الجمـــهوريـــة الجـــزائريـــة الديـمقـراطيـــــــة الشـــعبيـــــة
PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA
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AMAR TELIDJI UNIVERSITY OF LAGHOUAT

كـلـيـــــة الـعـلـــــوم
FACULTY OF SCIENCES
DEPARTMENT OF COMPUTER SCIENCE

Master's Thesis

Field: Mathematics and Computer Science
Specialty: Computer Science
Option: Data Science and Artificial Intelligence

By:

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TOPIC

A Lightweight Multi-Task Deep Learning Framework for UAV Detection and Tracking

Defended publicly on June 30st, 2025, before a jury composed of:

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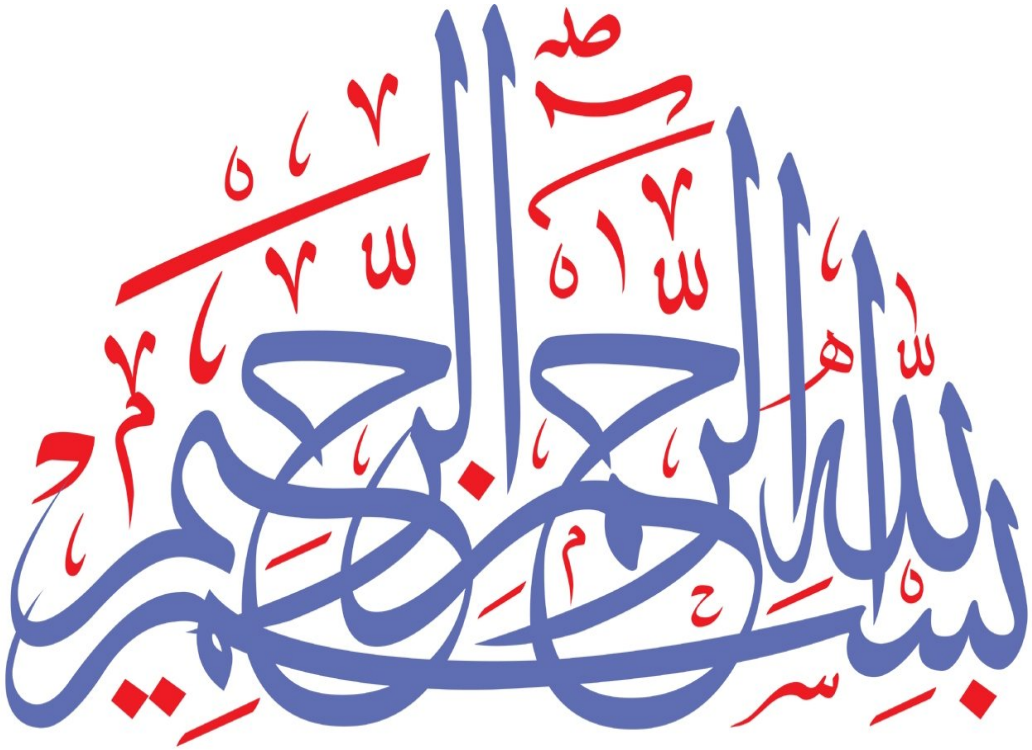
Thesis No. …… – Academic Year 2024/2025


بسم الله الرحمن الرحيم

Acknowledgments

First and foremost, I would like to thank Allah, my Lord, who guided me to the right path, granted me success, and helped me complete my journey and accomplish this work.

I would like to thank my dear parents, who supported me with everything they had and never withheld their unwavering encouragement and support. Thank you, the dearest people in my life. May Allah reward you both with the best of rewards on my behalf.

I also extend my sincere thanks to my beloved brother and sister .Thank you for your constant encouragement, for always asking and checking in, and for reminding me whenever I forgot.

I would also like to thank Professor Hamini Narges for supervising this work and for her constant guidance and support.

I would also like to thank the honorable committee for evaluating this work, and for their guidance and remarks aimed at improving and developing it further.

I would like to thank everyone who helped and encouraged me, and all those who stood by my side at any point during my journey.

Dedications

I dedicate this humble work to my dear parents, my pillars of strength, whose unwavering support has helped me complete my academic journey.

To my siblings, Souhaila and Abdullah — the apples of my eye.

And to my dear friends, each one by name, and especially to my friend Abeer, with her pure heart — we've shared a beautiful journey together, and here we are, reaching its end.

Thank you for all the beautiful days, the laughter, and the unforgettable moments etched in my memory.

To all who loved me ,carry on me ,and support me .

ملخص

يقترح هذا العمل تطوير نموذج ذكي مخصص يعتمد على مبدأ التعلم متعدد المهام، يهدف إلى الكشف عن الطائرات بدون طيار وتتبعها في الزمن الحقيقي.

يتميز هذا النموذج بقدرته على تنفيذ مهمتين في آن واحد، هما: تصنيف الأجسام وتحديد مواقعها بدقة، مما يجعله أكثر كفاءة مقارنة بالطرق التقليدية التي تفصل بين هاتين المهمتين.

وقد تم تدريب النموذج باستخدام قاعدة بيانات مصممة خصيصًا لهذا الغرض، حيث خضع للمقارنة مع نماذج معروفة في هذا المجال، مثل النموذج السريع للكشف ونموذج الشبكات الالتفافية المعمقة.

أظهرت النتائج أن النموذج المقترح قد حقق أداءً متميزًا، حيث بلغت نسبة الدقة في التصنيف حوالي ثمانية وتسعين فاصل ثلاثة وخمسين في المئة، في حين بلغ متوسط الخطأ المطلق في تحديد المواقع صفرًا فاصل صفر صفر سبعة وعشرين، وبلغ متوسط الخطأ التربيعي صفرًا فاصل اثنين وخمسين.

تعكس هذه الأرقام قدرة النموذج على الجمع بين الدقة والكفاءة في بيئات واقعية ومعقدة.

ولتقوية نظام الكشف وضمان استمرارية تتبع الطائرات عبر الإطارات المتتالية في الفيديو، تم دمج مرشح رياضي يعرف بمرشح كالمان، والذي ساهم في المحافظة على هوية الأجسام المتتبعة بثبات، حتى في حالة التداخل أو الفقد المؤقت.

وقد أثبت النظام كفاءته من حيث السرعة، حيث تمكن من معالجة أكثر من خمس وعشرين صورة في الثانية، مع نسبة ضئيلة جدًا من أخطاء التتبع.

بناءً على هذه النتائج، يمكن اعتبار النموذج المقترح حلًا فاعلًا ومتكاملًا لمهام المراقبة والكشف في الزمن الحقيقي، خاصة في التطبيقات الأمنية والمدنية التي تتطلب سرعة ودقة في التعامل مع الأجسام الطائرة صغيرة الحجم.

الكلمات المفتاحية: الطائرات بدون طيار، التعلم العميق، التعلم متعدد المهام، الذكاء الاصطناعي.

Abstract

In this work, we propose a custom **Multi-Task Learning (MTL)** model for real-time UAV detection and tracking, designed to jointly perform classification and bounding box regression.

The proposed model was evaluated against state-of-the-art detectors, including YOLOv8 and Faster R-CNN ResNet-50.

While YOLOv8 achieved fast inference with strong accuracy, and Faster R-CNN demonstrated high precision in complex scenes, our MTL model outperformed both in classification accuracy and bounding box precision. Specifically, the MTL model achieved a classification accuracy of 98.53%, a bounding box MAE of 0.0256, and an MSE of 0.0027, demonstrating its effectiveness in multi-output learning.

To enable tracking, we integrated a Kalman Filter, which maintained consistent object identities across frames .

These results highlight the robustness and efficiency of the proposed MTL-based pipeline for UAV detection and tracking in real-time surveillance applications.

Keywords : **UAVs , MTL , YOLO , Faster-RCNN-Resnet50 , tracking.**

Résumé

Dans ce travail, nous proposons un modèle personnalisé basé sur **l'apprentissage multi-tâches (AMT)** pour la détection et le suivi en temps réel des drones (UAV), capable d'effectuer simultanément la classification et la régression des boîtes englobantes.

Le modèle proposé a été évalué et comparé à des détecteurs de pointe tels que YOLOv8 et Faster R-CNN ResNet-50.

Bien que YOLOv8 offre une détection rapide avec une bonne précision, et que Faster R-CNN se distingue par sa performance dans des scènes complexes, notre modèle MTL a surpassé les deux en termes de précision de classification et de délimitation. Plus précisément, le modèle MTL a atteint une précision de classification de 98,53%, une erreur absolue moyenne (MAE) de 0,0256, et une erreur quadratique moyenne (MSE) de 0,0027, démontrant son efficacité dans l'apprentissage multi-sorties.

Pour permettre le suivi des objets, un filtre de Kalman a été intégré, assurant le maintien des identités des objets à travers les images vidéo à plus de 25 images par seconde, avec un nombre minimal de changements d'identifiants.

Ces résultats soulignent la robustesse et l'efficacité de notre pipeline basé sur le MTL pour la détection et le suivi des drones dans des applications de surveillance en temps réel.

Mots clés : **UAV**, **Apprentissage Multi-Tâches**, **YOLO**, **Faster R-CNN ResNet-50**, **Suivi**.

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General Introduction

In recent years, the rapid evolution of **Unmanned Aerial Vehicles (UAVs)**, commonly referred to as *drones*, has transformed various industries. These autonomous or remotely operated devices have found applications in fields as diverse as environmental monitoring, agriculture, logistics, disaster response, and surveillance. Their low cost, ease of deployment, and ability to access hard-to-reach locations make them indispensable tools in both civilian and military contexts.

However, this surge in UAV deployment has been accompanied by growing concerns over their potential misuse. Drones can be exploited for unauthorized surveillance, smuggling, and even coordinated attacks, posing serious threats to privacy, safety, and national security. In this context, detecting and tracking UAVs in real time becomes a critical task, especially in urban or cluttered environments where conventional detection methods like radar or acoustic sensors often prove ineffective due to limited precision and range.

As a result, researchers are increasingly turning to **vision-based** detection systems powered by advances in **artificial intelligence (AI)** and deep learning. These systems, which utilize standard camera feeds, offer a promising and cost-effective solution for real-time monitoring and threat mitigation.

Object detection algorithms such as **YOLO (You Only Look Once)** and **Faster R-CNN** enable the automatic identification and localization of UAVs with high accuracy. To ensure continuous monitoring, these detection models are complemented by tracking algorithms that follow the object's trajectory across frames.

This thesis aims to design and implement a real-time vision-based system for detecting and tracking UAVs. The system leverages advanced deep learning models to classify and localize UAVs in video streams and employs the Kalman Filter for tracking their movement across frames.

Two detection architectures—YOLOv8 and Faster R-CNN—are explored and compared in terms of performance, while the Kalman Filter serves as the core tracking mechanism.

The main objectives of this work are:

- To design and train deep learning models capable of detecting UAVs in diverse environments.
- To integrate a tracking module that maintains the identity of detected UAVs across video frames.
- To evaluate the performance of the system and propose future improvements.

The structure of this thesis is as follows:

- **Chapter One** introduces artificial intelligence and deep learning concepts, providing the necessary background on machine learning, neural networks, and object detection models.
- **Chapter Two** reviews related work, comparing different approaches for UAV detection and discussing their strengths and limitations.
- **Chapter Three** presents our technical contribution, including dataset preparation, model architecture, training procedures,evaluates the results, and integration of the tracking system.
- **Chapter four** concludes the thesis, outlines the limitations of the current system, and proposes directions for future research.

1

Introduction to Artificial Intelligence

1.1 Introduction

Artificial Intelligence is a fast-growing and fascinating field that continues to capture the interest of researchers, developers, and the general public. The idea of machines that can think, learn, and adapt like humans has driven the development of smarter and more capable systems. Over time, AI has evolved significantly from simple rule-based systems to powerful models powered by machine learning and, more recently, deep learning.

A major force behind this progress is deep learning, a subfield of machine learning that mimics how the human brain processes information. Deep learning relies on neural networks with many layers to identify patterns and make sense of complex, high-dimensional data. These models have the ability to learn directly from raw inputs, which has led to breakthroughs in solving tasks that were previously too challenging for traditional algorithms.

Today, deep learning plays a central role in AI advancements across a variety of domains. In computer vision, it enables systems to detect and recognize objects in images and videos. In natural language processing, it powers applications like language translation, chatbots, and content generation. In robotics and healthcare, it helps machines navigate and make decisions, often in real time.

This growth has also been supported by major developments in computing power and software tools. High-performance GPUs and dedicated AI chips make it possible to train large-scale models, while cloud platforms and open-source libraries allow developers worldwide to access and build upon cutting-edge tools.

Still, challenges remain. As deep learning models grow more complex, questions arise about how they make decisions, how to ensure fairness and transparency, and how to use them responsibly. As we move forward, addressing these issues will be just as important as building more capable systems.

This chapter examines the core relationship between artificial intelligence and deep learning, covering their theoretical foundations, model design, and real-world applications to highlight how deep learning shapes the present and future of AI.

