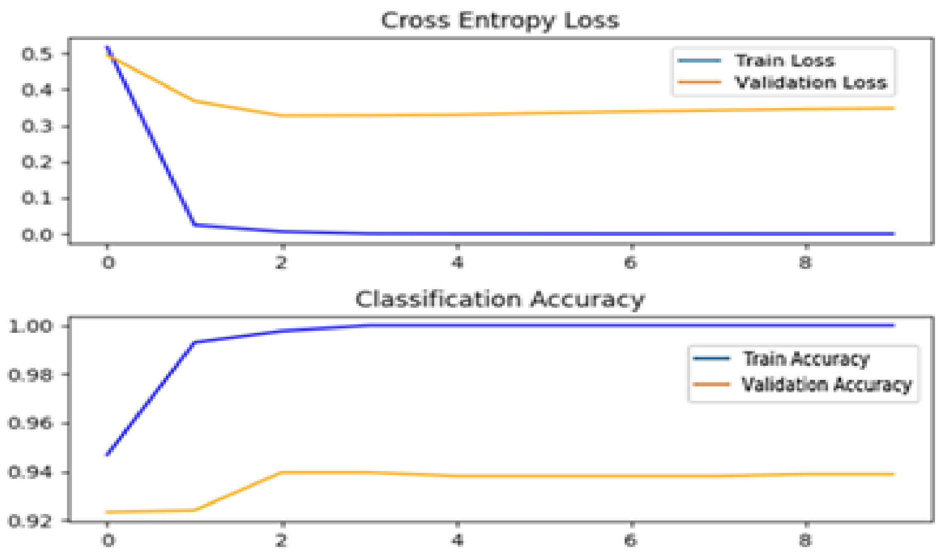

Figure 3.7: Linear Plots Of Learn Curves For Loss And Accuracy For Basic Model, Transfer Learning VGG16 On The 2 Nd Drone And Non-Drone Database

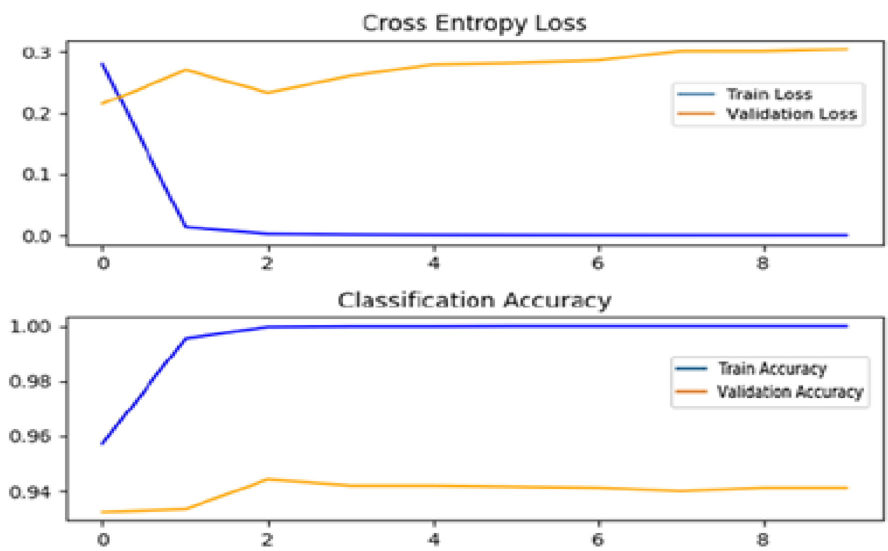

Figure 3.8: Linear plots of learn curves for loss and accuracy for basic model, transfer learning VGG16 on the 3 rd drone and non-drone database

We have tried static and dynamic images that we did not use during the robustness test. The results for detection are displayed below. According to the detection, we find that the program has revealed very good performance in terms of precision and loss presented a detection of drones about 96 %, 100 %, no detection for a flying plastic bag, detection of drone with a bird around 99 % as shown in Figure ??. The model performance is considered the separation capacity, detection rate and progress time in the learning case. The model's training process included a learning rate of 0.001, along with dropout regularization with a probability of 0.50, to ensure more generalized results. These findings demonstrate the effectiveness of this approach in accurately detecting drones and differentiating them from other objects in various scenarios.

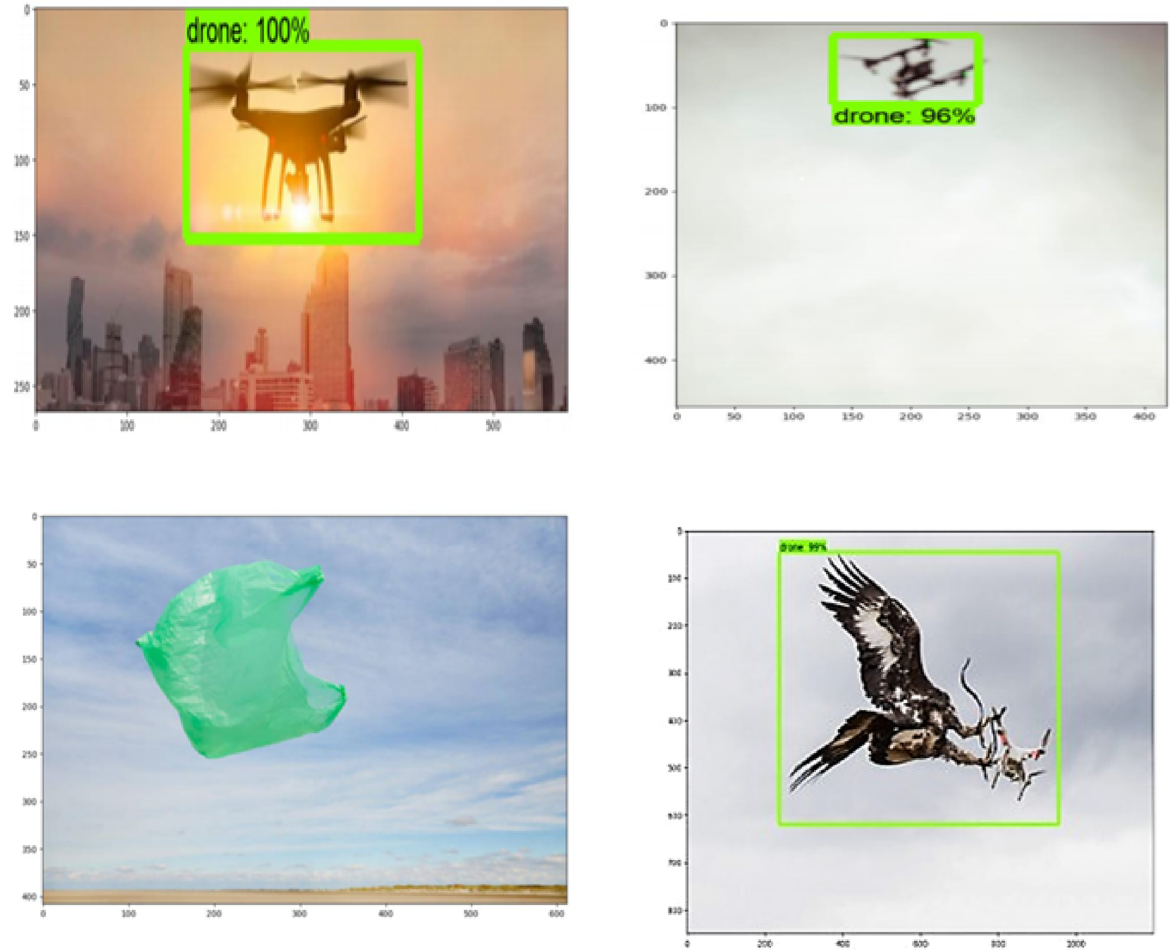

Figure 3.9: Some examples for execution of our optic detection model

For object detection tasks, Convolutional Neural Networks (CNNs) are the preferred choice over conventional neural networks. This preference arises from CNNs' intrinsic ability to extract hierarchical features from images, leading to higher accuracy, efficiency, and adaptability. The key distinction lies in their architecture and capability. CNNs, with convolutional and pooling layers, excel at capturing spatial patterns, making them superior for image-related tasks like object detection. They autonomously learn features from data, reducing the need for extensive manual feature engineering. In contrast, conventional neural networks struggle in this context as they cannot effectively capture spatial relationships and patterns, requiring more manual feature engineering efforts.

3.5 Conclusion

This chapter provides a preliminary investigation of drone detection algorithms utilizing fully deep CNNs. Firstly, we enhance the data images constructed database for the specific task, to improve the quality and detect the drone images. Secondly, to address the application's computational and memory limitations, a completely convolutional architecture was presented. Thirdly, the extracted features have been preprocessed as input in a machine learning classifier to classify the drone and non-drone images. Lastly, we have designed and validated the proposed model with three databases to detect the existence of a drone and classify it in which this tool progressively converges to the best detection and identification system with testing of unseen images. Experimental evaluation of the drone's database indicates the effectiveness and outperforming of the VGG 16. In the future, it is expected that the proposed detection tool will play a key role in object detection and classification field integrated with other detectors as well as it is one of the most successful techniques.

CHAPTER 4
ACOUSTIC DETECTION TECHNIQUE FOR DRONE DETECTION

Chapter 4

Acoustic Detection Technique for Drone Detection

4.1 Introduction

The advancement of Artificial Intelligence, data-driven decision techniques, and the deployment of drones in swarm technology has raised significant concerns about their potential as tools for mass destruction. Their small size and autonomous flight capabilities enable them to evade detection by traditional methods such as Radar, Radio Frequency, and Vision-based techniques, thereby increasing the threat they present to sensitive military zones. However, despite these challenges, Acoustic Based Drone Detection has proven to be effective by leveraging drones' unique acoustic signatures for detection, offering a reliable means of countering their covert operations [74, 75]. Acoustic detection of UAVs holds promise among various detection methods, as recent publications showcase interesting results achieved through the application of machine and deep learning techniques. However, challenges arise in adverse conditions, like heavy wind or construction noise. Researchers mitigate this issue by expanding the feature set to better distinguish between background noise and UAV signatures. They utilize a support vector machine (SVM) classification algorithm, leveraging an augmented training dataset tailored for binary classification [76]. Recognizing acoustic signatures presents notable challenges, including tasks such as identifying isolated characteristic frequencies and distinguishing unmanned aerial vehicles based on their acoustic profiles. Neural networks have proven their effectiveness in various applications, including automated speech recognition, establishing them as a valuable tool for addressing these complexities [77, 78]. This chapter presents a detailed exploration of the acoustic detection approach, incorporating analysis performed on sound recordings obtained from the acoustic atmosphere of the CLA. Several analytical techniques, including FFT, TFCT, wave decomposition, spectrogram, and periodogram, have been applied to these recordings. The drone detection methodology outlined in this study is based on decomposing the received signal into two distinct components: the engine sound and propeller noise. This decomposition is achieved through filtering techniques and correlation/autocorrelation methods. The preliminary results are obtained in the experiments regarding accuracy, efficiency, and overall system performance following the implementation of this method. Subsequently, a comprehensive discussion addresses the implications of these findings and potential challenges.

4.2 Acoustic detection methodology

An acoustic object detection device is designed for capturing digital sound, aiming to enhance the accuracy of UAV (Unmanned Aerial Vehicle) detection by mitigating the identification of erroneous combinations. Sound detection and probability assessment are contingent on the object category. The audio sensor, integrated with the processing device and/or hearing aids, utilizes multiple strategically positioned microphones in the listening environment. These microphones receive audio signals from directions ensuring optimal coverage within the associated field of view. Optionally, the audio sensor can discern sounds associated with infants or objects near them. The audio detection subsystem consists of an audio collecting module, an audio training, a video service module and identification module, a storage module, and a primary communication module. Additionally, each sensor device may include an audio sensor device, a radio frequency sensor device, or an auxiliary device, potentially leading to enhanced audio detection capabilities. Python is what is referred to as an interpreted programming language in this work. The reason for selecting Python is the fact that it has a huge range of libraries which are suitable for aspirational and open-source projects. It has a very simple learning curve and is easy to maintain, and its code is very easy to read. Every effective sound detection system requires its audio fingerprint, which is the first step in the creative process. It captures the unique characteristics of the recording and all the accompanying metadata, which makes it easy to index and search in a database. Basically, an audio fingerprint is a kind of signature which is represented as a vector. A successful acoustic footprint takes into account both physical factors like minimizing sound waves, and it is a requirement that the information be encoded in a way that preserves the summary of the information as well as be insensitive to certain types of interference like ambient noise and signal compression. This allows the system to identify a particular audio segment even from a very short extract [79].

4.2.1 Data collection

The data storage device could be equipped with an audio sensor and programmed to recognize voice commands that are captured by the sensor. Moreover, an extra audio detector can be utilized to distinguish the sounds that are related to drones or nearby objects. To assess the gathered data, different sound categories are included such as the noise of the drone, engine, propeller, industrial, nature and animal sounds, and automation sounds. The aggregation process contains several activities like data duplicate sensor removing, uploaded records categorization, sensor data metadata generation, collected data validation through backup and validation procedures. The audio data backup is done using a Python program that imports two modules, tkinter and pygame, to facilitate the reading of the collected sounds, as shown in Figure 4.1. An arrangement is applied to the audio input to enhance the accuracy of object recognition. It secures object detection capability by identifying an object that is coming towards it and one that is moving away.

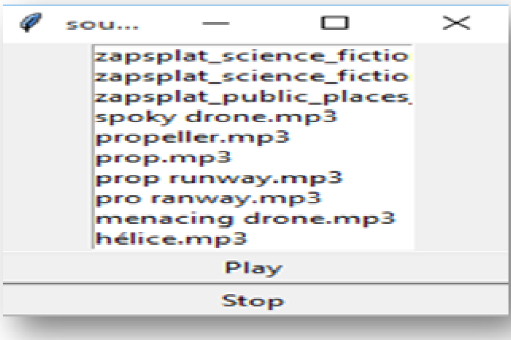

Figure 4.1: The interface created by tkinter to play sounds

4.2.2 Acoustic analysis model

A sound anomaly detection system designed for a power supply device comprises an audio detection subsystem and a wireless computer subsystem that communicates with the audio detection subsystem. An active audio detection circuit is employed to identify the activation of one or more audio sources. Upon confirmation of a non-voice audio detection signal, the computer system executes an indication command or action. The Doppler effect becomes evident in the perception of drone sound waves, influencing the pitch based on the movement of the drone. The sound varies depending on whether the drone approaches the source, resulting in a higher pitch, or moves away, producing a lower pitch. To characterize the biological sounds or other sounds spectrum by means of their strength or other parameters various graphical representations are the most common ones such as time and frequency representation, spectrogram, and wavelet transform. The temporal representation allows visualization of the maximum amplitude of the signal as well as the duration, shape, and periodicity of the sound, as shown in Figure 4.2. The frequency representation can provide the visualization of the sound sample spectrum by enabling interpretation of the contribution of each frequency component. For model analysis, we have selected a time interval of 50 seconds, as illustrated in Figure 4.3.

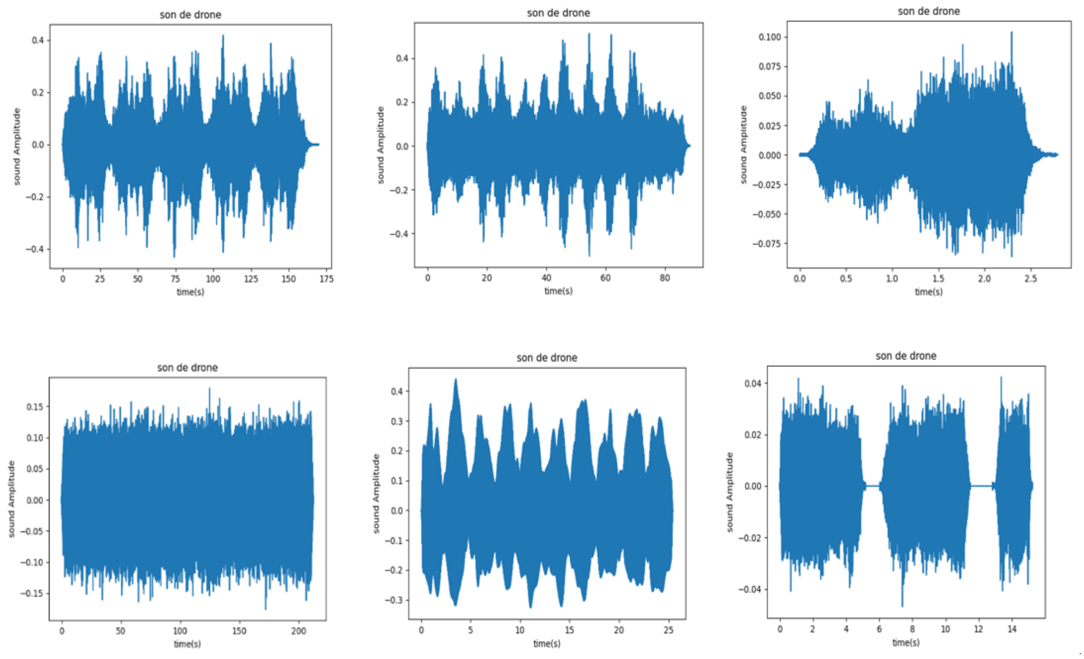

Figure 4.2: Temporal representation of the drone's sounds

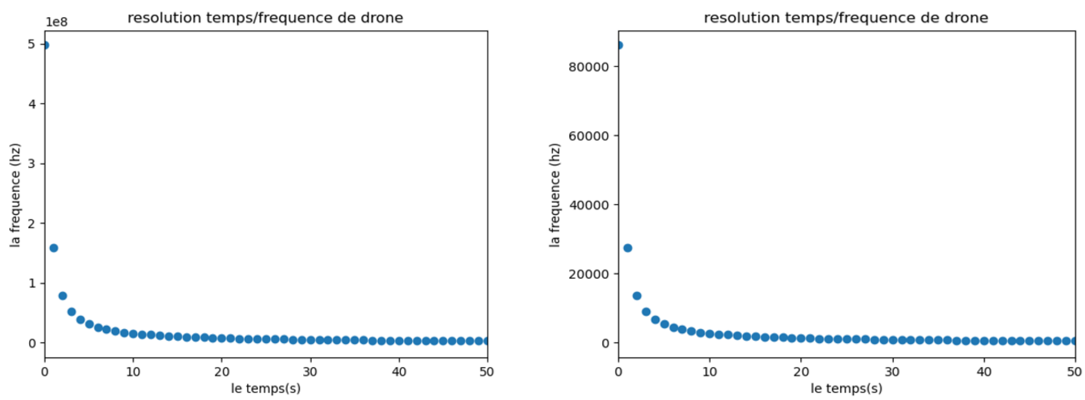

Figure 4.3: Time/Frequency Resolution of drone signals

We employed a TFD (Time-Frequency Distribution) discrete Fourier transform calculation algorithm, utilizing the thinkx and librosa modules in Python3. This algorithm converts a time-dependent function into a frequency-dependent function, providing sampled complex values for harmonic analysis on discrete signals. By doing so, we were able to analyze the harmonic composition of a sound signal, distinguishing between pure and complex sounds and facilitating the identification of sound sources. Each sound source generates a distinct timbre characterized by its harmonic frequencies.