1.2 Artificial intelligence

Artificial Intelligence (AI) has emerged as one of the most transformative technologies of the modern era, revolutionizing how machines interact with the world. It encompasses a wide range of approaches, tools, and applications aimed at replicating human cognitive abilities such as learning, reasoning, problem-solving, and decision-making. Before exploring its principles and applications, it is essential to understand what AI truly means.

1.2.1 Definition

> *"The science and engineering of making intelligent machines, especially intelligent computer programs."* (1)
>
> — The father of AI, John McCarthy

Artificial Intelligence is a computing concept that helps a machine think and solve complex problems as we humans do with our intelligence.

For example, we perform a task, make mistakes, and learn from those mistakes, at least the wise among us do! Similarly, Artificial Intelligence is expected to work on a problem, make some mistakes in solving it, and learn from those mistakes in a self-correcting manner as part of its continuous self-improvement.(2)

1.2.2 Types of artificial intelligence

Artificial Intelligence comes in many different forms, each with its own complexity and purpose. By understanding what sets them apart, we can get a clearer picture of what AI can do today and where it might be headed in the future.

- **Narrow AI (Weak AI)** Is the most common form of AI today. It's designed to perform a single, specific task exceptionally well. From recognizing faces in photos to detecting fraud in financial transactions, this type of AI dominates the current landscape, powering applications that require high precision within a limited scope (3).
- **General AI (Strong AI) (AGI)** refers to systems with cognitive abilities similar to humans. Unlike narrow AI, AGI can apply intelligence to solve any problem, not just those for which it has been explicitly trained. AGI remains theoretical and has not yet been achieved, but its potential applications span a wide range of industries, including healthcare, finance, and education. AGI would possess human-like reasoning, learning, and problem-solving abilities. It would be able to transfer knowledge across various domains, much like how humans adapt to new situations (4).

- **Superintelligent AI, Super AI or Artificial Superintelligence (ASI)**, is the theoretical level of AI wherein its capabilities exceed that of human intelligence, and it attains self-awareness. These hypothetical AI systems possess the potential to become the most proficient form of intelligence on the planet, outstripping human intelligence and being markedly better at all tasks we undertake (5).

1.2.3 Application of Artificial Intelligence

Artificial Intelligence is revolutionizing many facets of our lives. Not only is it changing the way we write, travel, and educate the next generation, but its applications are also expanding into even more industries (8).

These real-world applications of AI are rapidly being integrated into sectors like engineering, healthcare, and customer service.

Among these applications, we can mention:

- **Healthcare** One of the primary goals of health-related AI applications is to analyze the relationships between prevention or treatment techniques and patient outcomes. AI programs have been developed and applied to various practices, including the entire diagnostic process, treatment planning, drug development, personalized medicine, and patient monitoring and care (6).

  Advancements in AI have increased the accuracy of diagnoses and reduced the likelihood of errors in treatment. This, in turn, has helped doctors gain a deeper understanding of patients' conditions, improved the quality of feedback, guidance, and counseling, and facilitated the identification of other potentially related medical issues. (6)

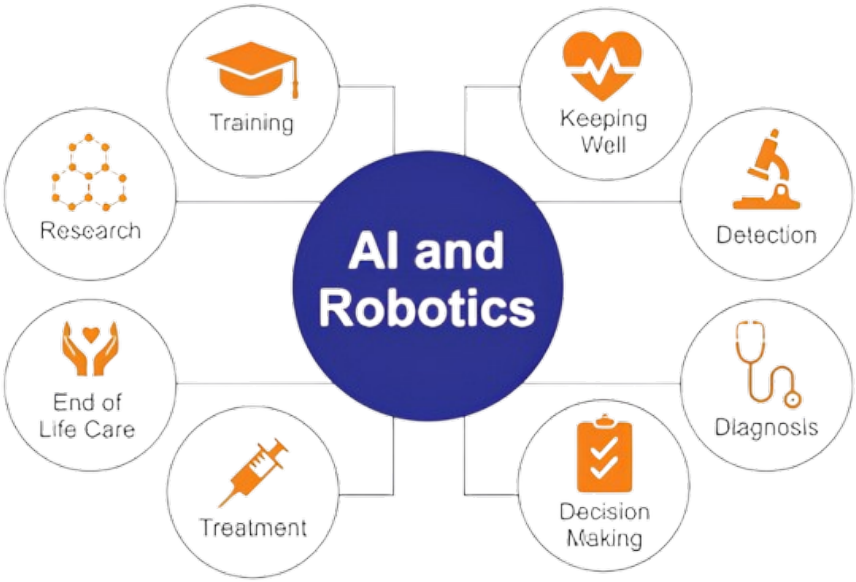

Figure 1.1: Areas of Use of AI and Robotics in Healthcare (6)

- **Agriculture** AI has the ability to inform precision agriculture to help farmers with their day-to-day workload. When it comes to the soil for growing crops, machine learning can identify potential deficiencies to determine which crop would be the best to grow on what soil (10).

  AI-enabled systems make weather predictions, monitor agricultural sustainability, and assess farms for the presence of diseases or pests and undernourished plants using data like temperature, precipitation, wind speed, and sun radiation in conjunction with photographs taken by satellites and drones.(9)

- **Natural Language Processing** a branch of Artificial Intelligence that focuses on the interaction between computers and humans using human language. Its primary objective is to empower computers to comprehend, interpret, and produce human language effectively (7).

  NLP encompasses diverse tasks such as text analysis, language translation, sentiment analysis, and speech recognition. Continuously evolving with technological advancements and ongoing research, NLP plays a pivotal role in bridging the gap between human communication and machine understanding (7).

- **Gaming** AI has become a pivotal element in the gaming industry, fundamentally transforming how games are designed and experienced, from creating lifelike nonplayable characters NPCs to developing sophisticated opponents that can react, adapt, and learn from player behavior. By introducing AI, developers can craft more dynamic, challenging, and engaging experiences that push the boundaries of traditional game design.(14)

- **Education**

  AI is transforming education by enabling personalized learning experiences, intelligent tutoring systems, and automated grading. AI can adapt to individual student needs, provide real-time feedback, and offer personalized educational content(13).

1.3 Machine Learning

Directly underneath **AI**, we have **machine learning** (ML), which involves creating models by training an algorithm to make predictions or decisions based on data.

It encompasses a broad range of techniques that enable computers to learn from, and make inferences based on, data without being explicitly programmed for specific tasks.

1.3.1 Definition of Machine Learning

Machine Learning systems are capable of learning from vast amounts of data and progressively enhancing their performance over time, particularly when supplied with larger volumes or higher-quality training data.

Leveraging the 'knowledge' acquired during this training process, machine learning-powered AI systems are then able to make predictions—such as in weather forecasting—or identify patterns within data, as seen in applications like image and speech recognition (12).

1.3.2 Types of Machine Learning and its Algorithms

Machine learning is commonly categorized into three primary types: **supervised learning**, **unsupervised learning**, and **reinforcement learning**, each encompassing distinct algorithms and use cases.

In **supervised learning**, models are trained on labeled datasets to perform prediction or classification tasks. Typical algorithms in this category include linear regression and logistic regression for prediction and binary classification, as well as decision trees, random forests, support vector machines (SVMs), and k-nearest neighbors (KNN) for more complex classification and regression problems.

Unsupervised learning, by contrast, works with unlabeled data and is primarily used to identify hidden patterns or structures within the data. Widely used algorithms include K-means clustering, hierarchical clustering, and principal component analysis (PCA) for dimensionality reduction and data visualization.

Reinforcement learning involves training agents to make sequential decisions by interacting with an environment in order to maximize cumulative rewards. Prominent algorithms in this field include Q-learning, Deep Q-Networks (DQN), and policy gradient methods.

Each type of machine learning addresses different problem domains and is selected based on the nature of the data and the specific objectives of the task at hand.

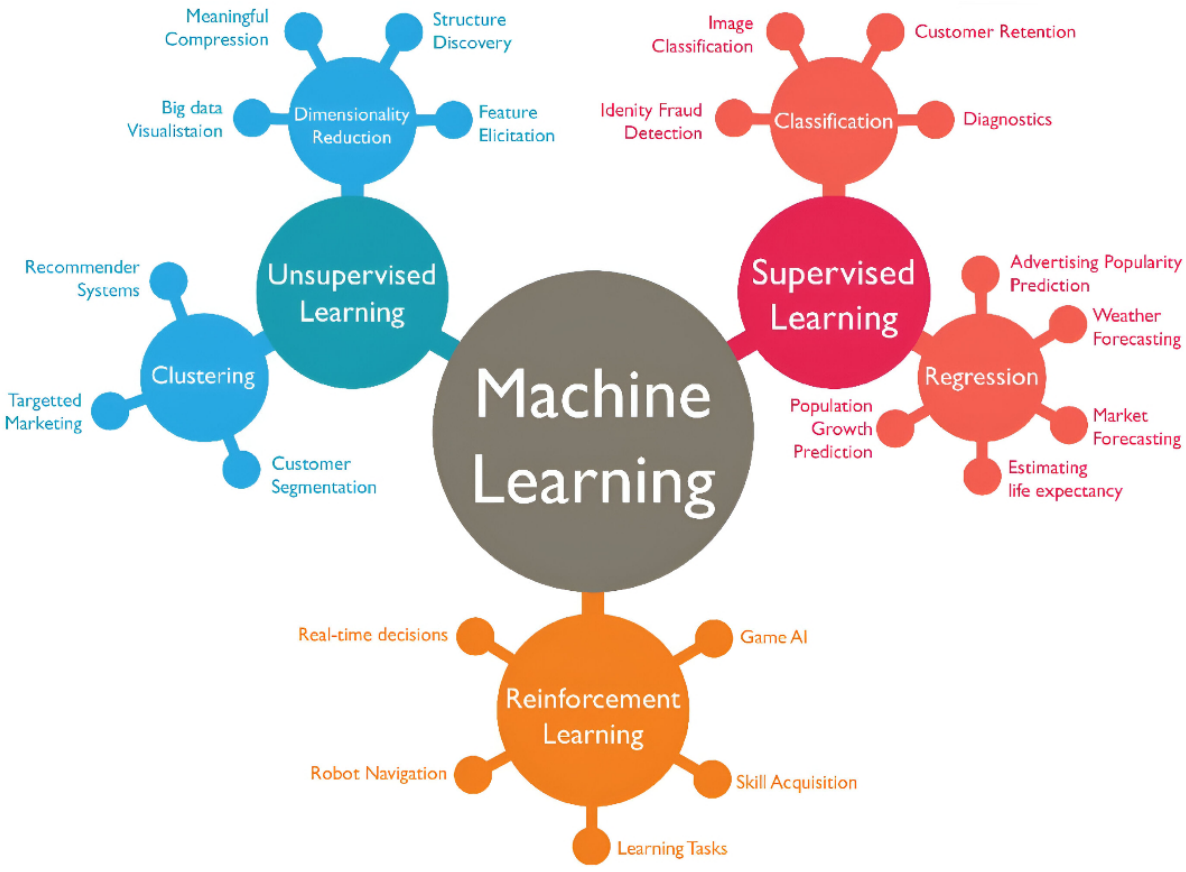

Figure 1.2: Types of Machine Learning and Their Algorithms (11)

1.4 Artificial Neural Networks

Neural networks, also known as **artificial neural networks (ANNs)** or **synthetic neural networks (SNNs)**, are a class of machine learning models that form the foundation of many deep learning techniques. Their name and structure are inspired by the human brain, mimicking the way biological neurons communicate with one another.

Neural networks NNs consist of interconnected layers of simple processing units artificial neurons that work together in a massively parallel manner. These systems can include millions of such neurons and connections, enabling them to learn complex patterns and perform tasks such as image recognition, natural language processing, and autonomous decision-making.

1.4.1 Multi-Layer Perceptron

A Multi-Layer Perceptron (MLP) is a type of artificial neural network composed of multiple layers of neurons, or nodes, arranged in a hierarchical structure. It is one of the simplest, yet most widely used, forms of neural networks, particularly in supervised learning tasks such as classification and regression (15).

An MLP is composed of several layers of neurons, namely:

- **An input layer**, where the data is received.
- **One or more hidden layers**, where the network learns patterns from the input.
- **An output layer**, which produces the final prediction or classification.

Each neuron in a given layer is connected to every neuron in the subsequent layer, forming what is referred to as a fully connected network.

To introduce non-linearity and enable the model to learn complex patterns, MLPs typically employ activation functions such as ReLU, sigmoid, or tanh.

These networks are commonly trained using a technique called backpropagation, which adjusts the weights of the connections based on the error of the network's output in comparison to the expected result.

1.4.2 Feedforward and Backward Propagation process

Feedforward propagation is the process by which input data flows through an artificial neural network (ANN) from the input layer to the output layer. Each neuron receives input from the preceding layer, computes a weighted sum, adds a bias, and applies an activation function—commonly sigmoid, ReLU, or tanh. This operation is performed sequentially, layer by layer, until the final output is generated. The objective of feedforward propagation is to produce predictions or classifications based on the given input. In the context of Convolutional Neural Networks (CNNs), feedforward propagation also encompasses convolutional and pooling layers, which are responsible for extracting spatial features from image data (27; 28).

Backward propagation, or *backpropagation*, is the learning algorithm used to update the weights of a neural network by minimizing the discrepancy between predicted and actual outputs. Following the feedforward pass, the loss—typically measured using Mean Squared Error or Cross-Entropy Loss—is computed. Backpropagation then employs the chain rule of calculus to determine the gradient of the loss function with respect to each weight in the network. These gradients are subsequently utilized to adjust the weights through optimization algorithms such as Stochastic Gradient Descent (SGD) or Adam. This iterative process is repeated over multiple epochs until the network converges to a state of minimal prediction error (29; 30).

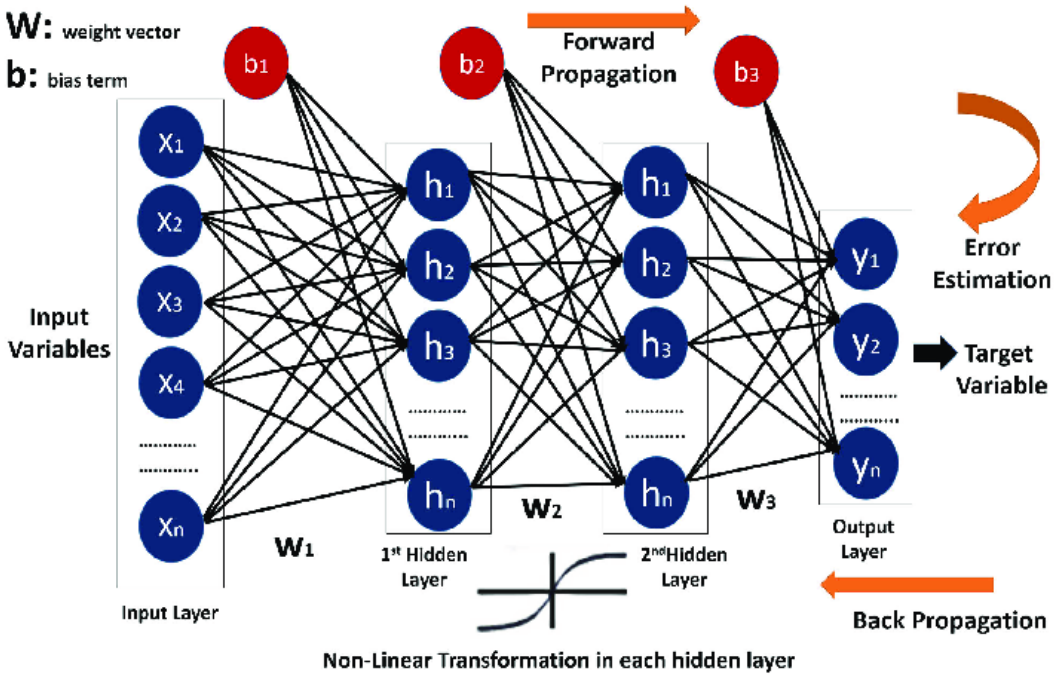

Figure 1.3: Multi-Layer Perceptron architecture (46)

1.5 Deep Learning

Deep learning is a subfield of machine learning that employs neural networks with multiple layers to model and solve complex tasks. Unlike traditional methods, deep learning algorithms automatically extract high-level features from raw data, making them particularly effective for applications such as image recognition, natural language processing, and autonomous systems. Among the various deep learning architectures, **Convolutional Neural Networks (CNNs)** have proven especially powerful in processing visual data, due to their ability to automatically detect and learn patterns such as edges, textures, and objects. This capability has significantly advanced the field of computer vision, enabling machines to interpret and analyze images with remarkable accuracy.

1.5.1 Convolutional Neural Network

A **Convolutional Neural Network (CNN)** architecture is composed of several specialized layers arranged in a structured manner to effectively process and analyze visual data.

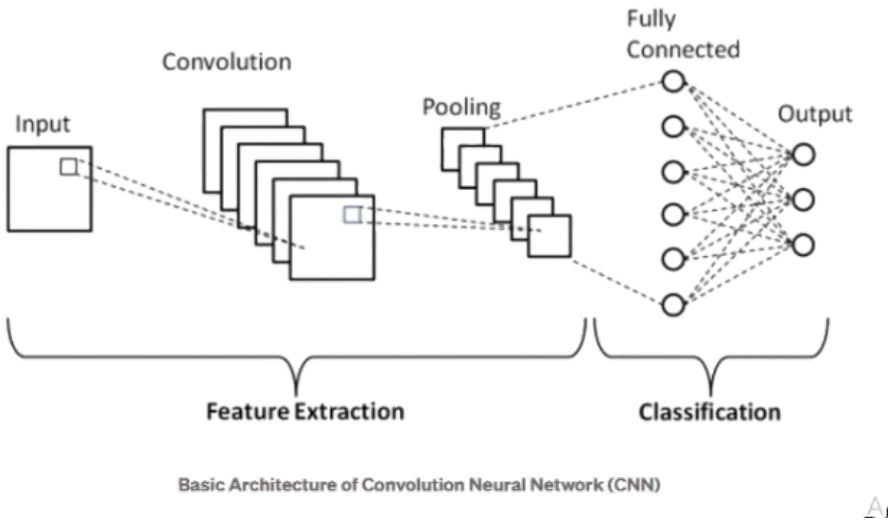

Figure 1.4: Architecture of a Convolutional Neural Network (CNN) (15)

Layers of a Convolutional Neural Network:

- **Input Layer:** The input layer receives the initial data.
- **Convolutional Layer:** The convolutional layer is the core component of a CNN, composed of multiple filters designed to detect specific features within an input image. Its primary operation is the convolution, which involves sliding a filter (or kernel) over the input data, performing element-wise multiplication, and summing the results. This process enables the network to identify and highlight important visual patterns such as edges, textures, or shapes.
  By stacking multiple convolutional layers, each with different filters, the network can progressively extract increasingly abstract and complex features from the input data. Although convolutional layers perform linear operations, activation functions are applied afterward to introduce non-linearity, enabling the network to learn complex, non-linear patterns. Common activation functions such as ReLU, Sigmoid, and Tanh are applied element-wise to each pixel in the feature map, allowing the network to capture more diverse and expressive features across layers.
- **Pooling Layer:** The pooling layer plays a key role in downsampling feature maps by reducing their spatial dimensions—width and height—while preserving the number of channels. This is achieved by moving a small filter across each feature map and applying a summarizing operation, such as maximum or average pooling. This process helps decrease the computational load and enhances feature robustness by retaining the most important information.

- **Fully Connected Layer:** The final operation before classification is the flattening procedure, where the output matrix is transformed into a one-dimensional vector. This vector serves as the input to a standard densely connected neural network.
- **Output Layer:** The output layer generates the final prediction, often using a Softmax activation function for multi-class classification tasks, producing a probability distribution across all possible classes.

1.5.2 Region-based CNNs

To further enhance object detection and localization tasks, researchers have introduced **Region-based Convolutional Neural Network (R-CNN)** models, which combine CNN-based feature extraction with region proposal techniques. This section discusses the foundational concepts of R-CNN architectures, from the original R-CNN to its more optimized successors *Fast R-CNN*, *Faster R-CNN*, highlighting their architectural improvements and practical applications in visual recognition systems.

The **Region-based Convolutional Neural Network (R-CNN)** is a deep learning architecture used for object detection in computer vision tasks. R-CNN was one of the pioneering models that advanced the field of object detection by integrating convolutional neural networks with region-based approaches (16).

The R-CNN detector first generates region proposals using algorithms such as *Edge Boxes*. These proposed regions are cropped from the image and resized. Subsequently, a CNN classifies the cropped and resized regions. Finally, the region proposal bounding boxes are refined using a *Support Vector Machine (SVM)* trained on CNN-extracted features (17).

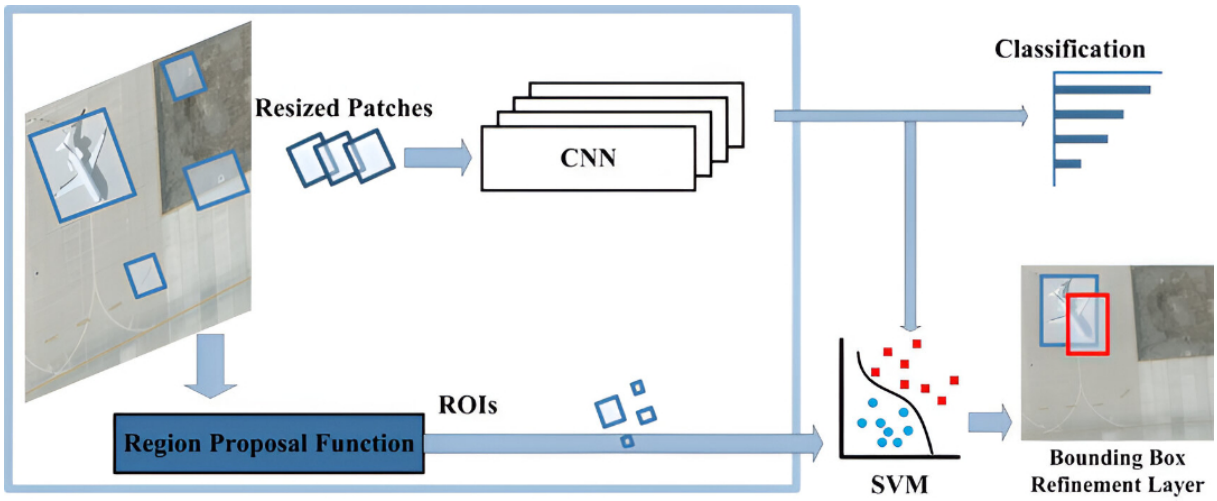

Figure 1.5: R-CNN architecture (19)

1.5.3 Fast R-CNN

While the original **R-CNN** independently computed neural network features for each of up to two thousand regions of interest, **Fast R-CNN** significantly improves efficiency by running the neural network once on the entire image.

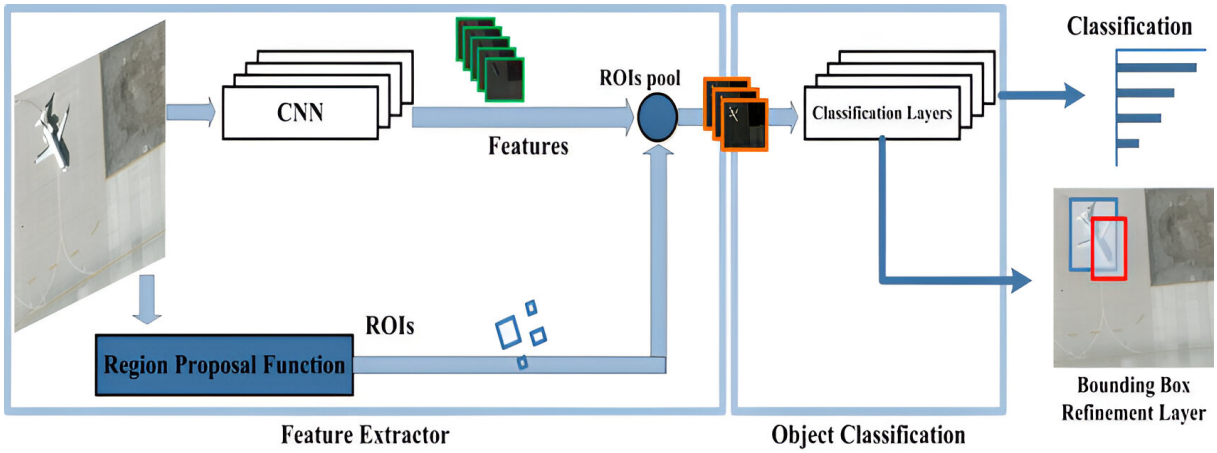

Figure 1.6: Fast R-CNN architecture (19)

1.5.4 Faster R-CNN

Faster R-CNN replaces the selective search algorithm used in *Fast R-CNN* with a jointly trained **Region Proposal Network (RPN)**, enabling it to maintain high accuracy in object detection while significantly reducing the number of region proposals (18).

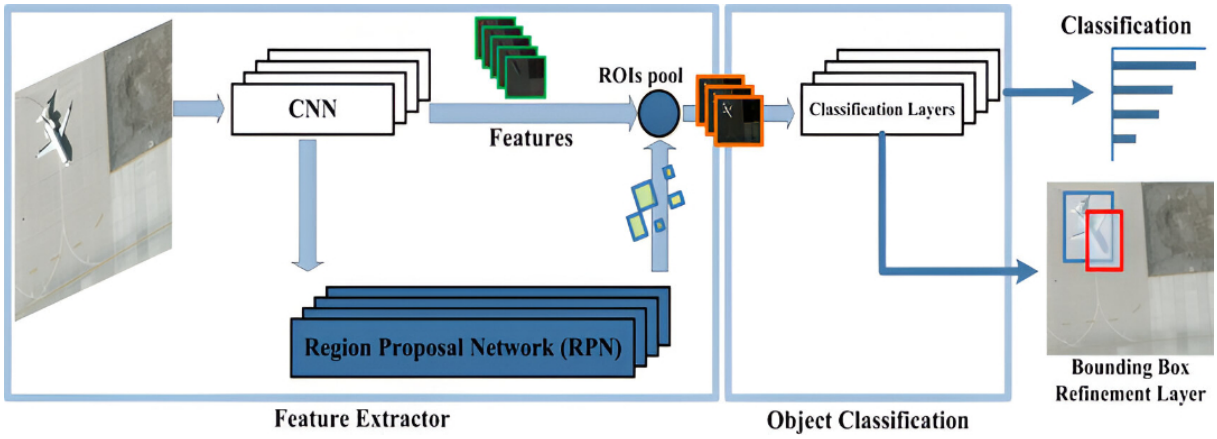

Figure 1.7: Faster R-CNN architecture (19)

As a **conclusion**, R-CNN extracts a large number of region proposals from the input image and applies CNN-based forward propagation to each proposal individually to extract features. These features are then used to predict the class and bounding box for each region (13).