In addition to the harmonic analysis, we utilized three-dimensional representations and spectrograms using the librosa module in Python3. These visualizations enable us to comprehend the time/frequency composition of a signal. The two-dimensional spectrogram, or sonogram, represents sound based on its frequency, amplitude, measurement of sound intensity, or duration. It offers a clear depiction of the variation in frequency over time. Furthermore, we conducted measurements of signal-to-noise ratios to evaluate the impact of factors such as distance, orientation, and amplification on both the visual detection of edges and the signal-to-noise ratio of recordings. This analysis provided insights into the effects of these factors on the overall quality and clarity of the recorded signals.

After all, this new gadget offers a more unbiased way to detect the presence of analyzed spectrograms than humans and it takes much less time to process recordings to detect bird species in a follow-up season. The spectrograms illustrate the number of True Positives, which are known as syllables, and also, it shows the value in the low frequencies indicating the source of noise pollution in the recording which might have affected the sensitivity. The recordings were analyzed via visualization of spectrograms which allowed us to opportunistically detect several other bird species. To process the audio signal, we employed the TFCT method with a Hamming window using advanced Python techniques. The drone signal's TFCT was then decoded into two parts: the engine and propeller parts, which give key data on drone sound characteristics for acoustic design and detection. We then depicted the spectrum of each component visually. To study the spectrum of specific sound signal components, we attenuated and modified them using a low-pass filter to separate the motor sound and a high pass filter to recover the propeller sound. A high-pass filter, commonly referred to as a low-cut filter, reduces the bass frequencies below a certain frequency (fc), while a low-pass filter, also called a high-cut filter, eliminates sharpness in the audio signals and only passes the frequencies that are below a certain frequency (fc) [79].

Besides, there are two classifications of filters: finite impulse response (FIR) filters and infinite impulse response (IIR) filters. FIR filters are digital ones designed to achieve a specific spectrum that cannot be generated with an analog filter. The filter selection was made according to the execution time measured by the "time" module. The filter was first applied to the signal, which was then passed to a SVM (Support Vector Machine) classifier. This is a machine learning algorithm that is used to generalize linear classifiers. Its aim was to classify the sound signal into one of the four classes: engine, propeller, engine and propeller, or neither engine nor propeller. This data analysis method integrates both machine learning and classification algorithms, while SVMs can approximate any continuous function given sufficient data for the algorithm to come up with the best possible optimal hyperplane to separate the four classes. Moreover, we also set out to develop a program that computes the desired TFCT using SciPy on a windowed frame based on audio samples, and then subsequently derives the magnitude spectrum.

Figure 4.4 and Figure 4.5 below illustrate stereo sounds with varying amplitude over time.

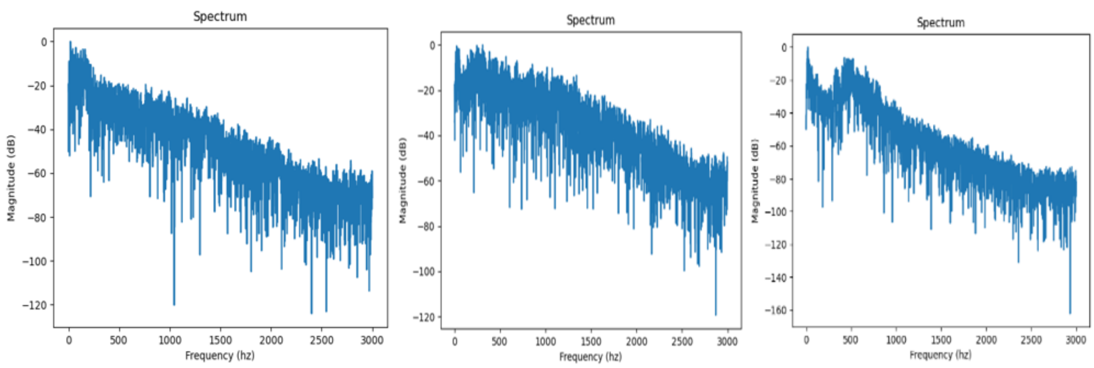

Figure 4.4: The TFCT with the Hemming window of animals

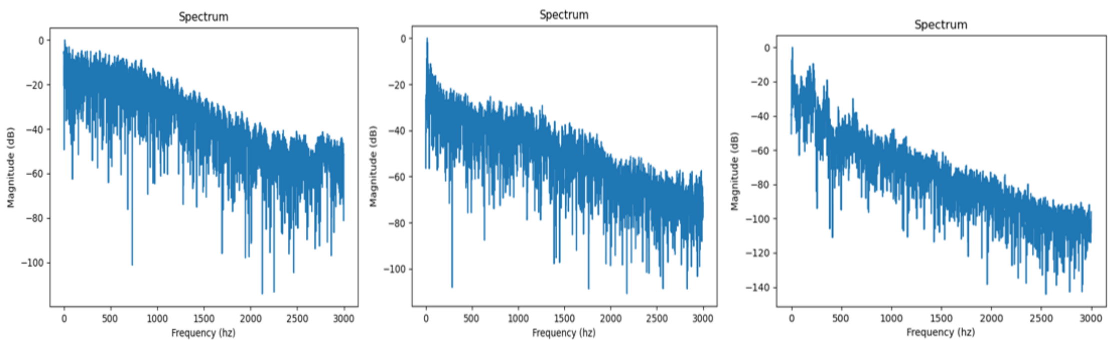

Figure 4.5: The TFCT with the Hemming window of drones

The second situation arises when the audio recording has long stretches of silence, which results in the program being unable to carry out TFCT. Figure 4.6 provides a visual representation of this example.

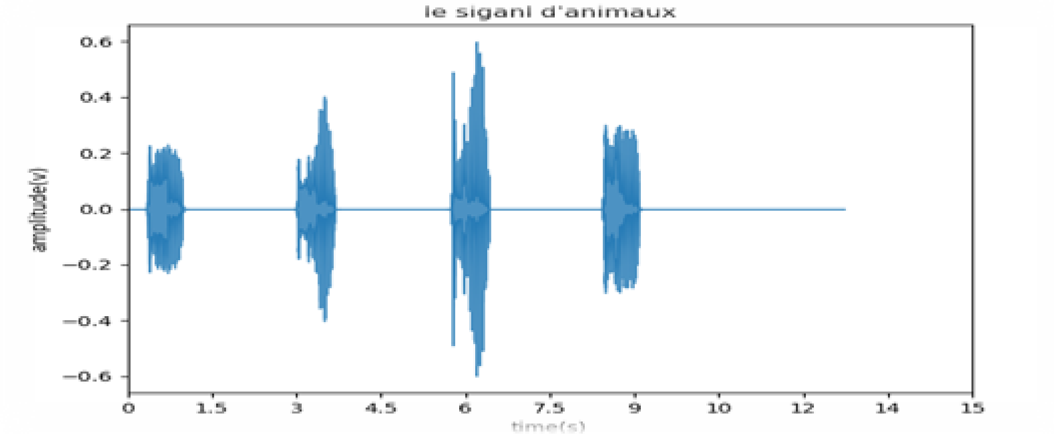

Figure 4.6: The signal with the silent areas

As a result of such spectrum visualizations, we got free motor, and propeller sounds from website. Engine frequency occupies the whole frequency spectrum, while the propeller part takes only a section from 1500 Hz. Figure 4.7 and Figure 4.8 illustrate the two sound signal components:

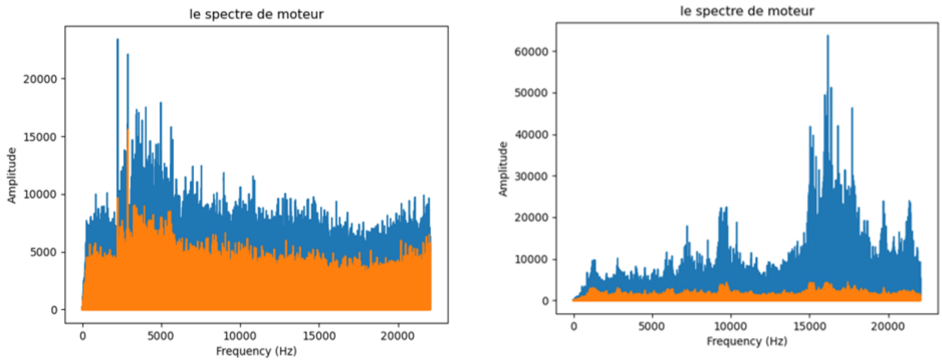

Figure 4.7: Illustration of the motor spectrum

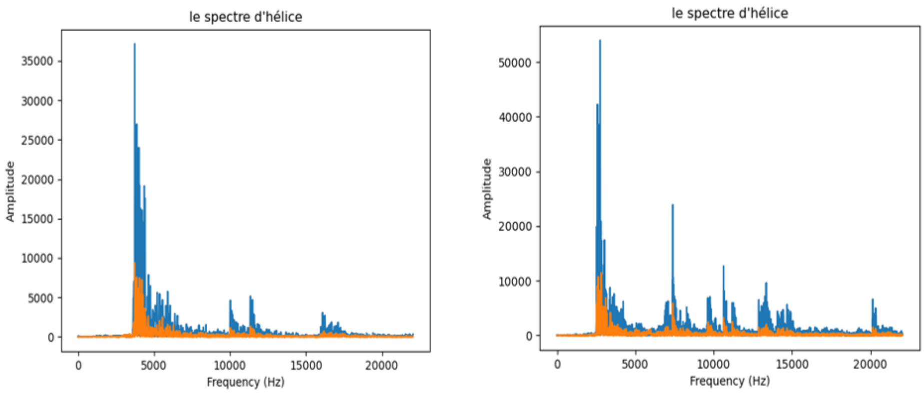

Figure 4.8: Illustration of the propeller spectrum

We chose our filter according to the execution time so we imported the import timeit module that will calculate the execution time of each filter, we tested with a simple mathematical function named in our program x for the filter FIR print $("FIRtime = ".format(timeit.timeit(lambda : sig.lfilter(t, a, x, axis = 1), number = 1)))$ and the RII filter print $("RIItime = ".format(timeit.timeit(lambda : sig.lfilter(b, a, x, axis = 1), number = 1))))$. The results are displayed in Figure 4.9.

As can be seen in this figure, we have noticed that the RII filter has a shorter response time. The comparison program showed that the RII filter took 0.39 seconds to execute, while the other filter took 0.53 seconds. Therefore, we decided to use the RII filter to filter that TS.

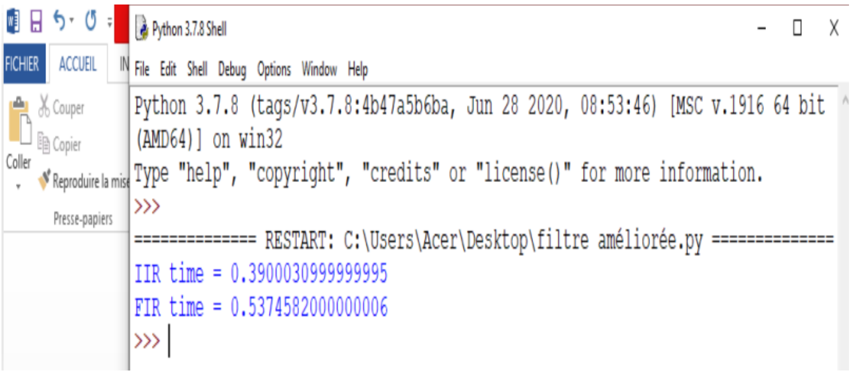

Figure 4.9: The execution time of each filter for a simple mathematical function

4.2.3 Low pass filter

This filter design has the aim of studying the engine spectrum alone. We used the butterworth filter of order 5 on a frequency axis of 3000 HZ which is part of the filter RII. We chose the cut-off frequency 1500 HZ and of normalized frequency. $w\_c = 2 * f_c/f_s$.
$[b, a] = sig.butter(n, w_c, btype = lowpass)$
$[w, h] = sig.freqz(b, a, worN = 3000)$. To filter our audio signal we worked with the module scipy.signal.lfilter audio-filter=sig.lfilter(b,a,audio).
Then we passed our output signal which is audio filtered in the program of TFCT $mags = abs(rfft(audio - filter))$, the results are presented in Figure Figure 4.10. We also visualized the TFCT of the audio before filtering and after filtering the drone signal in Figure Figure 4.11.

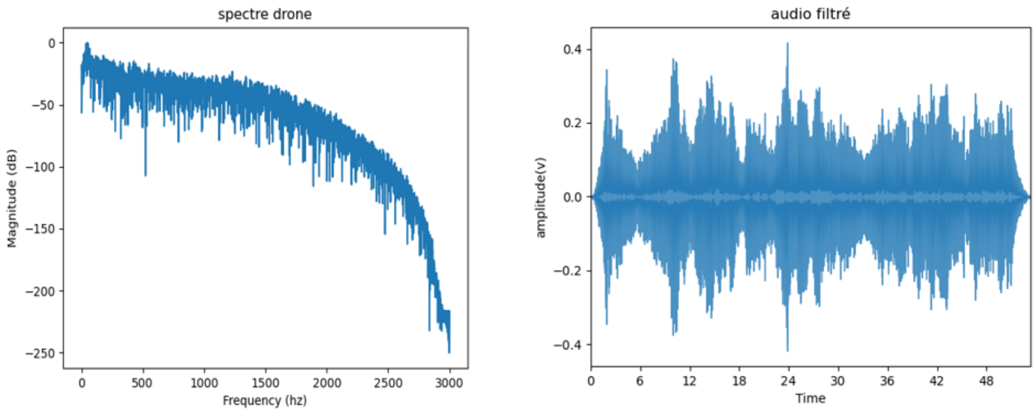

Figure 4.10: The TFCT of filtered audio signal and Filtered audio signal

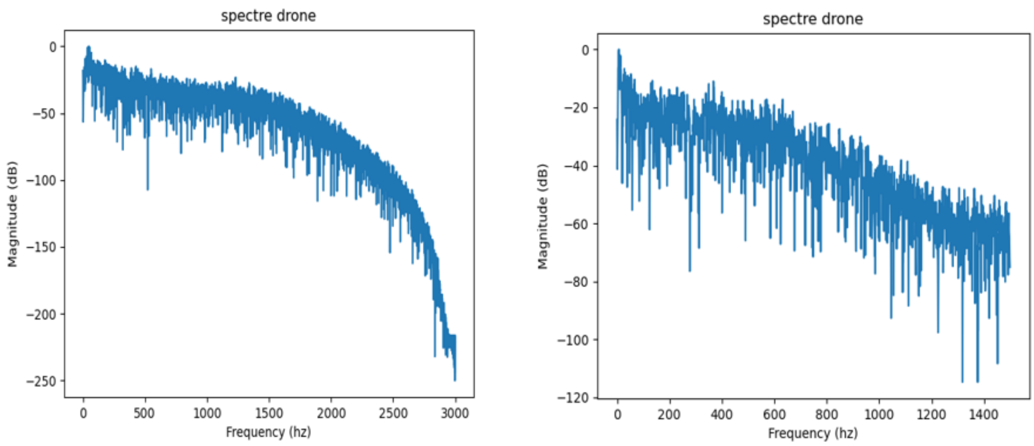

Figure 4.11: The TFCT of filtered signal and unfiltered audio signal

4.2.4 High pass filter

The purpose of the filter design is to study the helix spectrum only. We used the butterworth filter of order 5 on a frequency axis of 3000 HZ. We have chosen the cut-off frequency 1500 HZ and the normalized frequency $w_c = 2 * fc/fs$ $[b, a] = sig.butter(n, w_c, btype =' highpass')$. $[w, h] = sig.freqz(b, a, worN = 3000)$, After we have used the same path as the low pass filter, filtering with the module $scipy.signal.lfilteraudio_filter = sig.lfilter$ $(b, a, audio)$ and pass our output signal which is audio filtered in the program of TFCT $mags = abs(rfft(audio_filter))$, the results are presented in Figure Figure 4.12 and Visualizing the TFCT of sounds with filtering and without filtering gives the results shown in Figure Figure 4.13.

Based on that program, we can conclude that the cutoff frequency remains the same irrespective of the Butterworth filter order. While the slope of the cutoff is relatively low, it can be increased with a higher filter order.

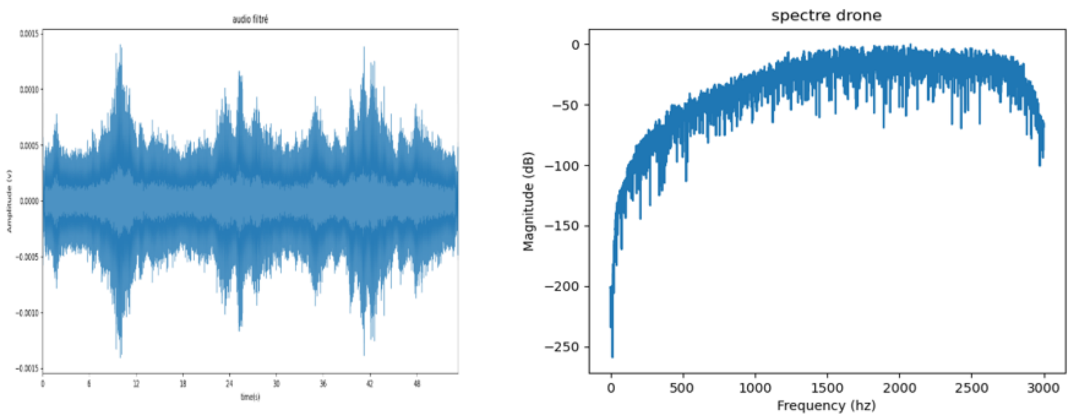

Figure 4.12: Filtered audio signal and its TFCT

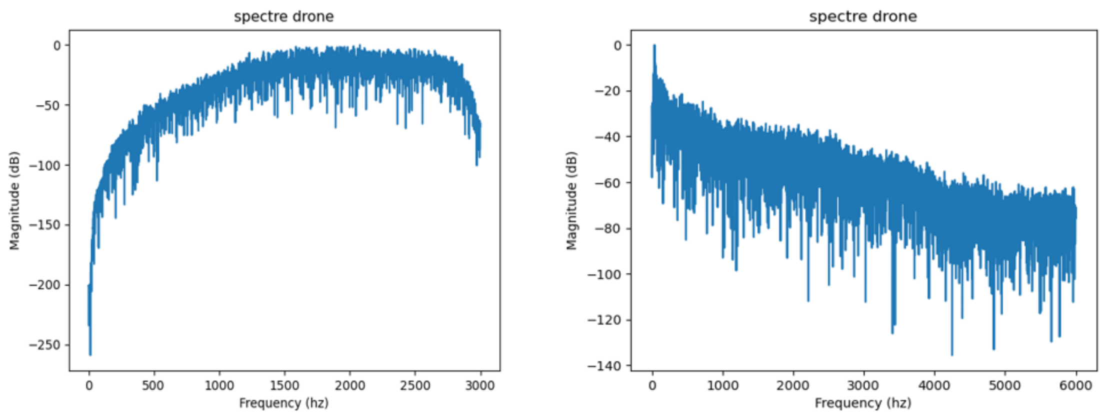

Figure 4.13: The TFCT of filtered signal and unfiltered audio signal

The Butterworth filter moreover has a very flat response in the bandwidth; thus the fast signals pass easily through it. The time/frequency representation is not reduced in the TFCT, which has the advantage of simplicity for presenting this approach. Yet, the TFCT can decompose Fourier series on a limited time horizon imposed by an analysis window centered on a moment (t).