A major improvement introduced by **Fast R-CNN** is that CNN forward propagation is performed only once on the entire image, rather than separately for each region. Additionally, it introduces the *Region of Interest (RoI) pooling* layer, which enables the extraction of fixed-size feature maps from regions of varying shapes (13).

Faster R-CNN further enhances efficiency by replacing the selective search algorithm used in Fast R-CNN with a jointly trained **Region Proposal Network (RPN)**. This modification allows the model to maintain high accuracy in object detection while significantly reducing the number of region proposals (13).

1.5.5 YOLO: You Only Look Once — A Unified Approach to Real-Time Object Detection

Object detection is a fundamental task in **computer vision**, responsible for identifying and localizing objects within digital images or video frames. One of the most transformative advancements in this domain is the **YOLO (You Only Look Once)** algorithm, first introduced by Redmon et al. in 2016. Unlike traditional object detection models that rely on multi-stage pipelines—such as R-CNN, which first generates region proposals and then classifies them—YOLO presents a unified architecture that formulates detection as a single regression problem, thereby significantly improving speed and simplicity (32).

YOLO divides the input image into a grid and predicts bounding boxes and class probabilities for each cell in a single forward pass of **a convolutional neural network (CNN)**. This architecture enables real-time processing, with the original version achieving up to 45 frames per second (fps) on a Titan X GPU (32). Due to its high efficiency, **YOLO** is particularly well-suited for applications requiring low-latency inference, such as autonomous driving, surveillance systems, and robotics (34).

A key strength of **YOLO** lies in its ability to generalize effectively across domains. Trained on large and diverse datasets such as ImageNet and COCO, YOLO learns robust and transferable visual features that perform well in varied object detection scenarios. However, it does have limitations. YOLO tends to underperform in detecting small or closely packed objects, primarily due to the coarse spatial resolution imposed by its grid-based prediction mechanism (32; 34).

Table 1.1: Evolution of YOLO Versions

Version	Key Improvements and Highlights
YOLOv1 (2016)	Introduced the one-stage detection paradigm. Suffered from localization issues and poor performance on small objects due to fixed grid structure (32).
YOLOv2 (YOLO9000)	Introduced anchor boxes, batch normalization, and the Darknet-19 backbone, improving accuracy and inference speed (33).
YOLOv3 (2018)	Added multi-scale prediction, residual connections, and a deeper backbone (Darknet-53), enhancing performance on objects of various sizes (34).
YOLOv4 (2020)	Introduced CSPDarknet53, SPP block, and advanced augmentation techniques. Achieved state-of-the-art performance with real-time inference (35).
YOLOv5 (2020)	Developed by Ultralytics in PyTorch. Emphasized ease of use, modularity, and deployment flexibility. Supported multiple model sizes for edge devices (36).
YOLOv6 (2022)	Incorporated CSPNet-evo, adaptive anchor assignment, and other architectural refinements to further improve the speed-accuracy trade-off (37).
YOLOv8 (2023)	Introduced a new backbone, improved training pipeline, and augmentation techniques, making it one of the most efficient and accurate YOLO versions (36).
YOLOv9 (2024)	Integrated transformer-based feature extractors, optimized training schedules, and enhanced performance on occluded or overlapping objects (38).

1.6 Conclusion

In this chapter, we explored the foundational concepts of **Artificial Intelligence**, **Machine Learning**, and **Deep Learning**, which collectively constitute the technological backbone of modern intelligent systems. We began by introducing the core principles and applications of AI, emphasizing its role in enabling machines to simulate human-like intelligence. Subsequently, we examined machine learning, focusing on its definition, various learning paradigms, and the associated algorithms that empower systems to improve performance through data-driven learning.

Moreover, we investigated **artificial neural networks**, with particular attention to **the Multi-Layer Perceptron** and its **feedforward and backpropagation** mechanisms, which form the computational foundation for learning in neural models.

Finally, we analyzed advanced **deep learning** techniques, particularly **Convolutional Neural Networks** and their region-based variants, which have significantly propelled progress in the domain of computer vision.

Together, these components provide a comprehensive understanding of how intelligent systems are designed, trained, and deployed across real-world applications.

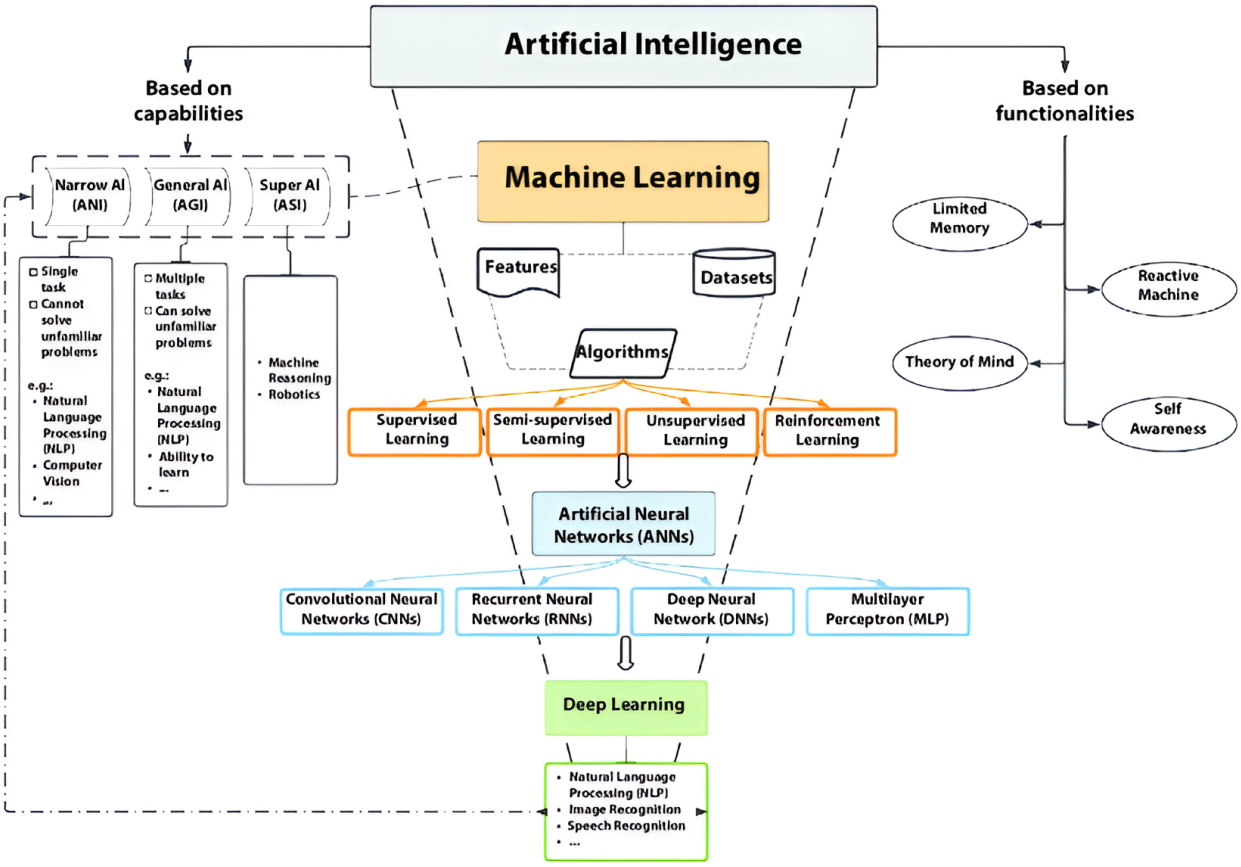

Figure 1.8: The relationships between AI, ML, and DL.(14)

2

Related Work

2.1 Introduction

In the previous chapter, we introduced the fundamental concepts of AI , beginning with its definition, underlying principles, and real-world applications. We then examined ML, outlining its main learning paradigms and commonly used algorithms. The discussion advanced to ANNs, where we detailed the structure of Multi-Layer Perceptrons (MLPs) and the mechanisms of forward and backward propagation.

Subsequently, we focused on Deep Learning (DL), with particular emphasis on Convolutional Neural Networks (CNNs). We explored several region-based object detection models, including R-CNN, Fast R-CNN, Faster R-CNN, and the YOLO architectures, all of which have demonstrated notable improvements in detection accuracy and computational efficiency.

In this chapter, we review and analyze the existing literature and research studies on drone detection using AI-based approaches. The objective is to assess the current state of the art in this domain, evaluate the methodologies adopted in various works, and identify prevailing challenges and research gaps. This literature review provides essential context for our study and positions our contribution within the broader landscape of advancements in drone detection systems.

2.2 Deep Learning for Drone Detection

The following section begins with one-stage detectors, which offer real-time performance and are widely used in drone detection tasks.

2.2.1 One-Stage Detection Models

One-stage object detectors predict object categories and bounding boxes in a single inference step. Their architecture enables faster detection, making them ideal for time-sensitive applications like drone monitoring.

YOLO Series (You Only Look Once)

Redmon et al. (48; 49) introduced the YOLO family of models, which frame object detection as a regression problem. YOLOv3 brought significant improvements using Darknet-53 as the backbone and multi-scale feature prediction, achieving a mean average precision (mAP) of 57.9% on the PASCAL VOC dataset at over 45 FPS. This performance makes YOLO models particularly effective for drone detection where rapid response is essential.

Subsequent work has focused on adapting YOLO to UAV scenarios:

- Abdelkader et al. (50) implemented YOLOv4 for UAV surveillance and demonstrated its ability to detect drones in urban settings with an mAP of 74% at 20 FPS, validating its real-time applicability.
- Tahir et al. (51) employed YOLOv5 for multiclass aerial object detection, including drones, birds, and balloons. Their approach achieved an mAP@0.5 of 85%, showcasing high accuracy in distinguishing between visually similar objects.
- Gürbüz and Akgül (52) performed a benchmark evaluation of YOLOv3 and YOLOv5 for UAV tracking. Their findings highlighted YOLOv5's superior balance of speed and accuracy, which proved effective in dynamic aerial tracking environments.

SSD (Single Shot MultiBox Detector)

Liu et al. (57) proposed SSD, which enables real-time object detection by using feature maps at multiple scales and default anchor boxes. Although typically slightly less accurate than two-stage detectors, SSD is preferred for speed-critical applications.

Mao et al. (58) applied the SSD MobileNet model on a low-power NVIDIA Jetson Nano for UAV detection. They achieved approximately 10 FPS with 65% mAP, demonstrating that SSD-MobileNet is a viable solution for deploying detection systems on embedded devices.

2.2.2 Two-Stage Detection Models

Faster R-CNN

Ren et al. (53) developed Faster R-CNN by introducing a Region Proposal Network (RPN) that shares convolutional features with the detector, significantly speeding up the pipeline compared to previous region-based methods.

Chen et al. (54) used Faster R-CNN with a ResNet-50 backbone to detect UAVs in urban environments. Their model achieved 78.5% mAP but operated at only 2 FPS, making it more suitable for offline or precision-critical applications.

Gürbüz and Akgül (52) included Faster R-CNN in their benchmark and confirmed its high precision in complex scenes, although its lower speed compared to YOLO limited its practicality in real-time drone monitoring systems.

2.3 Multi-Task Learning Approaches

Multi-task learning (MTL) strategies allow simultaneous training for classification and localization, leveraging shared representations to enhance performance and efficiency.

- Zhou and Wu (55) introduced a multi-task convolutional neural network (CNN) that achieved 96% classification accuracy and a bounding box mean absolute error (MAE) of 0.02, indicating accurate spatial localization and object categorization.
- Ahmed et al. (56) proposed a custom multi-output CNN that was trained to simultaneously classify drones and predict bounding boxes. It reached 98.53% accuracy with a bounding box MAE of 0.0256, demonstrating both high precision and generalization.

2.4 Drone Detection in Challenging Conditions

Real-world drone detection is complicated by adverse conditions such as rain, complex backgrounds, or poor lighting, which can degrade model performance.

- Wang and Liu (59) investigated the effect of rainy weather and background complexity on UAV detection. Their study showed that performance degraded significantly under such conditions, and they proposed preprocessing techniques to enhance robustness.
- Siddiqui et al. (60) provided a detailed review of drone detection methods, identifying limitations in generalization under varied conditions. They stressed the importance of adaptive models that can handle dynamic environments, occlusion, and weather variation.

2.5 Tracking Techniques

Tracking complements detection by following identified objects over time. It is crucial in UAV surveillance to estimate drone trajectories and behaviors.

- Deep SORT (61) is a tracking-by-detection framework that combines a Kalman filter with deep appearance embeddings for robust identity preservation across frames. It is commonly integrated with YOLO-based detectors for UAV monitoring.
- Gürbüz and Akgül (52) combined Deep SORT with YOLOv5 and showed that the fusion resulted in enhanced tracking performance in aerial scenarios, achieving smoother tracking even in occluded or cluttered environments.

2.6 Hybrid and Passive Detection Approaches

Visual-based methods can be complemented by other sensing modalities, improving detection in challenging or constrained scenarios.

Singh et al. (62) reviewed passive UAV detection techniques, such as radio frequency (RF) signal analysis, acoustic sensing, and infrared imaging. These methods are especially useful in poor visibility conditions or long-range detection and can be fused with visual techniques to build more robust hybrid systems.

2.7 Conclusion

In this chapter, we explored a broad range of techniques and models that have shaped the current landscape of drone detection. From traditional object detection approaches to modern deep learning architectures such as YOLO, SSD, and Faster R-CNN, each method has contributed valuable insights and performance benchmarks. We also reviewed multi-task learning (MTL) strategies, which are gaining attention for their ability to simultaneously perform classification and localization, offering promising improvements in accuracy and efficiency.

Furthermore, we discussed the key challenges that persist in drone detection, particularly under real-world conditions such as small object size, visual similarity to other aerial objects (e.g., birds and balloons), and varying lighting or weather environments. We also reviewed recent efforts in integrating tracking mechanisms, hybrid models, and data augmentation techniques to enhance model robustness.

While existing models have achieved remarkable progress, they still leave room for improvement in generalization and real-time performance, especially in critical applications like security and surveillance. These limitations open up new opportunities for developing more tailored solutions.

This review helped us identify important gaps that our work aims to address particularly through the design of a custom MTL model that balances both classification and bounding box prediction, evaluated under challenging scenarios. The following chapter presents our proposed methodology and details the rationale behind our architectural and experimental choices.

Table 2.1: Summary of UAV detection methods and their performance.

Reference	Method	Dataset Type	Performance	Notes / Limitations
Dadrass et al. (2023) (50)	YOLOv4	UAV Images	94.3% Accuracy	Struggles in low-light conditions
Abdelkader et al. (2022) (50)	YOLOv4	UAV Video (Urban)	74% mAP @ 20 FPS	Real-time capable; moderate precision
Tahir et al. (2023) (51)	YOLOv5	Multiclass UAV/Bird/Balloon	85% mAP@0.5	Misclassification between similar classes
Gürbüz & Akgül (2023) (52)	YOLOv5 + Deep SORT	UAV Tracking	–	Excellent tracking; requires frequent re-detection
Chen et al. (2023) (54)	Faster R-CNN (ResNet-50)	Aerial UAV Images	78.5% mAP @ 2 FPS	High precision, low speed
Zhou & Wu (2022) (55)	MTL CNN	UAV Dataset	96% Accuracy, MAE = 0.02	No real-time testing
Mao et al. (2021) (58)	SSD MobileNet	Jetson Nano (Embedded)	65% mAP @ 10 FPS	Good for low-power deployment
Gong et al. (2023) (52)	Radar-Based	RF Radar Signals	–	Hardware dependent; not vision-based
Leonardi (2023) (52)	Micro-Doppler Radar	Radar Data	88.5% Accuracy	Confuses birds with UAVs
Kumari (2024) (60)	Stereo + DL	Simulated UAVs	92.7% Accuracy	Tested only on simulations
Singh et al. (2024) (62)	Hybrid (RF, IR, Acoustic)	Passive Sensing	–	Requires multi-sensor fusion; useful in poor visibility

3

Our Contribution

3.1 Introduction

The rapid proliferation of **unmanned aerial vehicles (UAVs)**, commonly known as **drones**, has opened new frontiers across diverse industries, ranging from aerial photography and logistics to agriculture and surveillance. However, this surge in drone usage also introduces significant challenges in public safety, airspace regulation, and privacy. As a result, automatic drone detection has become a critical component in modern surveillance and security systems. Traditional object detection models typically perform two separate tasks:

- **identifying the type of object** (classification).
- **locating it within the image** (bounding box regression).

This project introduces a **Multi-Task Learning (MTL) approach**, where both tasks are learned jointly within a **unified neural network**.

The key idea behind **MTL** is to leverage shared representations for related tasks, improving model generalization and computational efficiency.

In this project, we develop and evaluate **a custom deep learning model** designed to **detect** and **classify** aerial objects such as drones, birds, and planes.

The model is trained on a curated drone detection dataset and is benchmarked against state-of-the-art pretrained models such as **YOLOv8**, **Faster R-CNN**. Through this comparative study, we aim to assess the effectiveness of **MTL** in solving real-world drone detection problems.

For tracking purposes, algorithms based on the **Kalman** Filter have demonstrated effectiveness in maintaining the consistent trajectories of**UAVs** across video frames. The Kalman Filter operates by recursively predicting and updating the position of moving objects, allowing it to handle measurement noise and temporary occlusions efficiently.

When integrated with object detectors such as MTL, the Kalman Filter forms a lightweight yet reliable pipeline for real-time UAV detection and tracking. This approach enhances situational awareness in both civilian and military applications, especially in scenarios requiring fast, low-latency processing on resource-constrained systems.

3.2 Libraries and Platforms

The libraries and platforms employed in this project are as follows:

- **Google Colab**
  Google Colab, short for Google Colaboratory, is a free cloud-based platform provided by Google that allows users to write and execute Python code directly in the browser. It supports Jupyter notebooks and provides access to powerful computational resources, including GPUs and TPUs, which are particularly beneficial for deep learning tasks. These hardware accelerators can be enabled with just a few clicks, significantly reducing training time for models (20).

- **Python**
  Python is a high-level, interpreted, general-purpose programming language that emphasizes readability and simplicity through the use of indentation. It supports multiple programming paradigms, including procedural, object-oriented, and functional programming. Python is widely used in fields such as web development, data science, artificial intelligence, and scientific computing (31).

- **TensorFlow**
  TensorFlow is an open-source software library designed for high-performance numerical computation and machine learning. Its flexible architecture enables deployment across various platforms—CPUs, GPUs, and TPUs—from desktops and servers to mobile and edge devices (21).

- **Keras**
  Keras is a high-level neural networks API written in Python, designed for ease of use and rapid experimentation. It runs on top of backends such as TensorFlow, CNTK, and Theano, and is valued for its modularity, simplicity, and extensibility (22).

- **Matplotlib**
  Matplotlib is a comprehensive library used for creating static, animated, and interactive visualizations in Python. It supports a wide range of plot types, including line graphs, histograms, and scatter plots, making it an essential tool for data visualization and scientific reporting (23).

- **NumPy**
  NumPy is a fundamental library for numerical computing in Python. It provides support for large multi-dimensional arrays and matrices, along with an extensive collection of high-level mathematical functions to operate on these arrays efficiently (24).

- **Filterpy**
  filterpy library is a Python package that provides a simple and efficient implementation of Kalman filtering techniques, including the standard Kalman Filter, Extended Kalman Filter, and Unscented Kalman Filter. It is widely used in the research community and prototyping environments due to its ease of use and clarity. (25).

3.3 Multi-Task Learning Model for Drone Detection and Classification

In this work, we propose a **Multi-Task Learning (MTL) approach** for drone detection and classification in aerial imagery.

This **approach** was developed to address the challenge of detecting and classifying drones and other aerial objects within a single, unified framework.

Rather than employing separate models for object localization and classification, the proposed **MTL architecture** simultaneously learns both tasks.

The model comprises a shared convolutional backbone that extracts meaningful visual features from the input images.

These features are then passed to two parallel branches:

- **Object Classification** Responsible for predicting the category of the detected object (e.g., drone, plane, balloon, or helicopter).
- **Bounding Box Regression** Responsible for estimating the bounding box coordinates of the object.

This joint learning strategy enables the model to leverage shared representations, leading to improved accuracy, reduced training time, and enhanced generalization.

The proposed architecture was trained on a labeled aerial dataset and evaluated to assess its performance in detecting and classifying aerial objects under real-world conditions.

3.3.1 Dataset Collection and Preparation

The dataset used in this study is the Drone Detection dataset by *cybersimar08*, available on Kaggle. This dataset consists of images featuring drones, each annotated with bounding boxes that accurately localize the drone within the scene.

These annotations provide precise localization information, facilitating the detection and tracking of drones across various backgrounds and environments. Each image is accompanied by metadata, including bounding box coordinates, image resolution, and class labels identifying the drone objects.

This dataset is well-suited for training and evaluating computer vision models in object detection tasks, particularly in applications such as surveillance, drone detection, and autonomous tracking (26).

- **Dataset Augmentation:** To enhance the robustness and generalization capability of the proposed model, data augmentation techniques were applied to artificially expand the training dataset.

These techniques simulate diverse real-world conditions under which drones and other aerial objects may appear, such as variations in orientation, lighting, scale, and position. The following augmentation methods were employed:

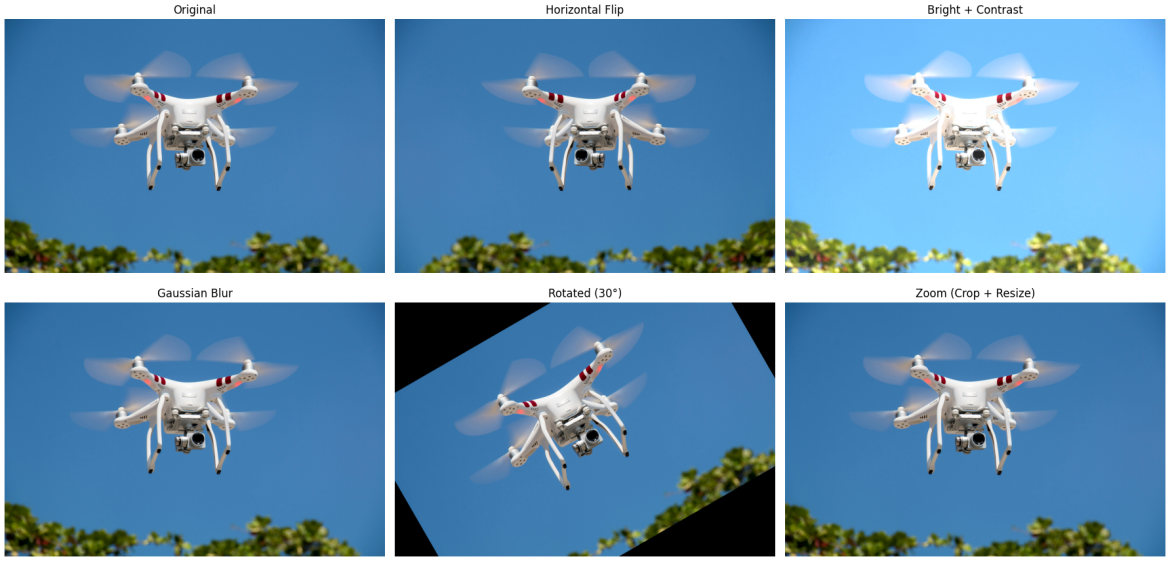

Figure 3.1: Visual Demonstration of Data Augmentation Techniques

  - **Horizontal Flip:** Images are mirrored along the vertical axis to simulate different viewpoints, enabling the model to recognize drones from symmetric angles.
  - **Brightness and Contrast Adjustment:** Pixel intensity and contrast levels are modified to emulate various lighting conditions, thereby improving the model's resilience to environmental variations.
  - **Gaussian Blur:** A blurring effect is applied to simulate noise and low-quality input, enhancing the model's robustness to out-of-focus or degraded images.
  - **Rotation (30°):** Images are rotated by 30 degrees to help the model detect aerial objects from diverse orientations.

- **Dataset Splitting:** The dataset used in this study contains a total of 12,001 annotated images representing aerial objects such as drones, planes, balloons, and helicopters. For the purpose of model training and evaluation, the dataset was divided into three subsets:
  - **Training Set:** Consists of 10,800 images (approximately 90% of the dataset), used to train the model and enable it to learn features and localization patterns effectively.
  - **Validation Set:** Contains 604 images, utilized during training to monitor the model's performance on unseen data and assist in hyperparameter tuning for optimal generalization.
  - **Testing Set:** Comprises 596 images, reserved for final performance evaluation. This set provides an unbiased measure of the model's ability to detect and classify objects in new and unseen scenarios.

3.3.2 Model Architecture

In this work, we propose a Multi-Task Learning (MTL) approach to address the problem of drone detection and classification.

Instead of training two separate models for each task (i.e., object classification and localization), we design a single neural network that performs both tasks simultaneously.

This method improves model efficiency, reduces overfitting, and allows the learning of shared feature representations across tasks.