4.2.5 Acoustic stamp

The quality of sound is what distinguishes the tone of different instruments and voices, even if the sounds have the same pitch and volume. The signature design of the classic sound has to do with frequency spectrum, and it consists of four stages: "attack" sound accumulate, "decreases" sound stabilizes and reaches a regular periodic scheme, "sustain" energy remains quite constant, "release" sound fades . ADSR "Attack Decrease Sustain Release" is a simplified model that does not necessarily model the amplitude envelopes of all sounds, as shown in Figure 4.14. Acoustic stamp, also known as spectral indicator, which is a method of providing information about the frequency spectrum and the acoustic stamp level. To better visualize the resemblance, we shaped a histogram, as shown in Figure 4.15.

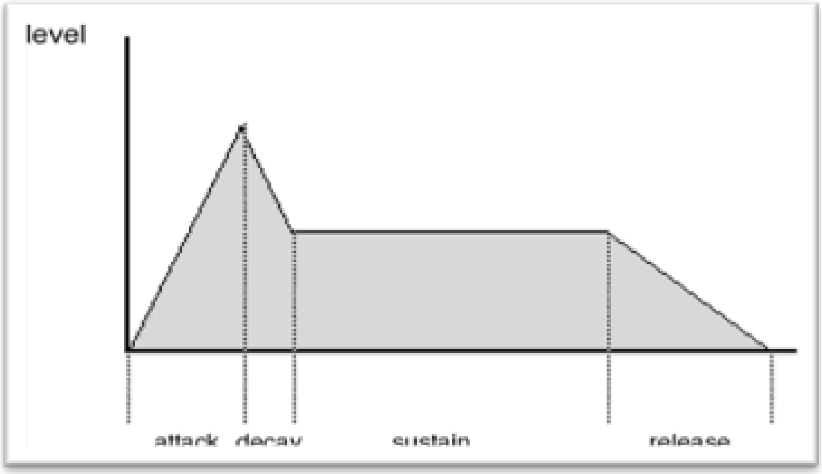

Figure 4.14: ADSR method of the acoustic stamp

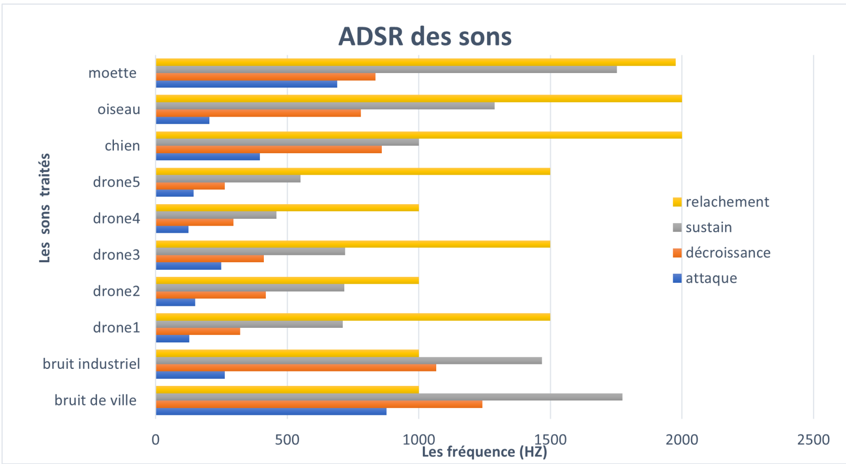

Figure 4.15: Histogram of acoustic stamp for sounds with ADSR method

4.3 Results and Discussion

We have developed an acoustic detection method using correlation that can be integrated into this sensor using Python and Audacity software. Python is a programming language, whereas Audacity is a tool for audio processing. Initially, we cut the signals through high and low-passed filters and approximately made a correlation between the time-frequency complex transform (TFCT) of the filtered signals. Subsequently, we tabulated the correlation coefficients of these filtered signals. By checking the TFCT of the filtered received signal (high pass and low pass) and the filtered drone signal with the filtered received signal, we could say that these two signals are similar. This resulted in auto-correlation results of 1 for both the high pass and low pass filtered sounds. The correlation results of this method can be seen in Figure 4.16,Figure 4.17.

```
Python 3.7.8 Shell
File Edit Shell Debug Options Window Help
Python 3.7.8 (tags/v3.7.8:4b47a5b6ba, Jun 28 2020, 08:53:46) [MSC v.1916 64 bit
(AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.
>>>
= RESTART: C:\Users\Acer\Desktop\programme\programme run\corrélation TFCT les 2
filtrés\tableau TFCT les2 filtrés.py
>>> dfb
                     correlation filtre passe bas
Drone1                                   0.958286
Drone2                                   0.960771
drone3                                   0.947418
drone4                                   0.936091
Bruit                                    0.958093
canard                                   0.951865
Drone5                                   0.956550
Drone6                                   0.946162
Drone7                                   0.931828
drone8                                   0.948444
drone9                                   0.949127
Véhicule spatial                         0.960766
Robot1                                   0.955231
Robot2                                   0.956872
Oiseau                                   0.953869
Airplane engine                          0.961156
Moteur Airplane                          0.955948
overhead                                 0.947292
Hélice                                   0.957221
 Hélice légère                           0.959850
```

Figure 4.16: The TFCT correlation coefficient of signals filtered by low pass

```
>>> dfh
                     correlation filtre passe haut
Drone1                                    0.915366
Drone2                                    0.921688
drone3                                    0.872276
drone4                                    0.915199
Bruit                                     0.896240
canard                                    0.916099
Drone5                                    0.897108
Drone6                                    0.893074
Drone7                                    0.913048
drone8                                    0.915182
drone9                                    0.883285
véhicule spatial                          0.916231
Robot1                                    0.910402
Robot2                                    0.912364
Oiseau                                    0.894820
Airplane engine                           0.913155
Moteur Airplane                           0.902719
overhead                                  0.918050
Hélice                                    0.918409
 Hélice légère                            0.912384
```

Figure 4.17: TFCT correlation coefficient of signals filtered by high pass

Autocorrelation of 1 for both high pass and low pass filtered sounds indicates a strong correlation between the drone sounds, which can be further utilized for detection. To clarify, the drone's view was converted into a cloud of related points which helped the detection study to be more accurate. Moreover, we employed the correlated between the filtered torque reference (motor/propeller) of the drone and the acoustic ambiance chosen based on the sensor environment of the drone to enhance the type of detection. The results obtained from this method may not be considered entirely professional since the detection test of some non-drone sounds, such as those of CLA, may also yield positive results as seen in Figure 4.18.

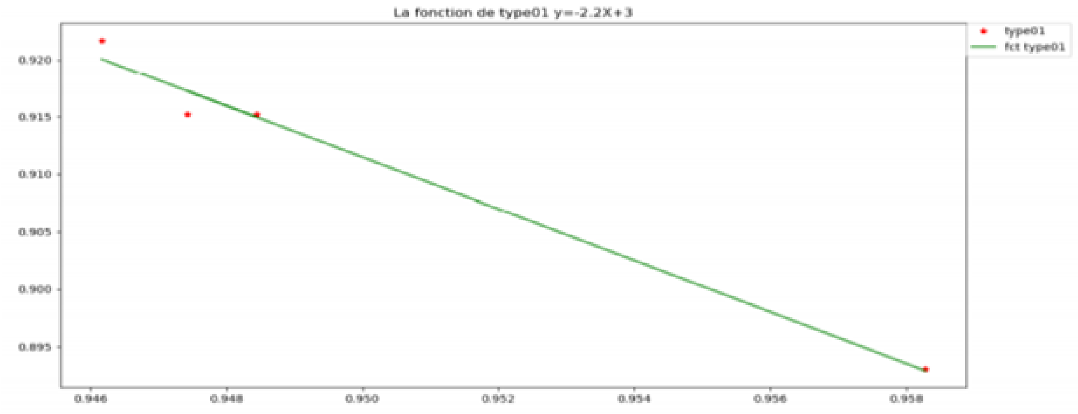

Figure 4.18: Drone's fitting type 01

4.4 Conclusion

In conclusion, this chapter has provided a thorough investigation into the acoustic detection approach, leveraging various analytical techniques applied to sound recordings gathered from the CLA's acoustic environment. By employing FFT, TFCT, wave decomposition, spectrogram, and periodogram analyses, we've explored the feasibility of detecting drones based on their acoustic signatures. The methodology proposed in this study involves decomposing the received signal into engine sound and propeller noise components, achieved through sophisticated filtering techniques and correlation/autocorrelation methods. Preliminary results from experiments assessing accuracy, efficiency, and overall system performance following the implementation of this method are promising. Nevertheless, it's crucial to consider the possible hindrances and restrictions. Further refinement and validation of the detection methodology are necessary to ensure robustness across various environmental conditions and drone types. The findings presented in this section contribute valuable insights to the evolving landscape of decentralized surveillance systems, further emphasizing the relevance and potential advancements in audio detection and analysis technologies. Future work should focus on refining algorithms, integrating complementary detection technologies, and addressing practical implementation challenges to enhance the efficacy of acoustic-based drone detection systems.

CHAPTER 5
DRONE DETECTION USING MAGNETIC FIELD SENSORS

Chapter 5

Drone Detection Using Magnetic Field Sensors

5.1 Introduction

As the world becomes increasingly electrified, the demand for improved positional and current sensing has correspondingly increased. That's why researchers are exploring magnetic field detectors as a potential solution to significant security and safety risks posed by drones. Magnetic field sensors play a pivotal role across diverse industries, facilitating early fault detection, refining control systems for Unmanned Aerial Vehicles (UAVs), and supporting advancements in medical diagnostics. This development is propelled by emerging use cases and demands, such as those driven by the Internet of Things (IoT), as well as advancements in technologies like flexible and stretchable devices. These sensors operate on different physical principles, leading to variations in specifications such as sensitivity, linearity, field range, power consumption, and cost. Moreover, the primary sensor types include Hall Effect, Giant Magnetoresistance, Tunnel Magnetoresistance, Anisotropic Magnetoresistance, and Giant Magnetoimpedance [80, 81]. Their applications extend to human-machine interaction, search and rescue operations, and impact various domains, including magnetic storage, automotive sensors, navigation systems, non-destructive material testing, security systems, structural stability, medical sensors, and military instruments [82, 84]. Object detection systems, utilized in various applications like drones, can be controlled using a Micro-bit board and sensors such as ultrasonic, infrared, or lidar. These sensors, connected to the Micro-bit card, enable the detection of obstacles [85]. This chapter presents a modern approach for automating the monitoring and control of drones using magnetic field sensors with the Micro-bit Card. It offers a detailed exploration of the adopted approach, including the functionality of magnetic field sensors, integration processes, and data collection techniques, emphasizing their critical role in improving drone surveillance and control. Furthermore, the chapter provides insights into the results obtained from implementing this approach, including findings related to accuracy and the overall system performance. A thorough discussion follows, addressing potential challenges associated with this magnetic field sensor-based monitoring system.

5.2 Exploring Magnetic Field Sensor Types: A Comprehensive Overview

Magnetic Field Sensors are designed to identify and quantify magnetic fields around magnets, current conductors, and electrical devices. With the world experiencing a surge in electrification, there is a rising need for enhanced positional and current sensing capabilities. Different sensing principles can be applied to cater to various detection tasks. The selection of the most suitable sensing principle for a specific application depends on factors such as the material of the object to be detected, the environmental conditions of the application, and the required detection distance. In comparison to the near-field sensors discussed earlier, magnetic field sensors provide increased operating distances while maintaining a compact housing design. These sensors are employed to gauge magnetic flux and/or ascertain the strength and direction of a magnetic field. Primarily utilized in scientific measurements, navigation systems, and industrial applications, magnetic field sensors necessitate a thorough examination of their performance specifications for effective selection. Performance considerations involve the analysis of parameters such as flux density, denoted by the total measurement range in gauss (G), which often corresponds to the linear output region of the sensing technology. Instruments designed for magnetic field measurements encompass meters, gauges, recorders, and other specialized tools. These devices play a crucial role in measuring magnetic fields and/or magnetic flux. Resolution, defined as the smallest measurable increment, and bandwidth, representing the frequency range within which magnetic field sensors maintain their accuracy specifications, are critical factors to evaluate when selecting these sensors.

• **Some Applications:** By means of magnetic field sensor which detects electromagnetic disturbances, it is possible to classify on-road vehicles. Magnetic field sensors that have been integrated with MEMS technology generate new capabilities that are applicable in industries such as automotive, navy, health, oceanographic, space exploration, and environmental science. Figure 5.1 illustrates a magnetic signal from several sources and applications falling in the range specified.

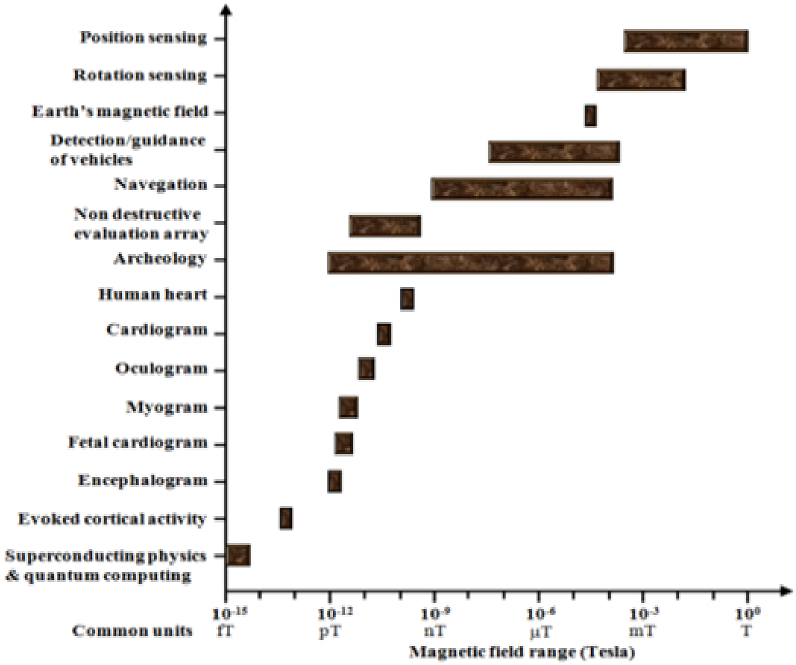

Figure 5.1: Typical magnetic signals range of several sources and applications [86]

Magnetic field sensors are organized by type, this section explains the typical sensor types and their features:

5.2.1 Hall Effect Sensor

It is based on the phenomene that the electromotive force appears in the direction orthogonal to both the current and the magnetic field when applying a magnetic field perpendicular to the current to the object through which current is following. They convert the energy stored in a magnetic field to an electrical signal by developing a voltage between the two edges of a current- carrying conductor whose faces are perpendicular to a magnetic field. It measures the hall voltage generated by Lorentz force [82, 83]. When a direct current is passed through a thin film semiconductor, the Hall Effect phenomenon produces a voltage output that depends on the magnetic flux density and its direction. The hall effect is used to detect a magnetic field, shown in Figure 5.2. Hall elements can sense the magnetic field, even when it is static and there is no change in magnetic flux density. Hall elements are therefore applied in different areas such as non-contact switches that work with magnets, angle sensors, and current sensors.

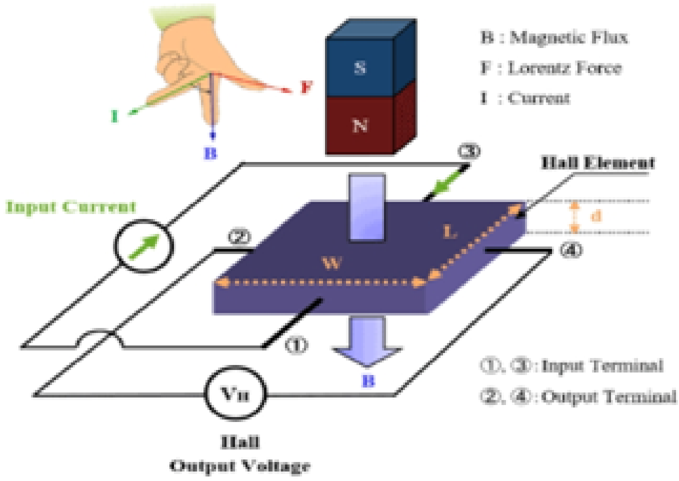

Figure 5.2: Principal diagram of hall element [87]

5.2.2 Magneto-Resistive Sensor

They measure electrical resistance as a function of the applied or ambient magnetic field. That detect a magnetic field using a material, that resistance changes when magnetic force is applied, is called a Magneto-resistive (MR) element. There are three kinds of sensors as representative examples of Magneto resistive element using a ferromagnetic thin film material such as anisotropic Magneto-resistive element (AMR), giant Magneto-resistive element (GMR), and tunnel Magneto-resistive element (TMR). It is a sensor that utilizes the change in the resistance value caused by the Lorentz force [88].

5.2.3 Anisotropic Magneto-Resistive Element (AMR)

This type of sensor is based on the transverse measurement of the anisotropic Magnetoresistance effect in a ferromagnetic thin film. Compared to the classical longitudinal measurement, this geometry makes principal diagram of AMR as shown in Figure 5.3. The scattering degree of electro could vary greatly in the two cases, (a) when the direction of magnetization of the ferromagnetic film is parallel to the current and (b) when the direction of magnetization is vertical to the current direction. Therefore, the resistance value also changes.

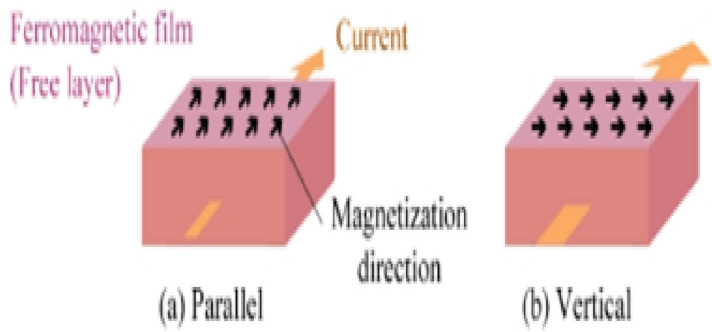

Figure 5.3: Anisotropic Magneto-Resistive Element [89]

5.2.4 Giant Magneto Resistive Element (GMR)

In the situation of a laminated film of ferromagnetic material, (pinned layer), nonmagnetic metal and ferromagnetic material, (free layer), the electron scattering degree changes as the direction of Magnetization of the pinned layer and the free layer are antiparallel (a) or parallel (b). therefore, the resistance value changes like in Figure 5.4.