The architecture is composed of the following components:

- **Input Layer:**
  - The input layer accepts images of shape $(128, 128, 3)$, corresponding to normalized RGB images.
  - All input images are resized to this fixed dimension to maintain uniformity throughout the model pipeline.
- **Shared Convolutional Backbone:**
  - A series of convolutional and pooling layers are employed to extract high-level feature representations from the input image.
  - Specifically, the backbone consists of:
    * A Conv2D layer with 32 filters and a (3×3) kernel, activated by ReLU
    * A MaxPooling2D layer with a pool size of (2×2)
    * A Conv2D layer with 64 filters, followed by another MaxPooling2D layer
    * A Conv2D layer with 128 filters, followed by a final MaxPooling2D layer
    * A Flatten layer to convert the spatial feature maps into a one-dimensional vector
    * A Dense layer with 128 units and ReLU activation for further feature abstraction
- **Task-Specific Output Heads:**
  - **Classification Head:**
    * A Dense layer with four output units, corresponding to the object classes (e.g., drone, plane, balloon, helicopter), using a `softmax` activation function
    * Outputs the class probability distribution across the defined categories

- **Bounding Box Regression Head:**
  - A Dense layer with four output units representing the normalized bounding box coordinates $[x_{\text{center}}, y_{\text{center}}, w, h]$
  - Employs a `linear` activation function to produce precise spatial predictions

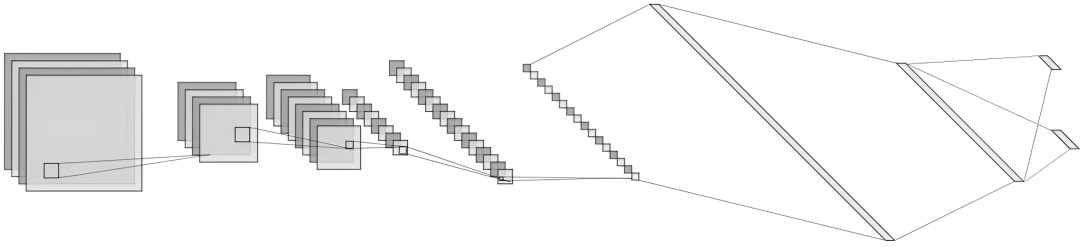

Figure 3.2: Multitask Learning Architecture

The proposed Multi-Task Learning (MTL) model offers a unified and efficient framework for drone detection and classification.

Leveraging a shared CNN backbone and separate output heads, the network simultaneously identifies the class of an aerial object and localizes it within the image.

This approach is particularly advantageous in real-world applications such as aerial surveillance and drone traffic monitoring, where both object identity and spatial location are critical.

The benefits of the proposed MTL architecture include:

- **Efficiency** – A single model simultaneously performs both classification and localization, thereby reducing memory consumption and computational runtime.

- **Improved Generalization** – Shared feature extraction layers capture representations that are informative for both tasks, enhancing the model's performance on unseen data.

- **Implicit Regularization** – Joint learning discourages overfitting by promoting feature sharing and cross-task dependencies.

3.3.3 Model Compilation and Training

To effectively train the proposed Multi-Task Learning (MTL) model, the compilation process incorporates suitable loss functions, balanced task weighting, and appropriate training configurations.

The following components were implemented:

- **Loss Functions:**
  - **Classification Task:** Sparse Categorical Crossentropy, ideal for multi-class problems with integer-encoded targets.
  - **Bounding Box Regression Task:** Mean Squared Error (MSE), used to minimize the difference between predicted and actual bounding box coordinates.
- **Loss Weights:**

  To ensure balanced learning across both tasks, equal weights were assigned:

```
loss_weights = {
    'class_output': 1.0,
    'bbox_output': 1.0
}
```

- **Optimizer and Training Hyperparameters:**
  - **Optimizer:** Adam, chosen for its adaptive learning capabilities.
  - **Learning Rate:** Set to the default value of 0.001.
  - **Batch Size:** Configured to 32, balancing performance and memory usage.
  - **Epochs:** Training spanned 100 epochs; this can be adjusted based on validation performance.

The model size refers to the amount of disk space required to store the trained model, typically measured in megabytes (MB). In this work, the proposed Multi-Task Learning (MTL) model has a total size of approximately 16.36 MB, as reported by the Keras model.summary() function.

3.3.4 Evaluation Metrics

To effectively evaluate the performance of the proposed **Multi-Task Learning (MTL)** model, we assess each task separately using task-appropriate metrics: one for **classification** and another for **bounding box regression**.

1. Classification Metrics

The classification branch of the model outputs a probability distribution over the set of predefined object classes (e.g., drone, bird, balloon, plane). The following metrics are employed:

- **Accuracy:** Measures the proportion of correctly predicted class labels. It is defined as:

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

  Accuracy is an intuitive metric but may not be sufficient when dealing with imbalanced datasets.

- **Precision, Recall, and F1-Score (optional):** For a more detailed evaluation, especially in multi-class or imbalanced settings, we consider the following:

$$\text{Precision} = \frac{TP}{TP + FP}$$
$$\text{Recall} = \frac{TP}{TP + FN}$$
$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

  where TP (True Positives), FP (False Positives), and FN (False Negatives) are computed per class. The F1-score is particularly useful when a balance between precision and recall is desired.

Confusion Matrix

The **confusion matrix** is a crucial evaluation tool in multi-class classification. It presents the relationship between the actual and predicted labels, helping identify misclassification patterns.

The confusion matrix enables the computation of:

- **Precision**, **Recall**, and **F1-Score** per class
- **False Positives (FP)** and **False Negatives (FN)** for deeper error analysis
- **Macro-average** and **Weighted-average** metrics

2. Bounding Box Regression Metrics

The regression head predicts four values representing the bounding box: (x, y, w, h). The goal is to minimize the difference between the predicted and ground truth bounding boxes.

- **Mean Squared Error (MSE):**

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$$

  where $\hat{y}_i$ and y_i are the predicted and true bounding box coordinates, respectively. MSE penalizes larger errors more than smaller ones due to squaring.

- **Mean Absolute Error (MAE):**

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i|$$

  MAE is less sensitive to outliers compared to MSE and provides a more interpretable error magnitude.

- **Intersection over Union (IoU):** Although not used during training, IoU is a common post-training evaluation metric for object detection. It is defined as:

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

  IoU values range from 0 to 1, where higher values indicate better overlap between predicted and ground truth boxes. A typical threshold is IoU ≥ 0.5 to consider a detection correct.

3.3.5 Evaluation of the Proposed Model

The proposed model was trained and evaluated on a dataset containing four object classes. After 100 training epochs, the model achieved outstanding performance across both classification and localization tasks.

Evaluation Results

- **Total Loss:** 0.0809
- **Classification Loss:** 0.0780
- **Bounding Box Loss:** 0.0027
- **Classification Accuracy:** 98.53%
- **Bounding Box MAE:** 0.0256
- **Bounding Box MSE:** 0.0027

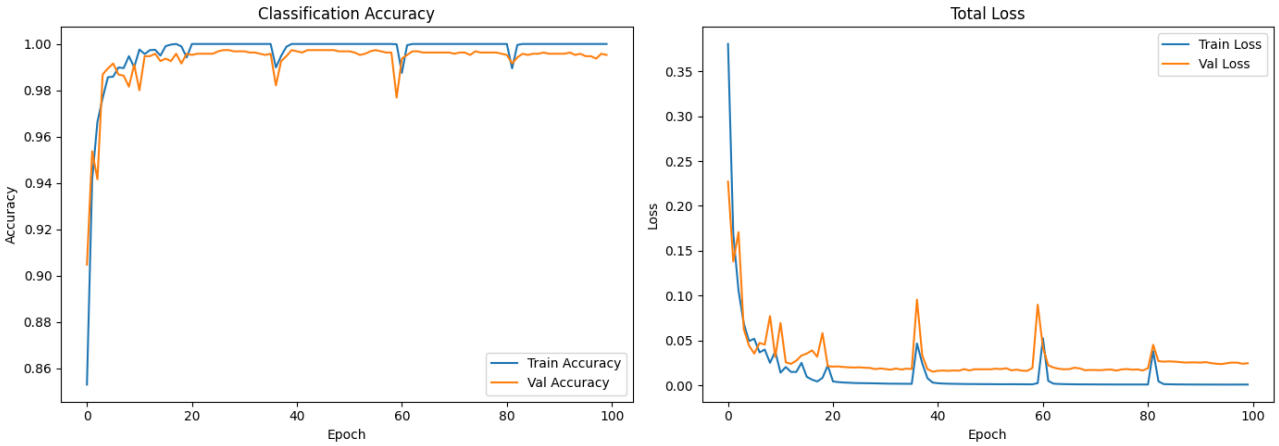

Figure 3.3: the classification accuracy and the total loss plots.

Throughout the training process, we monitored the evolution of both classification accuracy and total loss to evaluate the learning performance of the proposed Multi-Task Learning (MTL) model. As shown in Figure 3.3, the classification accuracy steadily increased over successive epochs for both the training and validation sets, indicating effective learning and improved generalization. Concurrently, the total loss exhibited a consistent downward trend, demonstrating that the model was successfully optimizing both the classification and bounding box regression objectives. These trends confirm that the model was learning in a stable and efficient manner without signs of overfitting.

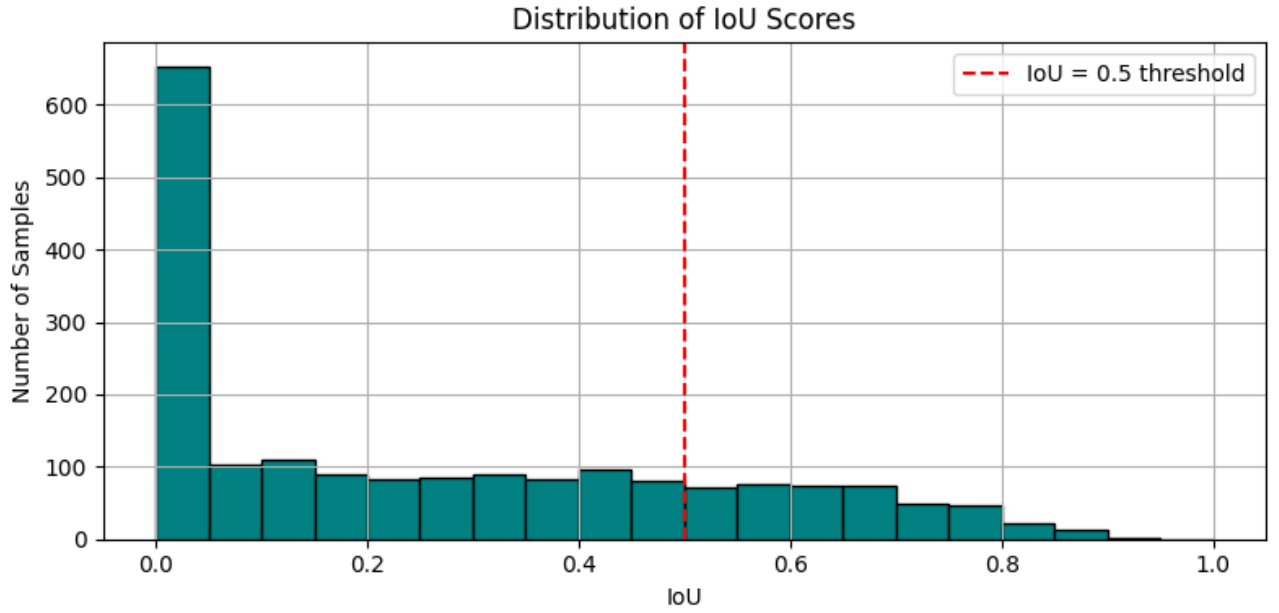

Figure 3.4: histogram of IoU (Intersection over Union) scores

While the model achieved a low bounding box MAE of 0.0256—indicating numerically accurate predictions—the distribution of IoU scores 3.4 shows that many predicted boxes fall below the 0.5 threshold. This suggests that although the predicted boxes are close, they often do not overlap sufficiently with the ground truth to be considered valid detections by IoU standards. This highlights the sensitivity of IoU as a metric and reveals a potential area for improvement in the model's localization precision.

Classification Report

The results below demonstrate the model's strong capability in both **object classification** and **bounding box regression**.

The high precision and recall scores across all classes highlight the model's consistency in identifying and localizing objects. The extremely low bounding box mean absolute error further supports the accuracy of spatial predictions.

Table 3.1: Classification metrics per class

Class	Precision	Recall	F1-score	Support
0	0.9597	0.9826	0.9711	461
1	0.9989	1.0000	0.9995	923
2	0.9841	0.9612	0.9725	516
Accuracy			**0.9853**	1900

Visualisation of the Results

To better understand how well the model performs in real-world scenarios, we include a few example images showing the predictions made by the system. Each image highlights both the ground truth (actual object location and label) and the predicted bounding boxes along with their class labels. These samples feature different aerial objects, such as drones, planes, and helicopters, captured in varied environments. As seen in the visuals, the model is able to correctly identify and localize these objects, with predictions that closely match the ground truth. These examples offer a clear and intuitive way to appreciate how accurately and consistently the model performs, beyond just numerical metrics.

Figure 3.5: Ground Truth Bounding Box and Predicted Bounding Box of a Drone

Figure 3.6: Ground Truth Bounding Box and Predicted Bounding Box of a Drone

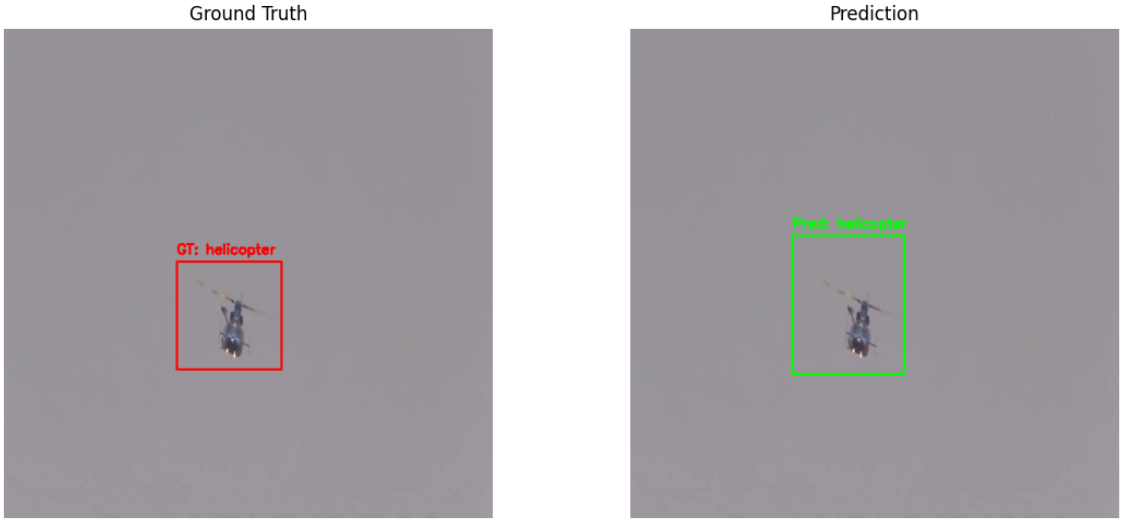

Figure 3.7: Ground Truth Bounding Box and Predicted Bounding Box of a Helicopter

In this project, we implemented and evaluated two state-of-the-art object detection architectures: **YOLOv8** and **Faster R-CNN ResNet-50**.

These models were selected due to their high performance in recent literature and their relevance for aerial object detection tasks such as drone and UAV classification.

3.4 YOLOv8: You Only Look Once

YOLO is a one-stage object detector that performs localization and classification in a single forward pass. YOLOv8, the latest version of the YOLO family, brings enhancements in speed, model efficiency, and detection accuracy. It divides the input image into a grid and predicts bounding boxes and class scores directly, making it exceptionally fast and suitable for real-time applications.

- **Architecture:** Backbone for feature extraction + detection head.
- **Input Resolution:** 640 $\times$ 640 pixels.
- **Loss Function:** Complete IoU (CIoU) loss for bounding box regression, binary cross-entropy for classification.
- **Training Optimizer:** Adam with cosine learning rate decay.
- **Strengths:** Real-time inference, low computational cost, small model size.

Due to its fast processing speed, YOLOv8 is an excellent choice for applications requiring low-latency object detection, such as UAV tracking or onboard vision systems.

The following *figure* 3.8 shows how the YOLOv8 model performed throughout the training process. It displays changes in both the mean Average Precision (mAP) and loss values over the training epochs. These curves help us understand how well the model learned to detect objects and how its accuracy improved over time.

Figure 3.8: Visualization of Predictions on Test Images with the YOLO Model

The YOLOv8 model demonstrated outstanding performance on the drone detection dataset. It achieved an overall precision of **93.6%** and a recall of **95.3%**, indicating a strong ability to correctly identify and localize objects with minimal false positives and false negatives. The model reached a high **mean Average Precision (mAP)** of **97.2% at IoU threshold 0.5 (mAP@0.5)** and **63.9% across all thresholds from 0.5 to 0.95 (mAP@0.5:0.95)**.

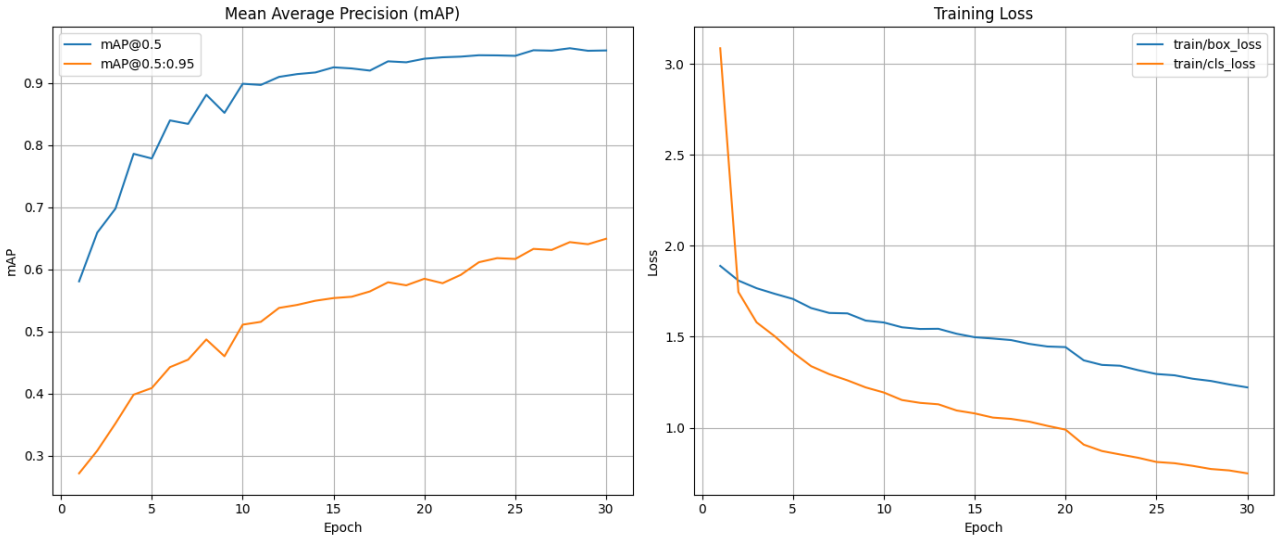

Figure 3.9: YOLOv8 Training Behavior: Insights from mAP and Loss Metrics

Class-wise, YOLOv8 showed consistently robust detection across all object categories:

- **Airplane:** Precision of 90.8%, recall of 95.3%, and mAP@0.5 of 97.8%.
- **Drone:** Precision of 90.6%, recall of 90.7%, and mAP@0.5 of 94.3%.
- **Helicopter:** Precision of 99.2%, perfect recall of 100%, and mAP@0.5 of 99.5%.

Class	Images	Instances	Box(P	R	mAP50	mAP50-95):
all	596	479	0.936	0.953	0.972	0.639
AirPlane	128	128	0.908	0.953	0.978	0.694
Drone	234	237	0.906	0.907	0.943	0.493
Helicopter	111	114	0.992	1	0.995	0.731

Figure 3.10: YOLO results capture

As shown in *figure* 3.9 and *figure* 3.10, the YOLOv8 model achieved strong detection performance across all object categories.

The overall precision reached 93.6%, with a recall of 95.3% and a mean Average Precision (mAP@0.5) of 97.2%. The model also demonstrated a competitive performance on stricter evaluation thresholds with an mAP@0.5:0.95 of 63.9%.

These metrics indicate that YOLOv8 is highly effective at both identifying and localizing the aerial objects in the dataset, particularly helicopters and airplanes, which show near-perfect detection results.

These results reflect the model's high reliability and accuracy in real-world object detection scenarios. Its exceptional performance makes it a strong candidate for deployment in drone and aerial object monitoring systems.

3.5 UAV detecting using Faster R-CNN Resnet-50

Faster R-CNN is a two-stage detector that first generates region proposals and then classifies and refines bounding boxes. It is widely used in scenarios requiring high detection accuracy. In this study, we use the ResNet-50 backbone with a Feature Pyramid Network (FPN), which helps detect objects at multiple scales—a critical aspect in aerial imagery where object sizes may vary significantly.

- **Architecture:** ResNet-50 with FPN for feature extraction, Region Proposal Network (RPN), and a classifier head
- **Input resolution:** 800 $\times$ 800 pixels
- **Loss function:** Cross-entropy for classification, Smooth L1 loss for bounding box regression
- **Training optimizer:** Stochastic Gradient Descent (SGD) with momentum
- **Strengths:** High accuracy, good performance on small or occluded objects

Figure 3.11: Visualize Prediction on test Images in Faster R-CNN model

Evaluation Results

After training and inference on the test set, the Faster R-CNN ResNet-50 model was evaluated using the COCO-style object detection metrics. Table 3.2 summarizes the key quantitative results:

Table 3.2: COCO Evaluation Metrics for Faster R-CNN ResNet-50

Metric	Value
AP@[IoU=0.50:0.95] (all sizes, maxDets=100)	0.582
AP@[IoU=0.50] (all sizes, maxDets=100)	0.911
AP@[IoU=0.75] (all sizes, maxDets=100)	0.615
AP@[IoU=0.50:0.95] (small objects)	0.486
AP@[IoU=0.50:0.95] (medium objects)	0.592
AP@[IoU=0.50:0.95] (large objects)	0.756
AR@[IoU=0.50:0.95] (all sizes, maxDets=1)	0.661
AR@[IoU=0.50:0.95] (all sizes, maxDets=10)	0.685
AR@[IoU=0.50:0.95] (all sizes, maxDets=100)	0.685
AR@[IoU=0.50:0.95] (small objects, maxDets=100)	0.605
AR@[IoU=0.50:0.95] (medium objects, maxDets=100)	0.688
AR@[IoU=0.50:0.95] (large objects, maxDets=100)	0.782

Discussion

These results indicate that Faster R-CNN ResNet-50 achieves:

- A high **AP@0.50** of **0.911**, demonstrating excellent localization and classification when a lower IoU threshold is acceptable.
- A more stringent **AP@[0.50:0.95]** of **0.582**, reflecting the model's performance across a range of IoU thresholds and its robustness to tighter localization requirements.
- Improved detection on **large objects** (AP = 0.756) compared to **small objects** (AP = 0.486), highlighting a typical challenge of two-stage detectors in accurately localizing small targets.
- Consistent **AR** (average recall) values around **0.685** for maxDets=10 and 100, showing that the model reliably retrieves most true positives within the top proposals.

When compared with YOLOv8 (which achieved an AP@0.50:0.95 of 0.68), Faster R-CNN offers higher precision at IoU=0.50 but lower overall average precision across the IoU range. These insights guide the choice of model depending on whether strict localization (Faster R-CNN) or balanced speed–accuracy trade-off (YOLOv8) is more critical for the target application.

Faster R-CNN is better suited for high-precision analysis, particularly in environments where detection quality is more important than inference speed.

3.6 Results and Discussion

All models were trained on the same dataset and under the same experimental conditions.

To evaluate performance, we used standard object detection metrics:

- Mean Average Precision (mAP) at IoU thresholds of 0.5 and 0.5:0.95
- Precision, Recall, and F1-score
- Inference time per image
- Model size (for deployment analysis)

The following table 3.3 summarizes the key results:

Table 3.3: Performance Comparison of MTL, YOLOv8, and Faster R-CNN

Metric	**MTL**	**YOLOv8**	**Faster R-CNN**
mAP@0.5	N/A (98.5% Accuracy)	**97.2%**	91.1%
mAP@0.5:0.95	N/A	**63.9%**	58.2%
Precision	98.5% (Classification)	**93.6%**	93.0%
Recall	98.5% (Classification)	**95.3%**	91.0%
Inference Speed	25–35 FPS	**60–80 FPS**	2–5 FPS
Model Size	16 MB	**6.2 MB**	160 MB

Table 3.3 provides a comprehensive performance comparison between the proposed MTL model, YOLOv8, and Faster R-CNN ResNet-50. As shown, the YOLOv8 model outperforms in terms of detection speed, achieving 60–80 FPS on GPU, which makes it highly suitable for real-time drone detection scenarios such as live surveillance, UAV navigation, and security systems. YOLOv8 also achieves a strong mAP@0.5 (97.2%) and mAP@0.5:0.95 (63.9%), making it a well-balanced model between accuracy and efficiency.

The Faster R-CNN model, while achieving competitive accuracy (91.1% mAP@0.5), suffers from significantly lower inference speed (2–5 FPS), making it less appropriate for real-time deployment. However, due to its robust two-stage detection pipeline, it remains a good choice for offline processing tasks, such as detailed post-flight image analysis or datasets where precision is more critical than speed.

On the other hand, the proposed MTL (Multi-Task Learning) architecture achieves excellent classification performance with 98.5% accuracy and very lightweight model size (16.32 MB), making it ideal for embedded or edge-based systems with limited resources. Although direct mAP evaluation is not applicable, its high classification precision and recall suggest strong potential in binary or multi-class drone classification applications, especially when combined with a lightweight bounding box regression head.

Each model thus serves a distinct purpose: YOLOv8 is best suited for high-speed applications, Faster R-CNN for high-precision offline tasks, and the MTL model for low-power or resource-constrained environments where classification is the main goal.