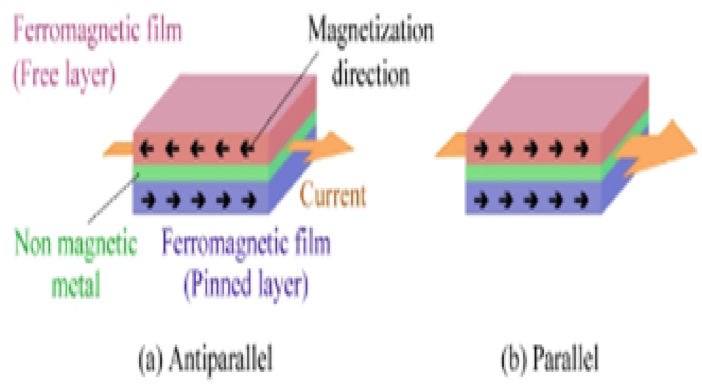

Figure 5.4: Giant Magneto Resistive Element [89]

5.2.5 Tunnel Magneto Resistive Element (TMR)

Dealing with a laminate of a ferromagnetic material, (pinned layer), insulator and ferromagnetic material, (free layer), one of the effects is the varying proportion of electrons passing through the insulator due to the tunnel effect and the resistance value varying depending on if the magnetization of the pinned layer and the free layer are antiparallel (a) or parallel (b) as in Figure 5.5.

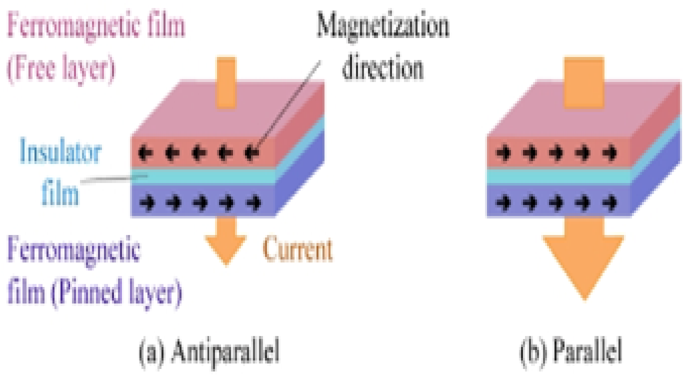

Figure 5.5: Tunnel Magneto Resistive Element [89]

5.2.6 Magneto Inductive Sensors

They consist of a coil that surrounds a ferromagnetic core whose permeability changes within the earth's magnetic field. For a L/R relaxation oscillator, the sense coil is the inductance element. An electronic oscillator's frequency is determined by the strength of the magnetic field being measured. They have been designed for the sole purpose of detecting only metallic objects. The relationship can be established by connecting the oscillator frequency output to the microprocessor's capture/compare port to monitor field values. These magnetometers have a very low, efficient power design, and are of low cost as shown in Figure 5.6. They are available from Precision Navigation, Inc. and used in compass applications [82].

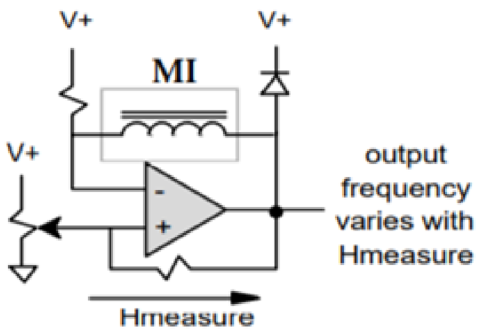

Figure 5.6: magneto-inductive (MI) sensor circuit [82]

5.2.7 Fluxgate or Coiled Sensors

Fluxgate magnetometers, which are the most common sensors for compass navigation systems. Coils are the simplest magnetic sensors that can detect changes of magnetic flux density. According to Figure 5.7, bringing the magnet near the coil increases the magnetic flux density by ΔB in the coil.

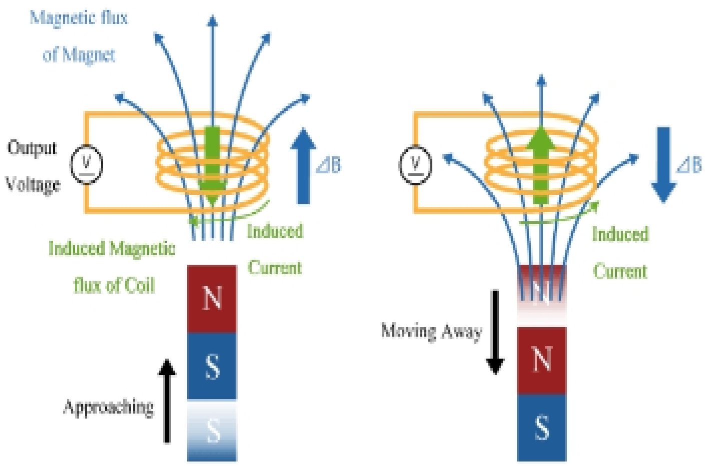

Figure 5.7: Principal diagram of Fluxgate [90]

Then, an induced electromotive force which appears in the coil due to a related physical principle and an induced current creates a magnetic flux which counteracts the magnetic flux density increase is produced. By contrast, if the magnet moves away from the coil, the flux density in the coil will decrease thus the electromotive force is induced and current is produced in the coil to increase the magnetic flux density. This core's magnetic induction is subjected to change with the application of an outer magnetic field. Through the use of a phase sensitive detector, the sense signal is demodulated, and low pass filtered to get the value of the magnetic field. Its structure being straightforward, a coil does not become damaged easily. Fluxgate signal processing is generally done by phase-sensitive detection of the second harmonic component of the output voltage. The precise magnetometers, made at the Danish Technical University, use short-circuited current output and feature a Reset function [91]. Despite the higher noise, the Acquirer-type fluxgate has the following important advantages: first, due to very low demagnetization, the sensor is insensitive to perpendicular fields. Then, unlike ring-core sensors, the sensing direction is well defined by the direction of the core. This device is the one that is used in gradiometers which are known to need very high precision and stability in a specific direction.

5.2.8 Microelectromechanical System (MEMS) Sensor

One of its features is a combination of magnetic field sensory devices with electronic elements, which utilize the Lorentz force to detect the external magnetic fields through the dislocation of the resonant structures which are measured with optical, capacitive, and piezoresistive sensing techniques. Integrated with several devices such as gyroscopes, accelerometers on the same chip for their Global Positioning System (GPS) have a look at the devices that have products for example car safety airbags, visual devices, and inkjet printers. And integrates the mechanical and electronic components on a single chip. In order to reduce the device dimensions. MEMS magnetic field sensors based on the operating principles and detection techniques of resonant structures are explained. Most resonant magnetic field sensors utilize the Lorentz force principle, where the Lorentz force pushes a resonant structure, which can be measured using optical, piezoresistive, or capacitive sensing techniques. These sensors rely on structures that are excited at their resonant frequencies by either electrostatic or Lorentz forces. The application of external magnetic fields causes variations in the deflections of the resonant structure, which can be detected through optical, capacitive, or piezoresistive sensing techniques. For instance, a resonant structure based on a clamped-clamped beam has its first resonant frequency associated to its first flexural vibration mode, as shown in Figure 5.8. MEMS technology-based resonant magnetic field sensors have simple operating principles that make it possible to create compact and lightweight structures with the integration of a few elements (e.g., clamped free microbeams, aluminum loop, piezo resistors, and electrodes). They can measure low magnetic fields around nanoteslas; although, the reduction of this level (to magnetic fields on the order of pico teslas) could be achieved with future optimized designs of the resonant structures and electronic circuits [86].

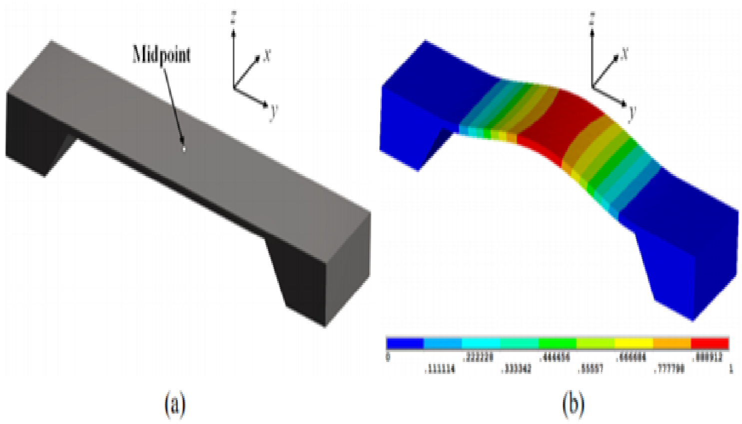

Figure 5.8: (a)clamped-clamped beam and (b) its associated first vibration mode [86]

•Comparison of Magnetic Field Sensors:

Typically, the sensitivity range of this type of sensor is altered due to the change of excitation current of the aluminum loop, which allows for the measurement of either lower or higher field of the magnetic field. These magnetic sensors of relatively small size are very close to magnetic field sources and have a very low power consumption of only a few milliwatts. A summary of the main characteristics of these sensors are shown in Figure 5.9. Moreover, the particularities of resolution, noise, power, and minimum size of these sensors are outlined. Figure 5.10 reveals the approximate sensitivity range of the most common magnetic field sensors, including the MEMS technology. As can be inferred from these findings, MEMS sensors can be a substitute for conventional sensors in many applications for measuring magnetic fields higher than 1 nT. The MEMS technology implements low-cost sensors via batch fabrication techniques and their possible integration with ICs (integrated circuits) on a common substrate. This is a feature of the MEMS sensors that is attractive to future markets, hence, it is an appealing factor.

Technology	Resolution (nT)	Noise ($nTHz^{-1/2}$)	Power consumption (mW)	Minimum size (mm × mm)
Hall effect [6,54]	~10^5	~4,000	~150	<1 [a]
GMR AAL002-02 [55]	10 @ 5V 1 Hz	10 @ 1Hz	~5	0.44 × 0.34 [a]
MEMS (Lorentz force) [49,50,52]	~1	~0.5 [b]	<10	<1 [a]
AMR HMC1022 [56]	8.5 @ 5 V 10 Hz	48 @ 5 V 1 Hz	~25	~ 1 [a]
Optical fiber [6,26,57]	<1	<10	<1,000	~100 × 25 [c]
Fluxgate [58]	60	~10^{-1}	~100	5 × 2.5
Search coil [6,13]	20×10^{-6}	30×10^{-3}	<10	50 × 25

Figure 5.9: Characteristics of some magnetic field sensors [92]

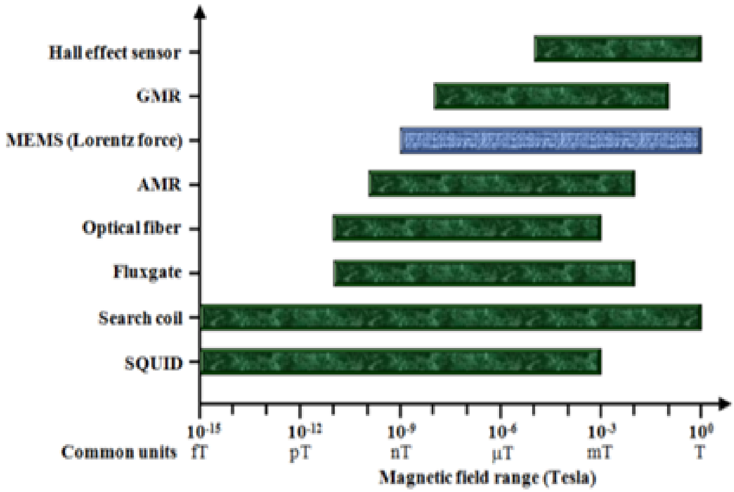

Figure 5.10: Approximate sensitivity range of different magnetic field sensors [86]

5.3 Magnetic Field Detection Methodology for Drone Surveillance

Introducing this approach, we've integrated the Micro-bit as a key element. Renowned for its educational utility, the Micro-bit offers diverse sensors, an LED display, and seamless connectivity. the drone detection methodology strategically leverages these features to achieve our objectives:

5.3.1 The BBC micro-bit

The BBC micro-bit card is a popular magnetic field sensor that uses a built-in magnetometer. It is a small, low-cost microcontroller board that can be programmed using a variety of programming languages, including Python and JavaScript. A Hall effect sensor is the basis of the micro-bit card's magnetometer, which senses variations in the magnetic field perpendicular to the sensor. The micro-bit card has a resolution of up to 0.1 microtesla (μT) and a magnetic field measurement range of $\pm$ 4912 μT. The provided device can detect the low-frequency magnetic field because it has a bandwidth of 600 Hz.

The micro-bit card also has a built-in accelerometer and compass, which can be used in combination with the magnetometer for more accurate positioning and orientation sensing. In addition to its small size and low cost, the micro-bit card has other features that make it suitable for a wide range of applications, including a 5×5 LED matrix, two programmable buttons that come with the functions of motion, gesture, magnetic field, temperature and light detection, and Bluetooth connectivity. For a multitude of purposes ranging from robotics through IoT and even education, it can be employed. A programmable device in 2016 the UK, introduced a programmable device that can be used for teaching computer science in a supplementary way. The device can be programmed through a desktop PC, laptop, or tablet using various operating system agnostic-web-based programming environments, including a block editor like Scratch, Microsoft's Touch Develop, Micro Python, or JavaScript. Research has demonstrated that physical computing, which combines software and hardware to create interactive physical systems that can sense and react to the real world [86], is highly effective. Here's a visual representation of the BBC micro-bit card which is the central part of this device in Figure 5.11. The micro-bit is not just a playful design, as it is an exposed printed circuit board that displays all its components. Despite its playful appearance, it is incredibly capable. The board is built around a modern 32-bit ARM Cortex- M processor with 16Kb RAM and 256Kb non-volatile flash memory. In addition, the device contains a USB interface and edge connector with touch-sensitive, digital/analog pins that allow external sensors and actuators to be connected [86].

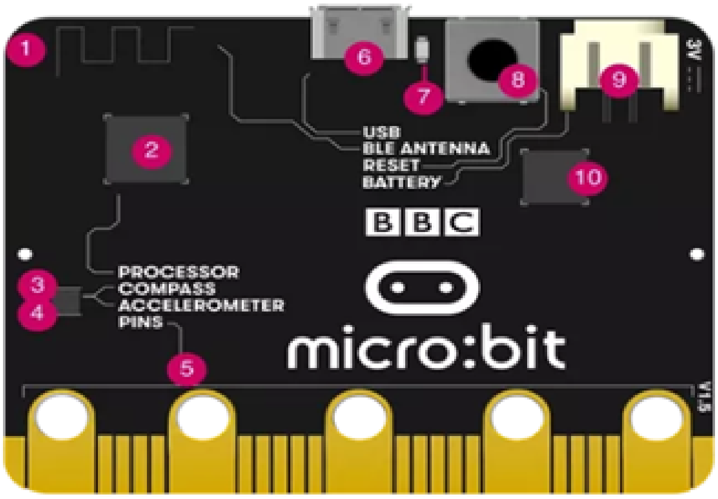

Figure 5.11: The BBC micro-bit card components [93]

•**Key of Micro-bit Card:** The micro-bit is an exposed printed circuit board with all components visible. This playful design should not be mistake for a lack of capability. The board is based around a modern 32-bit ARM Cortex-M processor (16Kb RAM; 256Kb non-volatile flash) and hosts an array 0f input/output capabilities including a 5*5 LED matrix, two programmable buttons, the ability to sense motion, gestures, magnetic fields, temperature, and light. the device also includes a USB interface and edge connector with touch sensitive, digital/analog pins that allow external sensors and actuators to be connected [85].

Number	Element	Function
1	Radio Antenna and Bluetooth	Communication with other micro-bits by radio and other devices by Bluetooth.
2	Processor and temperature sensor	search, decoding and execution of the instructions given and measures the heat of the environment.
3	Compass	Determination magnetic North or the force measurement of the magnetic field.
4	Accelerometer	Mesure gestures and forces wit 3 dimensions.
5	Pins	Mesure gestures and forces with 3 dimensions
6	Micro USB outlet	Supply and download programs.
7	Single LED	Flashes when the USB plug and download programs.
8	Reset Button	Resurgence of programs
9	Battery socket	Feeding
10	USB Interface chip	Manage USB connexion, flashes the new code, sending and receives the data in series from the front of the computer.

Table 5.1: Key of Micro-bit Card components

5.3.2 MFD Dataset

For the MFD datasets, we developed a software in the micro-bit map that estimates the Earth's magnetic field at the sensor position based on information collected about the field. We made use of the calibrate compass tool to bring the magnetic field lines to magnetic north and thus created the magnetic force calculation graph with the help of the serial tool. The obtained results serve as a reference for sensor detection and are measured in μT as indicated in Figure 5.12. We plan to enhance our sensor's performance by including details on the magnetic field and its direction with a compass. In order to establish the validity of our reasoning, we made use of a micro-bit card to carry out the experiments. Initially, we conceived an application for our card that entailed coding a compass that can detect all four cardinal directions and display them on the screen. The outcome of our compass was really good, being reminiscent of cell phone models. Using data obtained on the Earth's magnetic field, we were able to generate a program on our micro-bit card that calculates the magnetic field at the location of the sensor. The magnetic field lines on Earth are oriented towards the magnetic north, which we used as a reference point for the sensor's detection capabilities. To program the magnetic field calculator, we utilized the magnetic force tool on the micro-bit card, which includes a magnetometer. This program quickly calculates the magnetic force and displays it as a graph on the computer screen. All values detected by the sensor are saved as either an Excel file or a notebook. Although many low-cost electronic compasses are available on the market, this technology stands out due to its competitive pricing. The cost of manufacturing the card is directly related to the technology used, which we believe makes the product a great value for the customers. A magnetic sensor choosing process includes performance and argument consideration of the sensor, environmental conditions, and the applicable limits. Based on the tests using the micro-bit card, we have determined that adding a magnetic field detector to the sensor requires a compass and magnetometers. Other similar detectors have exposed this limitation to the magnetic field detector MFD as well. This constraint makes it more appropriate for use in confined spaces, such as indoors. In situations where the MFD fails, other sensors like luminous or acoustic will be used instead. By carefully considering the specific needs and constraints of each situation, we can choose the appropriate sensors to achieve the desired results [94].

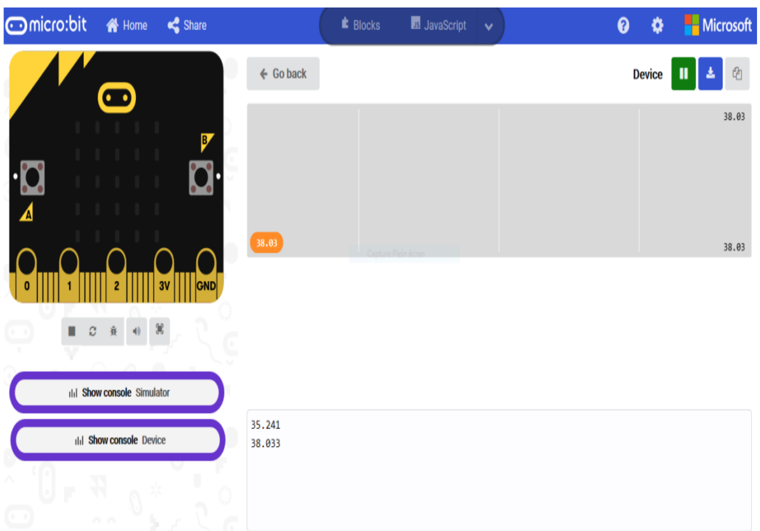

Figure 5.12: The BBC micro-bit card components.

5.4 Results and Discussion

The MFD method is about implementing a robot-like device called compass compatible with all four sides and making it possible for it to show the existing direction on the screen.

To do this, we connect the micro-bit card to a computer via USB cable and access the website that allows us to program our compass using the compass element. Once we have programmed the compass, we can test its functionality by sliding the program into the map and verifying that it is working properly. Using information obtained on the Earth's magnetic field, we have developed a program on the micro-bit card that can calculate the magnetic field of the sensor's location. The Earth's magnetic field lines are oriented towards magnetic north, which is calibrated using the compass tool. We apply the serial tool to depict the magnetic force calculations graphically, showing the change of the magnetic field over time in our tests. Figure 5.13 shows two curves: an empty curve representing the Earth's magnetic field used as a reference, and another curve that traces the external magnetic field variations observed during our tests.

Figure 5.13: Calculated values of detected magnetic field

For each detection event, a separate Excel file is created to store the detected values. The Excel file can include columns for the timestamp, location, magnetic field strength, and any other relevant parameters as shown in Figure 5.14, the values calculated of quadcopter and hexacopter drones. This allows for easy organization and retrieval of the detected drone data. Further analysis can be conducted on the stored values, such as generating statistical summaries, visualizing trends, or comparing multiple detection events. Recording the values discovered in Excel files, it aids in the management and analysis of data, which in turn allows the researchers and the security personnel to get the knowledge of drone activities, we have plotted these detected values as presented in Figure 5.15. The data acquired from the simulation showed that a magnetometer and compass can be used to easily sense and measure the magnetic field and its direction.

To illustrate this idea, a 3Dmodel was created using the Tinker cad online simulator, which accurately depicts the position of each detection component. Figure 5.16 demonstrates that the compass (grey object) and magnetometer (black object) must be positioned in opposition to one another. Furthermore, each card must have its own power system to facilitate magnetic field detection and direction indication.

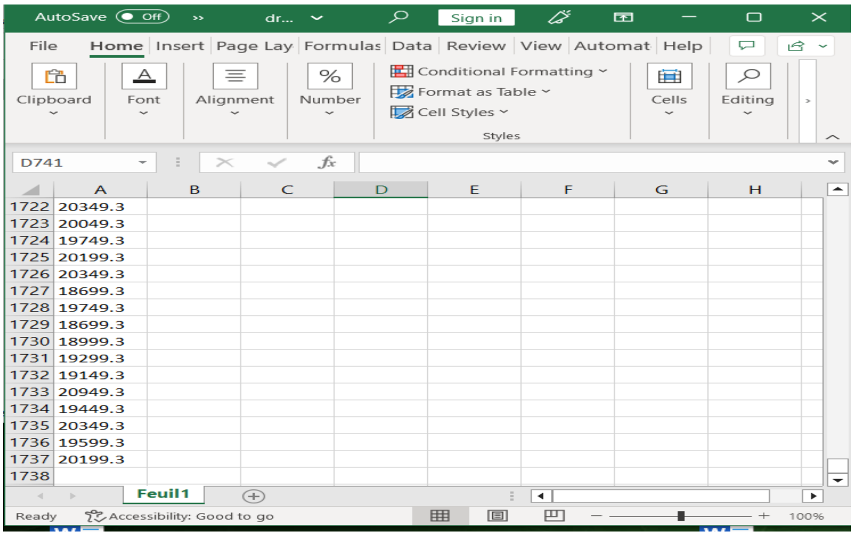

Figure 5.14: The detected values which are saved in Excel file for quadcopter and hexacopter drones

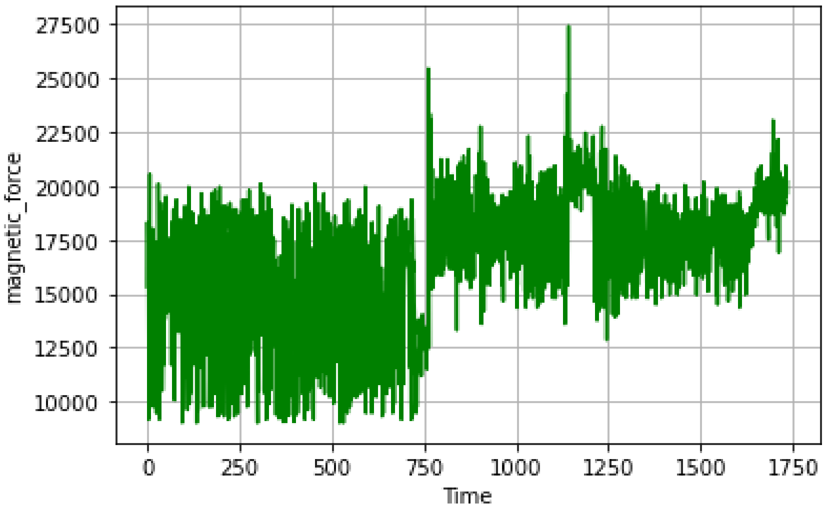

Figure 5.15: Detected Magnetic Field Disturbances of quadcopter and hexacopter drones

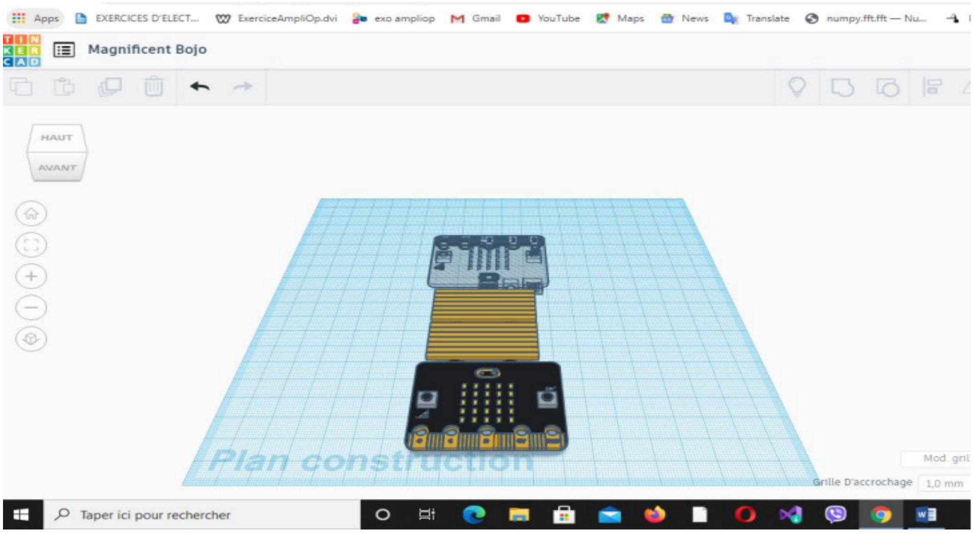

Figure 5.16: 3D modeling of magnetic field detection and direction

5.5 Conclusion

In brief, this chapter has provided a novel methodology for enhancing drone monitoring and control through the integration of magnetic field sensors with the BBC Micro-bit Card. We delved into the functionality of magnetic field sensors, the integration process, and the data collection techniques utilized. The results obtained from implementing this approach were thoroughly examined, shedding light on accuracy, efficiency, and overall system performance. This presented solution offers several notable advantages, including enhanced situational awareness and operational flexibility. The ability to accurately track drones using magnetic field sensors holds significant promise for various applications, from security and surveillance to environmental monitoring and infrastructure management. Through a comprehensive discussion, we explored the implications of the results and the potential challenges linked to the magnetic field sensor-based monitoring system. As we navigate the complexities of modern technological advancements, this chapter underscores the crucial intersection of magnetic field sensors and drone technology. Due to its exceptional adaptability, the BBC Micro-bit Card surpasses traditional detection methods, offering unparalleled utility in spacecraft tracking and anomaly detection, paving the way for continued advancements in automated monitoring and control mechanisms.

CHAPTER 6
BAYESIAN INFERENCE APPROACH FOR DRONE DETECTION

Chapter 6

Bayesian Inference Approach for Drone Detection

6.1 Introduction

As UAVs continue to proliferate and serve diverse purposes across various sectors, researchers are intensively investigating several methods for detecting and identifying drones in order to enhance security measures against drone threats. Despite the availability of numerous drone detection techniques, each faces limitations due to the specific environmental conditions. Hence, it's crucial to implement a robust system that integrates different sensors to overcome these limitations and improve detection capabilities. Indeed, a critical question arises: How can these sensors be effectively correlated to optimize detection capabilities?

Current research is focused on utilizing a Bayesian version of the network to enable the classifier to offer confidence levels in its decisions and to identify novel drones, which are instances where a detected craft is not included in the training data [95, 96]. Bayesian inference provides a robust approach to system detection and recognition. The application of Bayesian method is motivated by the fact that conflict decision problems in object detection, including drone monitoring, are often ill-conditioned and ill-posed when dealing with noisy incomplete data owing to various sources of modeling uncertainties [97]. Inference consists of determining the probabilistic query according to the model and a set of evidence. This process is fundamental for computing the posterior probability distribution of a set of query nodes, given values for some evidence nodes which is called belief updating or probabilistic inference [98, 99].

Bayesian probability offers a method for quantifying plausible knowledge about phenomena, considering limitations in assuming or estimation relevant information, rather than attributing randomness only to nature. Probability axioms serve as a multi-valued logic for quantitative plausible reasoning under uncertainty, forming a strong foundation for Bayesian inference. This approach refers to both parametric and non-parametric uncertainty, with a model's probability reflecting its plausibility compared to others. In Bayesian inference, updates are made through Bayes' theorem as new data emerges, making it preferable in object detection and identification over the Frequentist approach [100, 101].

This chapter presents a novel drone detection technique leveraging multiple detectors, including visual, acoustic, and magnetic field sensors by employing Bayesian inference to address their inherent limitations. The Bayesian Inference technique is employed to optimize decision-making particularly in scenarios where conflicts arise among the decisions made by the multi-sensors. To facilitate this optimization, indicators such as the Ephemeris indicator (EI) and the Acoustic Ambiance indicator (AI) are utilized to generate settings that determine the degree of conflict, aiding the detection process. We presented our results, showcasing the effectiveness of Bayesian inference technique. Through the integration of multiple detectors, this approach demonstrates improved decision-making capabilities, ensuring accurate and reliable identification of drone presence.

6.2 The Brain Bayesian

The scientific landscape of understanding the human mind has undergone a paradigm shift with the recognition that the brain operates on Bayesian principles. This transformative insight has driven our development of a decision-making and action selection model grounded in Bayesian inference, incorporating beliefs about various alternative policies. This involves the utilization, integration, and firing of diverse neuron types, encompassing sensory, motor, and relay neurons [102].

These neurons collaborate in reflex actions, characterized by automatic and swift responses to stimuli. These responses involve an afferent nerve and result in a stereotyped, immediate reaction of muscle or gland. The anatomical pathway of a reflex is termed the reflex arc, representing an inherent central nervous system activity that operates independently of consciousness. The primary purpose of the reflex arc is to mitigate potential harm to the body in response to adverse conditions. For instance, if there is accidental contact with something hot, a basic reflex arc triggers an immediate withdrawal of the hand. In cases where a stimulus is consistently repeated, two notable changes manifest in the reflex response: sensitization and habituation. Sensitization involves an amplification of the response, typically observed in the initial 10 to 20 responses. Through a comprehension of these fundamental principles of neural functioning, we can advance the development of more efficient models and techniques for decision-making, action selection, and detection [102, 103].

Habituation, contrary to sensitization, involves a gradual decrease in response until the response is eventually extinguished. This decline occurs when the stimulus is consistently repeated. However, when the stimulus repetition is irregular, habituation either does not occur or is minimal. Reflexes are comprised of an afferent (sensory) nerve, one or more inter-neurons within the central nervous system, and an efferent (motor) nerve. Reflex actions can be modified through impulses from higher levels of the central nervous system, indicating a learned response. This adaptation involves the engagement of the sensory and motor cortex, responsible for sensitization and reflex actions. The process entails the transmission of a nerve impulse to the motor neuron, disrupting the usual reflex action, for instance, preventing the automatic dropping of an object. The sensory cortex is a component of the brain responsible for processing and interpreting sensory stimuli. It encompasses the analysis of information received from various sensory inputs, such as visual and auditory sensors, which are crucial elements in our application [104]. The cortex comprises multiple areas dedicated to processing information from each of our sensors, as illustrated in Figure 6.1.

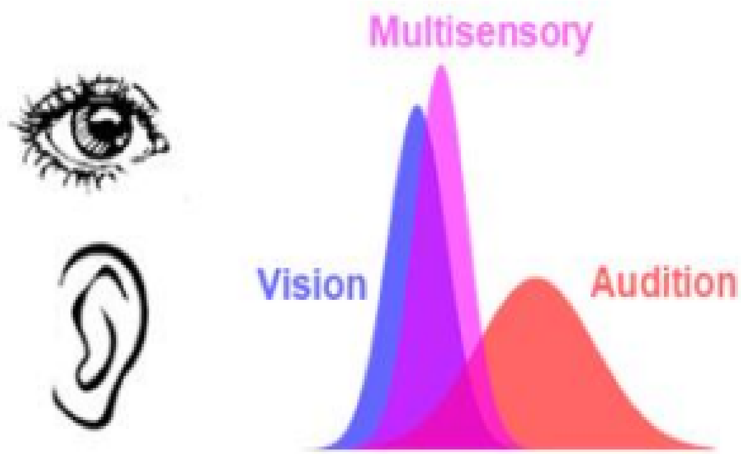

Figure 6.1: Combining information (across the senses) [105]

The motor cortex stands as a pivotal brain region engaged in the planning, control, and execution of voluntary movements. It holds a crucial role in motor learning and memory, facilitating the acquisition of new skills. Certain cells within the motor cortex exert direct control over movement by transmitting outputs to the brain stem and spinal cord, including direct projections to motor neurons [106].

6.3 Bayesian Inference Approach

Bayesian networks represent a category of probabilistic graphical models employing Bayesian inference for probability computations. Their objective is to model conditional dependence and causation by delineating conditional dependence through edges in directed graphs. These relationships enable efficient inference on random variables within the graph through the utilization of factors [106]. The primary goal of Bayesian inference is to determine the posterior distribution of latent variables given the observed data, denoted as $P(x/e)$. In the context of Bayesian networks, inference takes two forms: evaluating the joint probability of a specific assignment of values for each variable (subset) in the network and finding $P(x/e)$ or determining the likelihood of some configuration of a subset of the variables (x) under the condition that the remaining variables (our evidence) are fixed. The Bayesian approach contributes to understanding the brain on various levels, offering normative predictions on how an ideal sensory system should integrate prior knowledge and observation, providing a mechanistic interpretation of the dynamic functioning of the brain circuit, and suggesting optimal ways for interpreting experimental data, as illustrated in Figure 6.2.

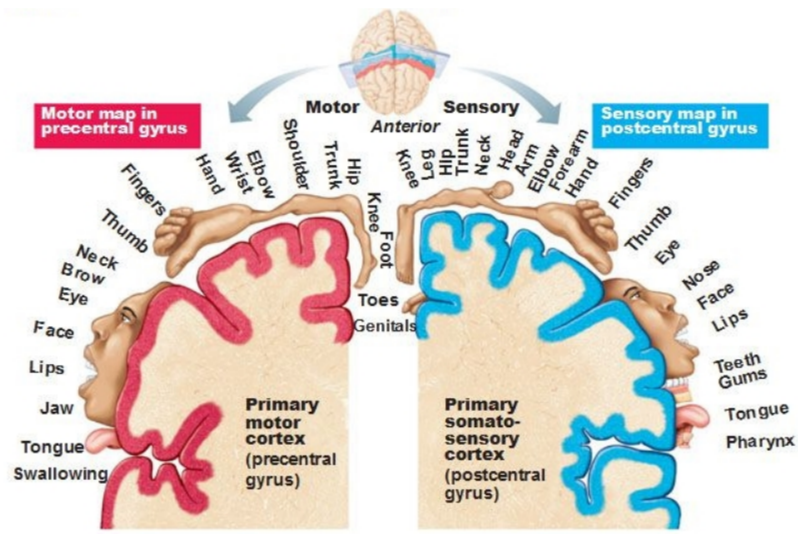

Figure 6.2: Bayesian inference on the brain [107]

The Bayesian brain framework integrates insights from both experimental and theoretical neuroscientists, focusing on the examination of brain mechanisms involved in perception, decision-making, and motor control according to the concepts of Bayesian estimation. Contributors delve into the exploration of dynamic processes underlying appropriate behaviors, encompassing aspects such as the accuracy of perceptual decisions and neural models of belief propagation [108]. Bayesian inference encompasses both approximate and exact methods. Exact inference becomes manageable by assuming a plausible form of probabilistic representation, enabling predictions of responses to alterations in the sensorium. The concept of active inference posits that behavior can be comprehended through inference, highlighting the interconnected nature of action and perception within the same inferential process. This perspective becomes particularly crucial for optimizing expected precision, essential for optimal inference about hidden states (perception) and control states (action selection). These beliefs must be associated with a confidence or precision that is itself optimized. Our approach incorporates three beliefs through Bayesian inference [60, 108]:

• **Perception $\hat{S}_t$:** is a belief system that updates beliefs about the state of the world by incorporating observations along with beliefs about the preceding state and action. This belief encompasses optic and acoustic sensors defined as hidden states.

•**Action Selection $\hat{\pi}$:** employs a SoftMax function to ascertain the expected value of competing choices given the current state. This SoftMax choice rule, frequently employed in normative models like Quantal Response Equilibrium (QRE), is crucial in decision-making processes. It is noteworthy that utilitarian theories frequently disregard the symmetry between the expected value over states, indicating the value of a choice, and the expected value over choices, signifying the value of a state. This step is defined as control states.

•**Precision $\hat{\gamma}$:** is the third belief in our approach, that considers both the content (expectations) and confidence (precision) of the beliefs. Optimizing both the expectations about behavior and the precision of these beliefs is crucial for offering a comprehensive account of bounded rationality, incorporating approximate Bayesian inference. The sensory information undergoes several levels of processing, as shown in Figure 6.3.