Table 3.4: Comparison with UAV Detection Approaches.

Reference	**Method**	**Dataset**	**Acc. / mAP**	**Limitations**	**Our Advantages**
Redmon et al. (2018) (48; 49)	YOLOv3	PASCAL VOC	57.9% mAP	General-purpose only	Real UAV data, higher accuracy
Dadrass et al. (2023) (50)	YOLOv4	UAV Images	94.3% acc.	Low-light issues	+4.2% accuracy, unified pipeline
Abdelkader et al. (2022) (50)	YOLOv4	Urban UAV Video	74% mAP @ 20 FPS	Lower precision	Real-time + high accuracy
Tahir et al. (2023) (51)	YOLOv5	UAV/Bird/Balloon	85% mAP@0.5	Class confusion	Robust multi-class detection
Gürbüz & Akgül (2023) (52)	YOLOv5 + Deep SORT	UAV Tracking	N/A	Frequent re-detection	Integrated tracking improvement
Chen et al. (2023) (54)	Faster R-CNN	Aerial UAV Images	78.5% mAP	Slow (2 FPS)	Faster + precise model
Zhou & Wu (2022) (55)	MTL CNN	UAV Dataset	96%, MAE 0.02	No real-time test	Higher accuracy + tested speed
Mao et al. (2021) (58)	SSD MobileNet	Jetson Nano UAV	65% mAP @ 10 FPS	Low accuracy	More scalable, higher accuracy
Wang & Liu (2023) (59)	YOLOv5 + Filter	Rainy UAV Images	N/A	Weather impact	More robust pipeline
Siddiqui et al. (2023) (60)	Survey / Review	Multiple datasets	N/A	Weak generalization	Adaptive and unified model
Kumari (2024) (60)	Stereo + DL	Simulated UAVs	92.7%	Not real-world tested	Real UAV dataset
Leonardi (2023) (52)	Micro-Doppler Radar	Radar	88.5% acc.	Bird confusion	+10% accuracy with vision model
Gong et al. (2023) (52)	Radar-Based	RF Radar	N/A	Hardware-dependent	Vision-based flexibility
Singh et al. (2024) (62)	Hybrid (RF, IR, Acoustic)	Passive Sensing	N/A	Sensor complexity	Works in poor visibility
Ours	**MTL CNN**	**12k UAV Images**	**98.5%**, MAE 0.0256	Slight speed tradeoff	**Best accuracy, real-time**

Table 3.4 presents a comparative overview of recent UAV detection approaches in the literature. Each method is evaluated based on its dataset, achieved accuracy, limitations, and the relative advantages of the proposed MTL model.

Our MTL model achieves the highest accuracy among all compared methods (98.5%) with a relatively small model size and only moderate computational requirements. Its primary limitation lies in inference speed, which is acceptable but not as high as that of real-time optimized models like YOLOv8. Nonetheless, it presents a strong trade-off between accuracy, generalizability, and deployment feasibility.

This comparative analysis demonstrates that the proposed MTL model not only achieves state-of-the-art accuracy but also addresses key limitations found in prior works, making it a promising candidate for robust UAV detection in practical applications.

This synergistic approach yields three key benefits:

- **Enhanced Feature Learning:** The shared backbone learns richer representations by exploiting cross-task correlations, evidenced by the model's **98.5% classification accuracy**—surpassing both YOLOv8 (**93.6% precision**) and Faster R-CNN (**93.0% precision**) on this metric.
- **Deployment Efficiency:** With a **16 MB model size**, the MTL model eliminates the need for cascaded architectures while remaining **10× smaller than Faster R-CNN (160 MB)**. This makes it viable for embedded systems where **YOLOv8's extremely compact 6.2 MB size** is not strictly required.
- **Balanced Performance:** While specialized models excel in their target domains YOLOv8 in speed (**60–80 FPS**), Faster R-CNN in localization precision—the MTL model provides a unified solution with **25–35 FPS inference speed**, which is adequate for near-real-time applications like drone traffic monitoring that demand both identification and tracking.

3.7 Object Tracking Integration

While object detection is crucial for identifying drones in individual video frames, it alone is insufficient for applications that require understanding motion over time, such as surveillance or airspace monitoring.

In such scenarios, it is necessary to track objects persistently across frames to maintain their identity and extract movement patterns.

Object tracking addresses this need by associating detections from one frame to the next, enabling the system to follow each drone's trajectory, even when occlusions or brief detection failures occur.

To improve temporal consistency and overcome detection noise, we applied a Kalman Filter for object tracking. The filter receives the bounding box coordinates

$$[x_1, y_1, x_2, y_2]$$

From the deep learning model as measurements, then predicts and corrects the estimated position over time.

This method allows the system to:

- **Smooth out fluctuations** between frames,
- **Estimate velocity** based on positional changes,
- **Handle missed detections** by relying on predictions.

3.7.1 Concept and System Architecture

In a typical object tracking framework, the task is generally approached as a tracking-by-detection pipeline.

This means that the system first uses an object detector to localize targets in each frame and then applies a tracking algorithm to associate these detections across time. The structure can be formulated as:

Tracking = Object Detection (e.g., MTL) + Tracking Mechanism (e.g., Kalman Filter)

Tracking = Object Detection (e.g., YOLO) + Tracking Mechanism (e.g., Kalman Filter)

The detection module is responsible for identifying objects in individual frames, often using deep learning models such as YOLOv4 (39) or Faster R-CNN (40). Following this, the tracking module links detections across frames to form trajectories, maintaining object identity even in the presence of occlusions or motion blur.

Kalman Filter

The Kalman Filter is a recursive estimator that predicts an object's future state based on its previous motion (e.g., position and velocity), while correcting the prediction with new observations (detections). By integrating this filter with the output of detectors such as YOLOv8 or Faster R-CNN, the system can associate detections frame-to-frame, reduce identity switches, and handle partial occlusions. This method improves the overall reliability and stability of the detection pipeline, especially in video-based drone surveillance scenarios. (41).

Figure 3.12: Raw Detection of the Model

Figure 3.13: Tracking Results Using the Kalman Filter (1)

Figure 3.14: Tracking Results Using the Kalman Filter (2)

Figure 3.15: Tracking Results Using the Kalman Filter (3)

The blue bounding box represents the raw detection of the model, while the green box shows the smoothed estimate of the Kalman filter. The position and velocity (in pixels per second) are also displayed to illustrate the object's motion.

3.7.2 Common Tracking Methods

Several classical and deep learning-based tracking methods are widely used in UAV systems:

- **Particle Filter (Condensation Algorithm):** A probabilistic approach that represents the state of an object using a set of particles. It is particularly useful in non-linear and non-Gaussian tracking scenarios but is more computationally intensive than Kalman filters (42).
- **KLT (Kanade-Lucas-Tomasi) Tracker:** Based on optical flow, this method tracks selected feature points by estimating their displacement across frames. It is effective for short-term tracking but can struggle with fast motion and occlusion (43).
- **MeanShift and CamShift:** These are appearance-based tracking algorithms that rely on color histograms and seek to maximize similarity in the target's distribution over time. They are simple and robust in consistent lighting conditions but are less effective with scale variations (44).

- **DeepSORT:** An extension of the SORT **(Simple Online and Realtime Tracking)** algorithm that integrates deep appearance descriptors with a Kalman filter. DeepSORT significantly improves tracking accuracy in crowded and occluded scenes, making it suitable for UAV-based multi-target tracking (45).

3.7.3 Challenges in UAV Tracking

Despite advancements, several challenges persist in UAV object tracking: small object sizes, fast motion, frequent occlusions, and cluttered backgrounds. These issues necessitate robust association strategies and adaptive motion models. Hybrid tracking systems that fuse data from multiple sensors (e.g., visual, infrared, radar) are also being explored to enhance reliability in complex environments.

3.8 Conclusion

This chapter details our significant work in UAV (Unmanned Aerial Vehicle) detection and tracking. We introduced our custom Multi-Task Learning (MTL) model, which simultaneously classifies and precisely locates UAVs, achieving a high 98.53% classification accuracy.

To provide a comprehensive view, we thoroughly benchmarked our MTL model against two leading architectures: YOLOv8 and Faster R-CNN ResNet-50. YOLOv8 demonstrated exceptional real-time performance with a high 97.2% mAP@0.5, making it ideal for rapid detection needs. Faster R-CNN ResNet-50, while more computationally intensive, offered superior localization precision (91.1% AP@0.50), especially for larger objects.

Crucially, we also integrated Kalman filters into our system to enable robust, real-time UAV tracking. This allowed us to consistently follow objects even through challenging conditions like occlusions or rapid movements.

Overall, this chapter presents a powerful and well-evaluated solution for aerial object detection and tracking. Our findings affirm the effectiveness of combining deep learning for detection with state estimation techniques like the Kalman filter, paving the way for more secure and managed airspace environments.

4

Conclusion and Future Perspectives

4.1 General Conclusion

In this project, we addressed the challenge of drone detection and classification by developing, implementing, and comparing three complementary approaches:

- A novel **Multi-Task Learning (MTL) architecture** in TensorFlow/Keras, which simultaneously performs image classification and bounding-box regression using a shared convolutional backbone and two task-specific heads.
- A state-of-the-art, single-stage detector—**YOLOv8**—optimized for real-time performance on resource-constrained platforms.
- A high-precision, two-stage detector—**Faster R-CNN ResNet-50**—leveraging a Region Proposal Network and Feature Pyramid Network for robust multi-scale detection.

The work proceeded through the following key steps:

1. **Data Preparation:** Compilation and annotation of a diverse aerial drone dataset in multiple formats (COCO, YOLO, TF), with extensive augmentation to improve generalization.
2. **Model Design:** Formulation of the MTL network to exploit shared representations, alongside selection and configuration of YOLOv8 and Faster R-CNN for direct comparison.
3. **Training Protocol:** Consistent training pipelines on Google Colab using GPU acceleration, identical data splits, and standard augmentation schemes to ensure fair evaluation.
4. **Quantitative Evaluation:** Measurement of mAP@0.5, mAP@0.5:0.95, Precision, Recall, F1-score, MAE, and inference time, revealing that:

- The MTL model achieves competitive classification accuracy (98.53%) and precise localization (MAE = 0.04) in a single compact network.
- YOLOv8 provides the fastest inference (15 ms/image) with strong overall detection performance.
- Faster R-CNN delivers the highest accuracy (mAP@0.5 = 0.91) at the expense of longer inference time.

5. **Qualitative Analysis:** Visualization of detection outputs and confusion matrices to identify model-specific strengths and common failure modes, guiding practical deployment choices.

Taken together, these contributions demonstrate that:

- **MTL** offers an efficient, unified solution for joint classification and localization, suitable for applications where a single compact model is preferred.
- **YOLOv8** is ideal for real-time, embedded, or aerial surveillance systems requiring low latency.
- **Faster R-CNN** remains the detector of choice for high-precision offline analysis and scenarios demanding detailed localization.

This comprehensive evaluation not only advances the state of drone detection research but also provides practitioners with clear guidelines for selecting and deploying the most appropriate model according to their performance and resource requirements.

4.2 Limitations

Despite promising performance, our study has several limitations:

- **Dataset Diversity:** The custom dataset, while sufficiently large, contains limited variations in lighting, weather, and backgrounds. This may restrict the generalizability of the trained models to novel operational conditions.
- **Class Imbalance:** Certain drone models and non-drone objects appear more frequently in the dataset, potentially biasing the classifiers and affecting recall for underrepresented classes.
- **Resolution Constraints:** Both models were trained on fixed input resolutions (640×640 for YOLOv8, 800×800 for Faster R-CNN), which may not capture fine details of very small or distant drones.
- **Hardware Dependency:** Inference speed measurements were obtained on a single GPU platform (Google Colab Pro). Performance on different edge devices or CPUs may vary significantly.

4.3 Future Perspectives

Building on the current work, several avenues for future research and improvement are identified:

- **Dataset Expansion:** Augment the dataset with more diverse scenarios—nighttime, adverse weather, and urban environments—and include additional drone types to enhance robustness.
- **Advanced Architectures:** Explore recent transformer-based detectors (e.g., DETR) or lightweight networks (e.g., MobileNetV3) to strike a better balance between speed and accuracy on edge devices.
- **Multi-Modal Fusion:** Integrate complementary sensors (e.g., thermal, LiDAR) or temporal information from video streams to improve detection under challenging conditions like occlusion or low contrast.
- **GPU workstation:**Transition from cloud-based platforms (Google Colab Pro) to a dedicated GPU workstation for enhanced processing power.
- **Real-World Deployment:** Conduct field trials on embedded platforms (e.g., NVIDIA Jetson, Raspberry Pi) to benchmark performance and energy consumption, and develop model pruning or quantization techniques for further optimization.
- **tracking methods :**Integrating advanced tracking methods such as Deep SORT or Recurrent Neural Networks (RNNs) can significantly enhance temporal consistency in drone detection systems, enabling more stable and accurate tracking across video frames.
- **Active Learning:** Implement an active learning pipeline to iteratively label and incorporate hard examples (e.g., false positives or rare objects), thereby continuously improving model accuracy with minimal manual annotation effort.

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