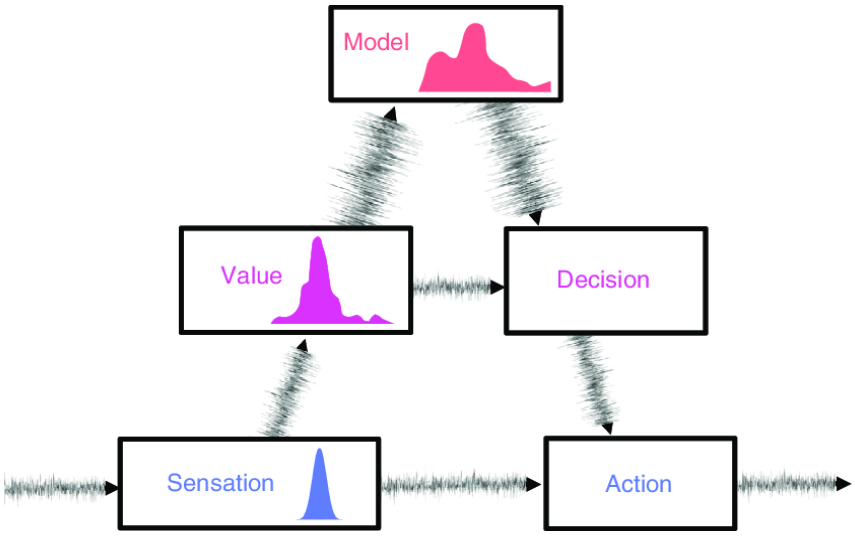

Figure 6.3: The levels of processing model from sensory action to making-decision [105]

The environment is defined by a distribution R over observations, true states, and actions, while the agent is characterized by two distributions: a generative model P connecting observations to hidden states and posterior beliefs Q parametrized by its expectations. Notably, the agent organizes hidden states based on its observations, with these hidden states encompassing control states that prescribe action. The agent and the environment collaborate in cycles, where, in each cycle, the agent determines the most probable hidden states by optimizing its expectations concerning the free energy of observations. Following the optimization of its posterior beliefs, the agent evaluates an action from the posterior marginal over control states. The environment subsequently executes this action, generating a new observation, and initiating a new cycle. The optimization process primarily revolves around perception (inference about hidden states) and action (a choice model where action is a function of inferred states).

In summary, the active inference framework entails an agent interacting with its environment, described by a distribution over observations, true states, and actions. The agent is equipped with a generative model that establishes connections between observations and hidden states, along with posterior beliefs regarding those states, including beliefs about control states dictating action. The agent optimizes its expectations with respect to the free energy of observations and selects actions from the ensuing posterior beliefs about control states [108, 109]. The generative model features policies being encoded in terms of prior beliefs regarding control states, which decide, next, the chosen action. These beliefs take the form of a Boltzmann distribution, and the precision of beliefs about policies is determined by a hidden variable $\gamma \in R^+$ [110, 111].

The intelligent aspect of our approach lies in its ability to accurate and optimized decisions when faced with conflicts arising from multiple sensor inputs. To illustrate this point, let's consider a scenario where the optic detector's decision is compromised by fog, and the acoustic detector's decision is muddled by the noise of a passing motorcycle. In the absence of Bayesian Inference, there would be two decisions in favor of "Non-Drone" and one for "Drone". However, our approach leverages Bayesian Inference, supported by indicators, to resolve such conflicts. Hence, in the absence of Bayesian Inference, there would be two conflicting decisions for "Non-Drone" and only one decision for "Drone" [60]. Bayesian Inference relies on indicators to effectively resolve conflicts and make optimal decisions. We illustrate this by presenting another example that demonstrates the application of our dataset, employing the methodology outlined in Figure 6.4.

Notably, influential Bayesian models of perception propose that our understanding of the surrounding world is formed through the integration of bottom-up sensory signals with top-down expectations regarding the world's content. In our specific case, the conclusive determination of "Drone or Non-Drone" is rooted in perception. The indicators providing data about acoustic and luminous ambiance play a crucial role in informing this decision, drawing from our accumulated experience of the surrounding environment.

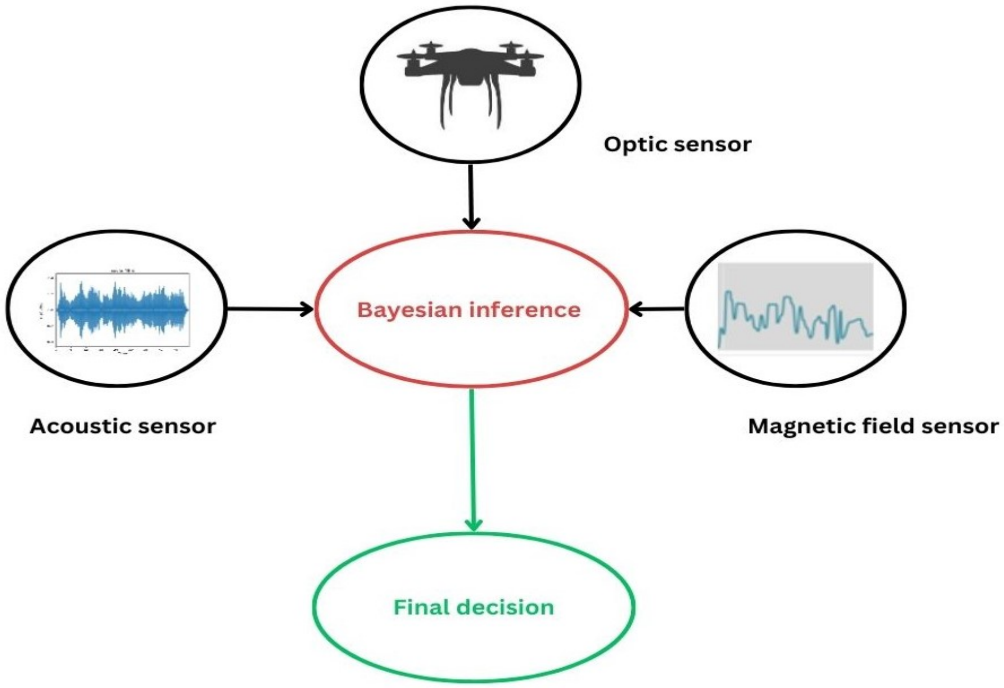

Figure 6.4: The application of datasets using the Bayesian inference approach

6.4 The Mathematical Model of BI

The Bayesian Network (BN) is grounded in the mathematical model of Bayes' theorem, as expressed in equations 6.1, 6.2, 6.3. Bayes' theorem establishes a relationship between conditional and marginal probabilities, providing the conditional probability distribution of a random variable A. This is contingent upon our knowledge of information regarding another variable B, expressed through the conditional probability distribution of B given A, as well as the marginal probability distribution of A alone. Equation 6.1 articulates that the probability of A given B is equal to the probability of B given A multiplied by the probability of A, divided by the probability of B [110].

$$P(A/B) = \frac{P(B/A)P(A)}{P(B)} \tag{6.1}$$

$$P(A/B,C) = \frac{P(B,C/A)P(A/C)}{P(B/C)} \tag{6.2}$$

Where,

$$P(B/C) = \int P(B/A,C)P(A/C)dA \tag{6.3}$$

The discussion before this one also illustrates the significance of either uncertainty or precision in the interaction of processes regarded as low-level ones such as perception and reward. In this context, these beliefs are parameterized using a SoftMax function $\sigma(.)$ [108].

$$Perception \longrightarrow \hat{S}_t = \hat{\gamma}(\ln(A^T).o_t + \ln(B(a_{t-1})).\hat{S_{t-1}} + \hat{\gamma}.Q^T.\hat{\pi} \tag{6.4}$$

$$Actionselection \longrightarrow \hat{\pi} = \sigma(\hat{\gamma}.Q.\hat{S}_t) \tag{6.5}$$

$$Precision \longrightarrow \hat{\gamma} = \frac{\alpha}{\beta - (\hat{\pi}.T.Q.\hat{S}_t)} \tag{6.6}$$

Perception $\hat{S}_t$ refers to our audio and visual detectors. Precision $\hat{\gamma}$ is used to define the indicators we employ, while Action selection $\hat{\pi}$ is related to our Bayesian Inference approach for decision-making. The decision itself is represented by a, while O_t is used to aid in making the final decision as demonstrated in the Eq. 6.4, 6.5, 6.6. The factor $\hat{S}_t$ will low the weight. the weight of the optical sensor decision. the factor $\hat{\pi}$ will lessen the weight of the acoustic sensor decision. The factor O_t will rise the effectiveness of the final decision of the Bayesian Inference approach. $\hat{S}_t$, $\hat{S_{t-1}}$ are the factors to weaken. The final decision will be "Drone" because our approach involved developing debilitation detectors [60]. These functions are described in Figure 6.5 of automatic CNS model below:

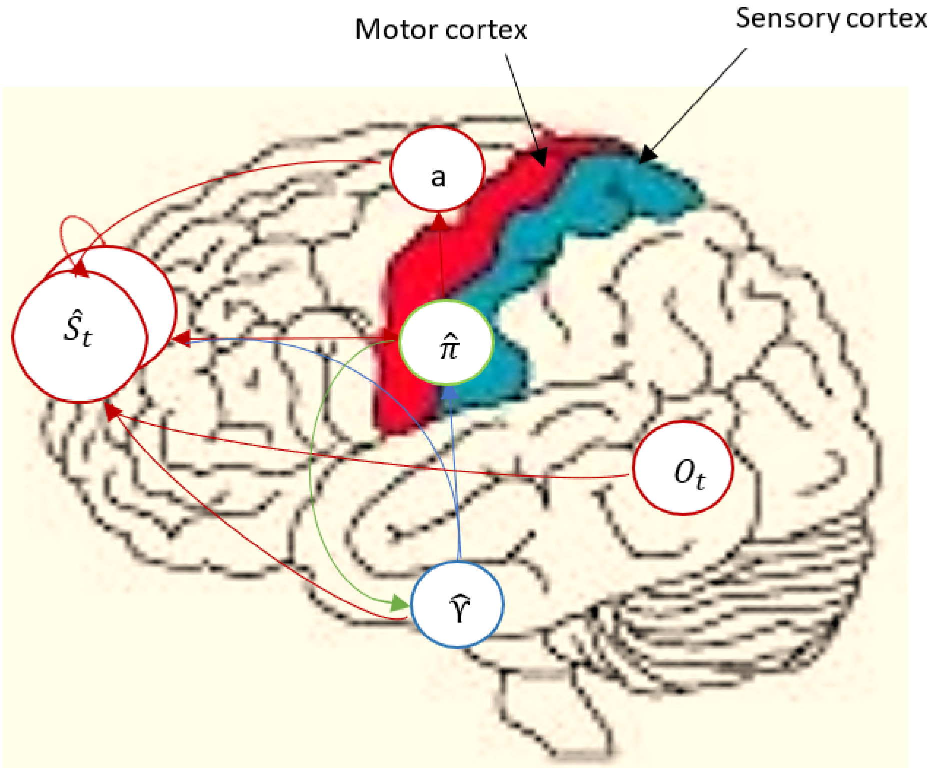

Figure 6.5: Scheme of automatic CNS model where $\hat{S}_t$ is Perception, $\hat{\pi}$ is Action selection, $\hat{\gamma}$ is Precision

6.5 Tools developed for applying Bayesian inference

Researchers have developed Sensor Fusion or hybrid systems that utilize a range of sensors to overcome some of these limitations. Such systems mostly use deep learning techniques to analyze information obtained from these sensors. In the current study, the objective is to use multiple sensors to attain improved identity in the identification of drones together with reliability. Late fusion is the key concept of the Bayesian inference approach. The last type of fusion, known also as "late fusion" or "decision-level fusion" is based on the integration of decisions or confidence scores of single sensors concerning the presence of a drone at a later stage of signal processing Figure 6.6. The individual decision or confidence scores are then summed in order to get a final decision. Aggregation is important for the late fusion since the detection of events feeds on data from diverse sensors to improve on the overall dependability of the detection procedure. Some of the voting systems applied in late fusion of drone detection are unanimity, majority, and plausibility. Other methods are weighted votes, Bayesian formulas, and Best machine learning algorithms.

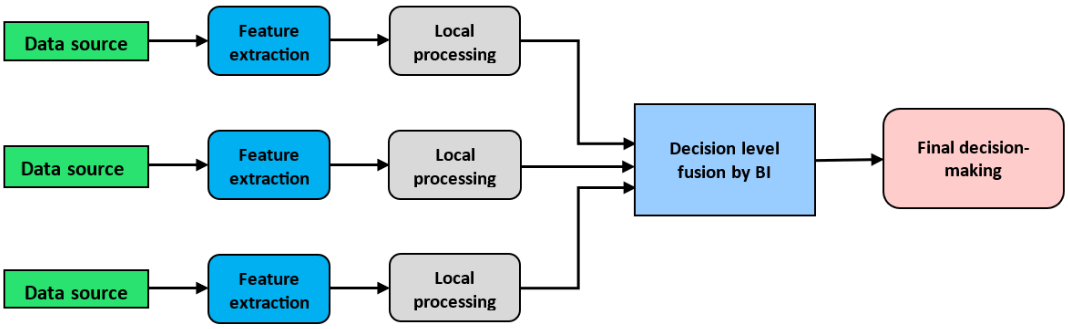

Figure 6.6: Late sensor fusion in drone detection

The Bayesian inference model developed for unmanned aerial systems (UAS) detection, employing a combination of visual and auditory cues, falls within the broader category of multisensory integration problems. This methodology involves the consideration of both sight and sound signals from sensors, merging them to reach a decision. While a simplistic approach might involve averaging these signals, our method employs a more sophisticated Bayesian approach to effectively combine information from both sources.

The experimental dataset used in our study encompasses images captured by a surveillance camera and audio recordings. Deep learning algorithms were applied to extract various features from the images, including pixel colors, contours, and shapes. For efficient data management and user interaction, we implemented a Python program utilizing the Pygame module for audio handling and the tkinter module to create a window interface. This interface allows users to listen or play the recordings, providing control options such as 'stop' and 'play'. This integrated approach enhances the accuracy and robustness of UAS detection by leveraging information from multiple sensory modalities.

In this case, the data is represented by numerical binary values, with each data point being treated independently. Decision-making is based on the outcome of individual data processing, categorizing each point as either belonging to a drone or not. The key factors considered in this process are ambient luminous and auditory indicators. The approach involves probabilistic management and Bayesian inference to derive a conclusive decision.

To achieve a community decision, the outcomes from each detector are manipulated and integrated. Recent research has emphasized the use of multisensors and Bayesian functions, such as belief, commulatality, plausibility, and implacability, emphasizing similarity. This is aimed at addressing the limitations of individual drone detectors and improving overall performance. To apply our approach, we examine different sources of information from the sensors.

In this specific example, the detection system considers both luminous and acoustic signals to discern between light and obscurity, effectively determining whether it is day or night. The Ephemeris indicator EI reflects the status of both sight and sound signals, with 0 indicating optimal conditions (optimal=0 and acoustic=0). In such instances, where there is good visibility during the day, the system relies on optimal detection. Conversely, during poor visibility at night, the sight signal registers as 0, and the sound signal as 1 (optimal=0 and acoustic=1), as indicated by the acoustic ambiance indicator AI. In this scenario, the system places reliance on acoustic detection to identify the presence of Unmanned Aerial Systems (UAS).

Based on the sensory information, the type of detection employed can be categorized into either optimal or acoustic, resulting in two distinct states: the control state and the stable state. Decision-making and action selection are approached as a pure inference problem, aiming to optimize beliefs regarding behavior and its consequences. For instance, optical detectors may exhibit inefficiency in detecting drones at night or in fog, while acoustic detectors might be susceptible to a noisy environment. To overcome these limitations, our proposed solution involves the utilization of three different drone detectors, each contributing a decision. In cases where the decisions from these detectors are unanimous, the decision-making process is straightforward, and a conclusive determination can be reached.

When conflicts arise among the decisions provided by different drone detectors, it becomes essential to assess the degree of conflict. Various factors may contribute to conflicts, such as inaccurately evaluated masses, diverse objects identified by different sources, and the possibility of a non-exhaustive frame of discernment (open world hypothesis). To tackle these challenges, we incorporate two indicators: the acoustic ambiance indicator and the ephemeris indicator. These indicators serve as tools to gauge the level of conflict and provide insights into the potential reasons behind conflicting decisions. The acoustic ambiance indicator focuses on auditory information, while the ephemeris indicator considers both sight and sound signals, offering a comprehensive assessment [60].

6.5.1 Ephemeris Indicator EI

The TEMT6000 which is a very cheap and easy ambient light sensor. It translates the amount of light it gets into a change in its resistance. The sensor uses an illuminance measure which gives a concrete way to classify brightness. The current intensity is higher for brighter light and lower for darker light. The breakout board for the TEMT6000 sensor is simple yet effective consisting of only three labeled pins on the top of board [18]. Additional information about the function of each pin can be found in shot Figure 6.7, Figure 6.8.

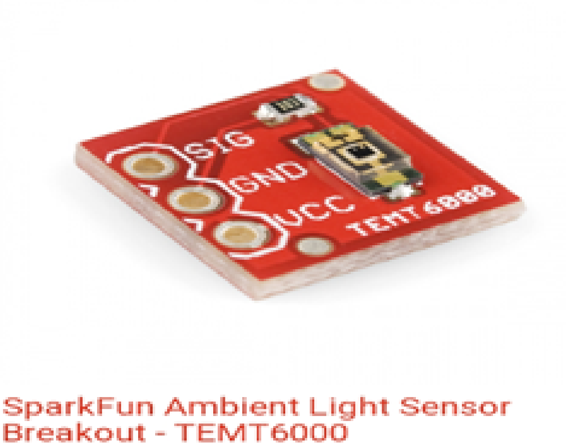

Figure 6.7: Spark-Fun ambient light sensor breakout TEMT6000 [112]

Symbol	Description
SIG	Output Voltage from the divider circuit
GND	GND (0V)
VCC	Collector Voltage (**should not exceed 6V**)

Figure 6.8: Ambient light sensor TEMT6000 and pins function

6.5.2 Acoustic Ambiance Indicator AI

The PCE-322A sound level meter is a professional acoustic device that has been created especially for industry, safety, and environmental control as shown in Figure 6.9. It can store data of up to a maximum of 262,000 values, thus allowing the user to make long-term recordings of the sound level meter with the help of windows sound meter software that offers visualization of tables and graphics data. The device is unique among all sound level meters because it has a mini tripod and an integrated analog output. The PCE-322A may be used for quick measurements or the recording of extensive data for a long time, and the values sent through the analog interface or output can be assessed in many ways. The sound level meter has automatic and manual measurement ranges [113], with a resolution 0.1dB and an accuracy of ± 1.4dB. The representation that it performs gets altered every 0.5s, and its frequency range is 31.5 Hz to 8kHz. The PCE-322A's dimensions are 2526633 mm, and it is compliant with IEC 651 TIPO ll (clause ll) regulation and IEC 61672-2 (clame ll).

Figure 6.9: PCE-322A professional acoustic indicator [114]

6.6 Results and Discussion of Bayesian Inference

Our methodology revolves around leveraging cutting-edge technology to enhance the decision-making capacity of automated machines. The Bayesian model of multisensory integration is a cornerstone, positing that perceptual systems amalgamate diverse signals based on their reliability or uncertainty. Notably, visual estimates of Unmanned Aerial Systems (UAS) exhibit significantly greater precision than auditory counterparts, leading to decisions grounded in beliefs about policies. This approach ensures a distinctive and Bayes-optimal sensitivity.

Our perceptual systems rely on a spectrum of signals from visual, auditory, and magnetic field detectors, their reliability or uncertainty governed by the Bayesian model of multisensory integration. Indicators, serving as agents monitoring noise or variation across multiple sensory modalities, are anticipated to utilize this information for decision-making, where lower noise levels signify higher accuracy, leading to a greater emphasis on more precise channels. Our objective is to investigate the effective weighting of multiple sources of incoming data within a system. To emulate the amalgamation of information across scenes in our detectors, we advocate the development of three distinct detectors, each with its own designated focus.

In the Figure 6.10, Figure 6.11, Figure 6.12, we have three detectors: OD for optical, AD for acoustic, and MFD for magnetic field. A green arrow indicates the presence of a drone, while a red arrow indicates its absence. In the first case, the three detectors which include the optical detector (OD), the acoustic detector (AD), and the magnetic field detector (MFD) all three were able to detect the drone with no conflict, and their decisions agreed. Hence, the last resolution was that a drone was present. In the second case, the optical detector (OD) failed to detect the presence of a drone due to the insufficiency of the luminous ambiance. Nevertheless, a drone was eventually confirmed. The detection was most likely the result of the two detectors, the acoustic detector (AD) and the magnetic field detector (MFD) which compensated for the weak signal from the optical detector and provided sufficient evidence for the decision. Therefore, the Bayesian Inference approach was able to integrate and weigh the different sources of data effectively to make a more accurate decision. The third case shows that both OD and AD detectors cannot sense the drone because of the inappropriate luminous and acoustic conditions. However, the final decision indicates the presence of a drone.

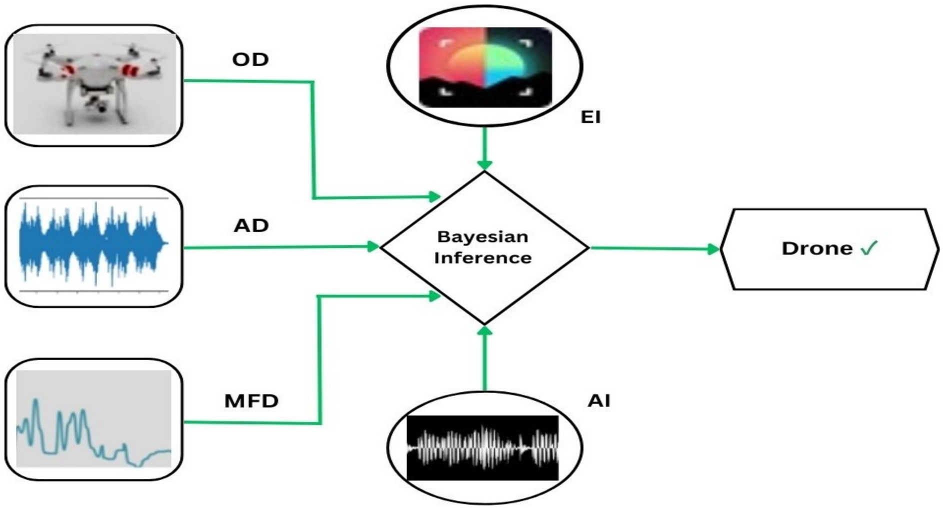

Figure 6.10: The final decision using Bayesian Inference in the case of agreed judgment

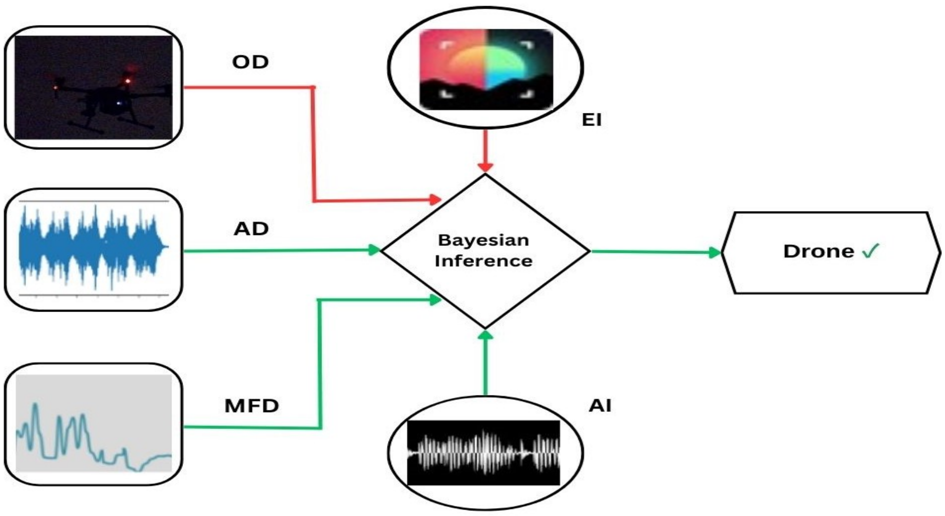

Figure 6.11: The final decision using Bayesian Inference in the case of luminous conflict

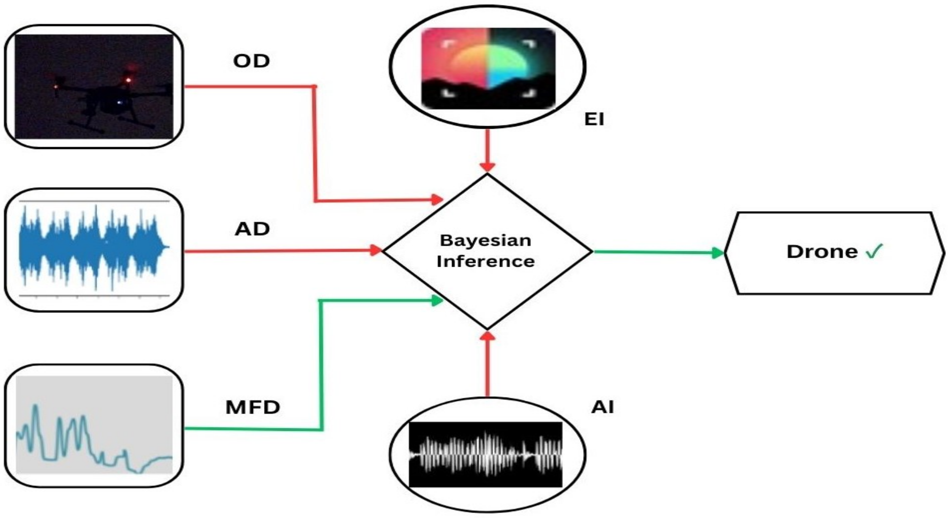

Figure 6.12: The final decision using Bayesian Inference in the case of luminous and acoustic conflict

We have prepared a summary table that effectively presents the findings from various detectors for the detection of some of the cases. The summary Table 6.1 allows us to clearly compare the performance of our approach with the state-of-the-art methods. By combining the optic, acoustic, and magnetic field detection methods, our approach offers a comprehensive detection capability that surpasses the limitations of individual methods. The detection system harnesses the wholesale of the individual methods in order to form a more complete and reliable system. This allows for cross-validation and increased accuracy in detecting and identifying objects or events.

By integrating complementary information from various sensing modalities, our approach effectively reduces false positives and false negatives, thereby bolstering overall detection reliability and enhancing the system's resilience to noise and interference. The synergy of these methods not only improves the system's performance and reliability but also enhances its adaptability, presenting a superior solution compared to individual detection methods. This comprehensive approach finds application across diverse fields, including surveillance, environmental monitoring, industrial automation, robotics, and more. The versatility of our methodology allows for broad applicability, opening the door to potential advancements in multiple areas simultaneously.

Table 6.1: Comprehensive Assessment of Detection Methods: Final Verdict and Performance Comparison with State-of-the-Art Approaches Across Different Cases

Detectors	**Cases**				
	Several drones	**Drone with Long range**	**Drone in the Night**	**Drone in a Noisy environment**	**Electric motor and no drone**
Optic OD	Doesn't detect	Doesn't detect	Doesn't detect	Detect	Doesn't detect
Acoustic AD	Detect	Doesn't detect	Detect	Doesn't detect	Doesn't detect
Magnetic field MFD	Detect	Doesn't detect	Detect	Detect	Detect
BI Approach	Detect	Doesn't detect	Detect	Detect	Doesn't detect

As referenced in [111, 115], it became clear no modality can be perfect for drone detection and classification. To address this limitation, our approach combines multiple modalities, including optic sensory detection [116, 117], acoustic detection [118, 119], and magnetic fields detection [120]. Through the synthesis of different sensing methods, our strategy can perform better and withstand various situations and challenges than when only one modality is used. For suggested bimodal [121] and multi modal systems [20], a comparative evaluation of different contributions poses challenges due to variations in drone types, detection ranges, sensors, features, classification/correlation methods, and performance metrics used by different authors. In the case of multi-modal detection, every detector compensates for the deficiencies of the others, but the problem is how to deal with the possible inconsistent choices. In our approach, the use of a Bayesian Inference (BI) serves as a robust solution for effectively integrating different sensors, addressing their limitations, and mitigating conflicting decisions.

6.7 Conclusion

In brief, the new perspective addresses the challenge of drone detection and classification through the integration of multiple detectors within a Bayesian inference framework. We have engineered optic, acoustic, and magnetic field detectors, each with inherent limitations, and harnessed Bayesian inference to integrate their outputs. Our model is designed to be robust, selective, and reliable, and has been evaluated using gathered data.

The presented findings demonstrate high precision in identifying observed flying objects.

This proposed method is a synthesis of physics and neural networks and incorporates indicators to aid in optimal or acoustic detection. This insight will inform future enhancements to our Bayesian inference model, promising superior performance in drone detection systems. As a final point, the integration of Bayesian inference methodology with multisensory detectors presents a robust and innovative approach to automated drone monitoring in structured environments. As the Technological scenery continues to evolve, the insights acquired from this exploration contribute not only to the field of automated drone monitoring but also underscore the broader applicability of Bayesian inference methodology in enhancing recognition systems across various domains. Through the application of Bayesian inference, we reveal a powerful tool for robust decision-making and pattern recognition, thereby laying the groundwork for more sophisticated and effective detection solutions in the future.

GENERAL CONCLUSION

General Conclusion

To ensure the safety of people, assets, and critical infrastructure from potential threats posed by the unauthorized use of civilian drones, a robust and reliable drone detection method is crucially needed. However, this study has provided valuable insights into multi-sensors approach for UAV detection based on a Bayesian inference framework. Although there are several detectors currently used for drone detection, such as optic, acoustic, and magnetic field detectors, it's important to acknowledge that each detector comes with its own set of limitations. This novel methodology involves these three detectors, commonly applied in classification and pattern recognition. These detectors are integrated and correlated through a Bayesian inference model, enabling each sensor to make an informed decision.

Initially, we began by highlighting the pivotal role of Unmanned Aerial Vehicles (UAVs), including their classification based on factors such as mass, operational altitude, propulsion/wings, and autonomy, exploring their wide-ranging applications across civilian and military sectors, followed by a discussion of the safety issues, and challenges related to this technology. Afterward, we conducted an examination of diverse detector types, revealing both their advantages and limitations. By delving into the state of art ML based drone detection, we have gained valuable insights and its impact into further explorations and studies on drone detection.

Moving forward, we constructed an optic detector utilizing conventional neural networks (CNN) and deep learning (DL) techniques to optimize its performance, but it encountered limitations due to luminous ambiance. To address this issue, we incorporated an ephemeris indicator to accurately detect these constraints. Then, we also engineered an acoustic detector using support vector machines (SVMs) and machine learning (ML) to enhance its performance, yet it faced constraints related to acoustic ambiance. By incorporating acoustic ambiance indicator, we can effectively check and account for these environmental factors. For the magnetic field detector (MFD), we have not found any previous study that addresses the drone detection task using magnetic field detector. We were the first to use the magnetic field detector with the assistance of the BBC card' for drone detection whereas its functionality is based on compass and magnetometer, commonly integrated within BBC card, being able to detect drones by adjusting the floating fields.

For the purpose of overcoming the inherent limitations of each detector while raising their quality, we proposed a Bayesian inference concept. It adopts decision-making of drone or non-drone and action selection as variational Bayesian inference to make a more confident and accurate final decision. This model represents a fusion of physics and neural networks, with the integration of indicators that we are pioneering in their use of advanced detection technology, to adjust the model process by tuning necessary parameters during execution and boost both optic and acoustic detection.

The drone detection process was fully automated, and the conflict decision was optimized, as the model is designed to be robust, selective, and reliable. It was evaluated using collected data. Our findings demonstrate that the novel approach enables us to determine the observed flying object with high precision. Additionally, they indicate that automatic drone detection with Bayesian inference showcased optimal performance for drone identification, excelling in accuracy, specificity, and sensitivity in preventing unwanted drone interventions. This perspective will drive enhancements to Bayesian inference model, paving the way for a more robust performance in future drone detection systems particularly in the realm of security and safety.

• FUTURE PERSPECTIVES

We provide insights on future drone detection systems, deeming that such perspectives will prove invaluable for novice researchers and practitioners to build more efficient solutions addressing privacy and security concerns:

First, there is still opportunity for research into developing a more accurate detecting method. While the general pattern is to rely on sensor fusion, sensor selection and system configuration remain an open research area. For Example: Fusion of visual and thermal data, for instance, can improve accuracy by capturing both visual appearance and heat signatures.

Moreover, many recently developed methods depend on deep learning and data collection to enhance detection accuracy. So, it is relevant to the advancements in computational techniques to handle increasingly complex models and datasets that will not only reinforce the existing methods but also surmounted their limitations successfully.

Furthermore, another interesting avenue for future research involves the application of Bayesian inference in other categories, not limited to detection but also in interdisciplinary fields such as healthcare, finance, and climate science. This approach is potentially more effective and reliable to address real-world challenges in making reliable decisions and solutions. Lastly, Advanced deep-learning algorithms have the aptitude to address certain challenges in drone detection systems by enhancing accuracy and robustness. Therefore, it is beneficial to explore other AI algorithms such as decision trees.

BIBLIOGRAPHY

Bibliography

[1] M. Belmote, R. Morales, and A. Fernandez-Caballero, "Computer vision in autonomous unmanned aerial vehicles-a systematic mapping study: A review," Applied Sciences, vol. 9, no. 15, p. 3196, 2019.

[2] A. Laith, A. Diabat, and G. Amir, "Applications, deployments, and integration of internet of drones (iod): a review," IEEE Sensors Journal, vol. 21, no. 22, pp. 25 532–25 546, 2021.

[3] G. Adel, B. Anuar, B. Ruzairi, S.ASM, and MA. Shukor, "Involvement of surveil- lance drones in smart cities: A systematic review," IEEE Access, vol. 10, pp. 56 611– 56 628, 2022.

[4] G. Lykou, D. Moustakas, and D. Gritzalis, "Review: Defending airports from uas: A survey on cyber-attacks and counter-drone sensing," Sensors, vol. 20, no. 12, p. 3537, 2020.

[5] F. Okpaleke, "The implications of drone proliferation for us grand strategy," in Drones and US Grand Strategy in the Contemporary World. Springer, 2023, pp. 211–239.

[6] N. Janet Mayowa, Y. Yang, P. Albert, and C. Hung-lin, "Application of drones in the architecture, engineering, and construction (aec) industry," Automation in Construction, vol. 150, p. 104827, 2023.

[7] K. AL-Dosari, Z. Hunaiti, and W. Balachandran, "Systematic review on civilian drones in safety and security applications," Drones, vol. 7, no. 3, p. 210, 2023.

[8] A. Morrow, "Couple accuses neighbor of stalking with drone," USA Today, December, vol. 13, 2014.

[9] D. Gritzalis, P. Grammati, and R. Roman Castro, "Sensors cybersecurity," Sensors, vol. 21, no. 5, p. 1762, 2021.

[10] P. Hicks, B. Mohammed, and K. Ahmed, "Watch the skies," the journal of international Security, vol. 2, pp. 22–24, 2020.

[11] P. Seongjoon, T. Hyeontae, L. Sangmin, J. Hyeontae, and K.Hwangnam, "Survey on anti-drone systems: components, designs, and challenges," IEEE access, vol. 9, pp. 42 635–42 659, 2021.

[12] P. Nguyen, H. Truong, M. Ravindranathan, A. Nguyen, R. Han, and T. Vu, "Cost-effective and passive rf-based drone presence detection and characterization," GetMobile: Mobile Computing and Communications, vol. 21, no. 4, pp. 30–34, 2018.

[13] D. Mototolea and C. Stolk, "Detection and localization of small drones using commercial of the-shelf fpga based software defined radio systems," in 2018 International Conference on Communications (COMM). IEEE, 2018, pp. 465–470.

[14] K. newsletter, "Kaspersky radar-based drone detection system," [Online]. Available: https://antidrone.kaspersky.com/en/solution/hardware/radar/, Sept 13, 2022.

[15] A. Bernardini, F. Mangiatordi , and E. Capodiferro , "Drone detection by acoustic signature identification," electronic imaging, vol. 29, pp. 60–64, 2017.

[16] S. Goldman, G. Borel-Donohue, and C. Christoph , "Detection of unmanned aerial vehicles using a visible camera system," Applied optics, vol. 56, no. 3, pp. B214–B221, 2017.

[17] S. Mahadevkar, B. Khemani, S. Patil, K. Kotecha, D. R.Vora, A. Abraham, and L. A. Gabralla, "A review on machine learning styles in computer vision—techniques and future directions," Ieee Access, vol. 10, pp. 107 293–107 329, 2022.

[18] L. Zhang, G. Yingming , and Z. Nianyu , "A lightweight distributed measurement method used to study illuminance estimation," Optik, vol. 223, p. 165590, 2020.

[19] S. Park, S. Shin, Y. Kim, E. Matson, and al., "Combination of radar and audio sensors for identification of rotor-type unmanned aerial vehicles (uavs)," in 2015 IEEE SENSORS. IEEE, 2015, pp. 1–4.

[20] F. Svanström, F. Alonso-Fernandez, and C. Englund, "A dataset for multi-sensor drone detection," Data in Brief, vol. 39, p. 107521, 2021.

[21] Classification of drones unmanned aircraft systems unmanned aerial vehicles. https://www.zentechnologies.com/, Jul 12, 2022.

[22] R.Shrestha, I.Oh, and S. Kim. A survey on operation concept, advancements, and challenging issues of urban air traffic management: Review article. Front. Future Transp, 2021.

[23] Ch. Hee-Wook, K. Hyung-Jin, K. Sung-Keun, and Na. Wongi. An overview of drone applications in the construction industry. Drones, 7(8), 2023.

[24] Classification of drones based on endurance. https://www.zentechnologies.com/, Jun 24, 2022.

[25] K. Hilson. Uav rc plane: Overview, applications, and regulations. https://www.swellrc.com/uav-rc-plane/, Nov 14, 2023.

[26] Hawk Aerospace. Drones and security. https://hawkaerospace.eu/, Oct 11, 2018.

[27] M. Jahangir and C. Baker. Persistence surveillance of difficult to detect microdrones with l-band 3-d holographic radar TM. In 2016 CIE International Conference on Radar (RADAR), pages 1–5. IEEE, 2016.

[28] M. Jahangir and C. Baker. Extended dwell doppler characteristics of birds and micro-uas at l-band. In 2017 18th International Radar Symposium (IRS), pages 1–10. IEEE, 2017.

[29] M. Jahangir, C. Baker, and G.A. Oswald. Doppler characteristics of micro-drones with l-band multibeam staring radar. In 2017 IEEE Radar Conference (RadarConf), pages 1052–1057. IEEE, 2017.

[30] B. Torvik, K.E. Olsen, and H. Griffiths. Classification of birds and uavs based on radar polarimetry. IEEE geoscience and remote sensing letters, 13(9):1305–1309, 2016.

[31] D.S. Zrnic and A.V. Ryzhkov. Observations of insects and birds with a polarimetric radar. IEEE transactions on geoscience and remote sensing, 36(2):661–668, 1998.

[32] L. Fuhrmann, O. Biallawons , J. Klare,, R. Panhuber, R . Klenke, and J. Ender. Micro-doppler analysis and classification of uavs at ka band. In 2017 18th International Radar Symposium (IRS), pages 1–9. IEEE, 2017.

[33] N. Mohajerin , J. Histon , R. Dizaji, and S. Waslander . Feature extraction and radar track classification for detecting uavs in civillian airspace. In 2014 IEEE Radar Conference, pages 0674–0679. IEEE, 2014.

[34] P. Molchanov, R.I Harmanny , J.J.M. de Wit , K. Egiazarian , and J. Astola. Classification of small uavs and birds by micro-doppler signatures. International Journal of Microwave and Wireless Technologies, 6(3-4):435–444, 2014.

[35] G.J. Mendis, T. Randeny, J. Wei, and A. Madanayake . Deep learning-based doppler radar for micro uas detection and classification. In MILCOM 2016-2016 IEEE Military Communications Conference, pages 924–929. IEEE, 2016.

[36] G.J. Mendis, J. Wei, and A. Madanayake. Deep learning cognitive radar for micro uas detection and classification. In 2017 Cognitive Communications for Aerospace Applications Workshop (CCAA), pages 1–5. IEEE, 2017.

[37] P. Zhang, L. Yang, and G. Chen and G. Li . Classification of drones based on micro-doppler signatures with dual-band radar sensors. In 2017 Progress in Electromagnetics Research Symposium-Fall (PIERS-FALL), pages 638–643. IEEE, 2017.

[38] B.K. Kim, H.S. Kang, and S.O. Park. Drone classification using convolutional neural networks with merged doppler images. IEEE Geoscience and Remote Sensing Letters, 14(1):38–42, 2016.

[39] D.A. Brooks, O. Schwander, F. Barbaresco, J.Y. Schneider, and M. Cord. Temporal deep learning for drone micro-doppler classification. In 2018 19th International Radar Symposium (IRS), pages 1–10, 2018.

[40] F. Fioranelli, M. Ritchie, H. Griffiths, and H. Borrion. Classification of loaded/unloaded micro-drones using multistatic radar. Electronics Letters, 51(22):1813–1815, 2015.

[41] F. Hoffmann, M. Ritchie, F. Fioranelli, A. Charlish, and H. Griffiths. Microdoppler based detection and tracking of uavs with multistatic radar. In 2016 IEEE Radar Conference (RadarConf), pages 1–6, 2016.

[42] M. Ritchie, F. Fioranelli, H. Borrion, and H. Griffiths. Multistatic microdoppler radar feature extraction for classification of unloaded/loaded micro-drones. IET Radar, Sonar Navigation, 11(1):116–124, 2017.

[43] W. Zhang and G. Li. Detection of multiple micro-drones via cadence velocity diagram analysis. Electronics Letters, 54(7):441–443, 2018.

[44] A. Rezantsev, V. Lepetit, and P. Fua. Detecting flying objects using a single moving camera. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(5):879–892, 2017.

[45] R. Yoshihashi, T. Trinh, R. Kawakami, S. You, M. Iida, and T. Naemura. Differentiating objects by motion: Joint detection and tracking of small flying objects. CoRR, Available: http://arxiv.org/abs/1709.04666, 2018.

[46] C. Aker and S. Kalkan. Using deep networks for drone detection. In 2017 14th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), pages 1–6, 2017.

[47] M. Saqib, S.D. Khan, N. Sharma, and M. Blumenstein . A study on detecting drones using deep convolutional neural networks. In 2017 14th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), pages 1–5, 2017.

[48] J. Peng, C. Zheng, P. Lv, T. Cui, Y. Cheng, and S. Lingyu . Using images endered by pbrt to train faster r-cnn for uav detection. In Computer Science Research Notes CSRN 2802, 2018.

[49] D. Lee, W. G. La, and H. Kim. Drone detection and identication system using artificial intelligence. In 2018 International Conference on Information and Communication Technology Convergence (ICTC), pages 1131–1133, 2018.

[50] M. Nijim and N. Mantrawadi. Drone classification and identification system by phenome analysis using data mining techniques. In 2016 IEEE Symposium on Technologies for Homeland Security (HST), May 2016.

[51] S. Jeon, J.W. Shinand Y.J. Lee, W.H. Kim, Y. Kwon, and H.Y. Yang. Empirical study of drone sound detection in real-life environment with deep neural networks. In 2017 25th European Signal Processing Conference (EUSIPCO), pages 1858–1862, 2017.

[52] V. Baron, S. Bouley, M. Muschinowski, J. Mars, and B. Nicolas. Drone localization and identification using an acoustic array and supervised learning. In Artificial Intelligence and Machine Learning in Defense Applications, volume 11169, page 111690F. International Society for Optics and Photonics, 2019.

[53] J. Kim, C. Park, J. Ahn, Y. Ko, J. Park, and J. C. Gallagher. Real-time uav sound detection and analysis system. In 2017 IEEE Sensors Applications Symposium (SAS), 2017.

[54] X. Yue, Y. Liu, J. Wang, H. Song, and H. Cao. Software defined radio and wireless acoustic networking for amateur drone surveillance. IEEE Communications Magazine, 56(4):90–97, 2018.

[55] Y. Seo, B. Jang, and S. Im. Drone detection using convolutional neural networks with acoustic stft features. In 2018 15th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), pages 1–6, 2018.

[56] E. Matson, B. Yang, A. Smith, E. Dietz, and J. Gallagher. Uav detection system with multiple acoustic nodes using machine learning models. In 2019 Third IEEE International Conference on Robotic Computing (IRC), pages 493–498, 2019.

[57] Z. Shi, M. Huang,C. Zhao, L. Huang, X. Du, and Y. Zhao. Detection of lssuav using hash fingerprint based svdd. In 2017 IEEE International Conference on Communications (ICC), pages 1–5, 2017.

[58] P. Nguyen, M. Ravindranatha, R. Han A. Nguyen, and T. Vu . Investigating cost-effective rf-based detection of drones. In Proceedings of the 2nd Workshop on Micro Aerial Vehicle Networks, Systems, and Applications for Civilian Use, page 17–22, 2016.

[59] M. Ezuma, F. Erdenand C. K. Anjinappa, O. Ozdemir, and I. Guvenc. Micro-uav detection and classification from rf fingerprints using machine learning techniques. In 2019 IEEE Aerospace Conference, pages 1–13, 2019.

[60] F.Z.Saadaoui, N. Cheggaga, and N.E.H. Djabri. Multi-sensory system for uavs detection using bayesian inference. Applied Intelligence, 53, 2023.

[61] P. S. Diao, T. Alvesand B. Poussot, and S. Azarian. A review of radar detection fundamentals. IEEE Aerospace and Electronic Systems Magazine, pages 1–1, 2022.

[62] Z.Q. Zhao, P. Zheng, S.t. Xu, and X. Wu. Object detection with deep learning: A review. IEEE Transactions on Neural Networks and Learning Systems, 30(11):3212–3232, 2019.

[63] Z. Soleimanitaleb, M. A. Keyvanrad, and A. Jafari. Object tracking methods:a review. In 2019 9th International Conference on Computer and Knowledge Engineering (ICCKE), pages 282–288, 2019.

[64] A.Krizhevsky, I. Sutskever, and G.E Hinton. Imagenet classification with deep convolutional neural networks. In Advances in Neural Information Processing Systems, volume 25. Curran Associates, Inc., 2012.

[65] E.Cakir, T. Heittola, H. Huttunen, and T. Virtanen. Polyphonic sound event detection using multi label deep neural networks. In 2015 International Joint Conference on Neural Networks (IJCNN), pages 1–7, 2015.

[66] O. Russakovsky, J. Deng, H. Su, J. Krause, and al. Imagenet large scale visual recognition challenge. International Journal of Computer Vision, 115, 2015.

[67] J. Tao, Y. Gu, J. Sun, Y. Bie, and H. Wang. Research on vgg16 convolutional neural network feature classification algorithm based on transfer learning. In 2021 2nd China International SAR Symposium (CISS), pages 1–3, 2021.

[68] I.H. Sarker. Deep learning: A comprehensive overview on techniques, taxonomy, applications and research directions. SN Computer Science, 2, 2021.

[69] I.H Sarker, Y. B Abushark, F.Alsolami, and A.I. Khan. A machine learning based cyber security intrusion detection model. Symmetry, 12(5), 2020.

[70] Python Deeplab. https://blog.csdn.net/L.goodboy/article/, Aug 26, 2022.

[71] Depthwise separable convlution. https://blog.csdn.net/u012426298/article/ details/80998547, Jul 11, 2018.

[72] S.Tammina. Transfer learning using vgg-16 with deep convolutional neural network for classifying images. International Journal of Scientific and Research Publications (IJSRP), 9, 2019.

[73] F. Z. Saadaoui, N. Cheggaga, and N. E. H. Djabri. Optical detection of uavs using deep convolutional neural networks. In 2023 2nd International Conference on Electronics, Energy and Measurement (IC2EM), volume 1, 2023.

[74] A. Sedunov, D. Haddad, H. Salloum, A. Sutin, N. Sedunov, and A. Yakubovskiy. Stevens drone detection acoustic system and experiments in acoustics uav tracking. In 2019 IEEE International Symposium on Technologies for Homeland Security (HST), pages 1–7, 2019.

[75] C. A. Ahmed, F. Batool, W. Haider, M. Asad, and S. H. Raza Hamdani. Acoustic based drone detection via machine learning. In 2022 International Conference on IT and Industrial Technologies (ICIT), pages 01–06, 2022.

[76] M. Ohlenbusch, A. Ahrens, C. Rollwage, and J. Bitzer. Robust drone detection for acoustic monitoring applications. In 2020 28th European Signal Processing Conference (EUSIPCO), pages 6–10, 2021.

[77] C. Dumitrescu, M. Minea, I.M. Costeaand I. Cosmin Chiva, and A. Semenescu. Development of an acoustic system for uav detection. Sensors, 20(17), 2020.

[78] B. Yang, E. T. Matson, A. H. Smith, J. E. Dietz, and J. C. Gallagher. Uav detection system with multiple acoustic nodes using machine learning models. In 2019 Third IEEE International Conference on Robotic Computing (IRC), pages 493–498, 2019.

[79] M. Gasmi. Detection par estimation du champ acoustique d'un uav. Master Thesis, Institute of Aeronautics and space studies, University of BLIDA 1, 2023.

[80] M. A. Khan, J. Sun, B. Li, A. Przybysz, and J. Kosel. Magnetic sensors: A review and recent technologies. Engineering Research Express, 3(2):022005, 2021.

[81] P. Ripka and M. Janosek. Advances in magnetic field sensors. IEEE Sensors Journal, 10(6):1108–1116, 2010.

[82] J.Michael Caruso and Dr. H.Smith Carl. A new perspective on magnetic field sensing. Honeywell, SSEC Nonvolatile Electronics, Inc, 1998.

[83] Y. Haddab, V. Mosser, M. Lysowec, J. Suski, L. Demeus, C. Renaux, S. Adriensen, , and D. Flandre. Low-noise soi hall devices. In Noise and Information in Nanoelectronics, Sensors, and Standards, volume 5115, pages 196 – 203. International Society for Optics and Photonics, SPIE, 2003

[84] J. Lenz and A. S. Edelstein. Magnetic sensors and their applications. IEEE Sensors Journal, 6(3):631–649, 2006.

[85] S. Sentence, J. Waite, L. Yeomans, and E. MacLeod. Teaching with physical computing devices: the bbc micro:bit initiative. page 87–96, 2017.

[86] L.Agustín, M. Herrera, A. Luz, P. J. García-Ramírez, and E. Manjarrez. Resonant magnetic field sensors based on mems technology. journal of sensors, 9(10):7785– 7813, 2009.

[87] Understanding current sensors: How they work, classification. https://www.thegioiic.com/, Jul 30,2022.

[88] O. Arif, E. R. Nowak, A. S. Edelstein, G. A. Fischer, C. A. Nordman, and S. F.Cheng. Magnetic-field dependence of the noise in a magnetoresistive sensor having mems flux concentrators. IEEE Transactions on Magnetics, 42(10):3306–3308, 2006.

[89] Magnetoelectric encoders. https://community.element14.com/learn/learning-center/essentials/w/documents/23151/magnetic-encoders, Sep 24, 2021.

[90] Cl. Byrd. Circuit symbol magnetising coil. https://www.circuitdiagram.co/ circuit-symbol-magnetising-coil/, Nov 25, 2019 .

[91] F. Primdahl, J. M. G.Merayo, and P. Brauer. Fluxgate magnetometry for precise mapping of the earth's field. Sensors Lett, 05, 2007.

[92] M.Krzywonos and T. H. Eberhard. High density process to cultivate lactobacillus plantarum biomass using wheat stillage and sugar beet molasses. Electronic Journal of Biotechnology, 14:6–6, 2011.

[93] Micro-bit V2 Review: A Must-Have For Every Modern Classroom. https://www.electromaker.io/blog/article/bbc-microbit-v2-review, Nov 30, 2023.

[94] K. Bakiri and N. Merabti. Détecteur de drone à base de capteur de champ magnétique. Master Thesis, Institute of aeronautics and space studies, university of BLIDA 1, 2023.

[95] T. Matthew, B. Y. Smolenski, and D. Haddad. Real-time acoustic detection and identification of drones in operational conditions. The Journal of the Acoustical Society of America, 152: A62–A62, 2022.

[96] L. Yin, X. Deng, and Y. Deng. The negation of a basic probability assignment. IEEE Transactions on Fuzzy Systems, 27(1):135–143, 2019.

[97] Y. Huang, C.Shao, B.Wu, J.L. Beck, and H.Li. State-of-the-art review on bayesian inference in structural system identification and damage assessment. Advances in Structural Engineering, 22, 2019.

[98] K. B. Korb and A. E. Nicholson. Bayesian artificial intelligence. CRC press, Book 2nd Edition Dec 6, 2010.

[99] D. Meng, H. Zhang, and T. Huang. A concurrent reliability optimization procedure in the earlier design phases of complex engineering systems under epistemic uncertainties. Advances in Mechanical Engineering, 8(10):1687814016673976, 2016.

[100] P. Shiguihara, A. D. A. Lopes, and D. Mauricio. Dynamic bayesian network modeling, learning, and inference: A survey. IEEE Access, 9:117639–117648, 2021.

[101] B. Kang, Y. Deng, K. Hewage, and R. Sadiq. A method of measuring uncertainty for z-number. IEEE Transactions on Fuzzy Systems, 27(4):731–738, 2019.

[102] M.Colombo and P. Series . Bayes in the brain—on bayesian modelling in neuroscience. The British Journal for the Philosophy of Science, 63(3):697–723, 2012.

[103] J.V. Baldo, N. Kacinuk, S. N Carl, Paulraj, A. Moncreif, V.Piai, B. Curranand T. Herron, and F.N. Dronkers. Voxel-based lesion analysis of brain regions underlying reading and writing. Neuropsychologia, 115:51–59, 2018.

[104] H. Adesnik and A. Naka. Cracking the function of layers in the sensory cortex. Elsevier, 100:1028–1043, 2018.

[105] D. Yon and Ch. D. Frith. Precision and the bayesian brain. Current Biology, 31(17), 2021.

[106] J. Donoghue. Neural representations of intended movement in motor cortex. 2001.

[107] Sensory cortex location. https://www.animalia-life.club/qa/pictures/ primary-somatosensory-cortex-homunculus, Jan 23, 2020.

[108] K. Friston, P. Schwartenbeck, T. FitzGerald, M. Moutoussis, T. Behrens, and R. Dolan. The anatomy of choice: dopamine and decision-making. Philosophical Transactions of the Royal Society B: Biological Sciences, 369(1655):20130481, 2014.

[109] N. Pinghe, L. Jun, H. Hong, H. Qiang, and D. Xiuli. Probalistic model updating via bayesian inference and adaptive gaussian process modeling. Computer Methods in Applied Mechanics and Engineering, 383:113915, 2021.

[110] E.Thrane and C.Talbot. An introduction to Bayesian inference in gravitational wave astronomy: parameter estimation, model selection, and hierarchical models. Publications of the Astronomical Society of Australia, 36: e010, 2019.

[111] B. Taha and A. Shoufan. Machine learning-based drone detection and classification: State-of-the-art in research. IEEE Access, 7:138669–138682, 2019.

[112] TEMT6000 Ambient Light Sensor and Arduino – Measure Illuminance and Light Intensity. https://how2electronics.com/temt6000-ambient-light-sensor-arduino-measure-light-intensity/google vignette,Aug 22, 2022

[113] A.F.Ayodele and T.S. Johnson. The effects of aircraft noise on psychosocial health. Journal of Transport and Health, 22:101230, 2021.

[114] Sound level meters. https://www.officer.com/investigations/ sound-level-meters/product/12251458/, Aug 15, 2016.

[115] M. Asif Khan, H. Menouar, A. Eldeeb, and A. Abu-Dayya and F.D. Salim. On the detection of unauthorized drones—techniques and future perspectives: A review. IEEE Sensors Journal, 22(12):11439–11455, 2022.

[116] M.Nalamati, A. Kapoor, M. Saqib, N. Sharma, and M. Blumenstein. Drone detection in long-range surveillance videos. In 2019 16th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), pages 1–6, 2019.

[117] M. Shovon, R. Gopalan, and B. Campbell. A comparative analysis of deep learning algorithms for optical drone detection. In Fifteenth International Conference on Machine Vision (ICMV 2022), volume 12701, page 1270104. International Society for Optics and Photonics, 2023.

[118] D. Utebayeva, L. Ilipbayeva, and Et Matson. Practical study of recurent neural networks for efficient real time drone sound detection: A review. Drones MDPI, 7(1), 2023.

[119] G. Lacava, F. Mercaldo, F. Martenelli, A. Santone, and M. Pizzi. Drone audio recognition based on machine learning techniques. Procedia Computer Science, 207:848–857, 2022.

[120] P. Lipovskya, J. Novotnaka, and J. Blazeka. Possible utilization of low frequency magnetic fields in short range multirotor uav detection system. Transportation Research Procedia, 65:106–115, 2022.

[121] Ding, X. Guo, T. Peng, X. Huang, and X. Hong. Drone detection and tracking system based on fused acoustical and optical approaches. Advanced Intelligent Systems, 5(10):2300251, 2023.