# Skywatch: Advanced Machine Learning Techniques for Distinguishing UAVs from Birds in Airspace Security

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***Abstract*—This study addresses the critical challenge of distinguishing Unmanned Aerial Vehicles (UAVs) from birds in real-time for airspace security in both military and civilian contexts. As UAVs become increasingly common, advanced systems must accurately identify them in dynamic environments to ensure operational safety. We evaluated several machine learning algorithms, including K-Nearest Neighbors (kNN), AdaBoost, CN2 Rule Induction, and Support Vector Machine (SVM), employing a comprehensive methodology that included data preprocessing steps such as image resizing, normalization, and augmentation to optimize training on the "Birds vs. Drone Dataset." The performance of each model was assessed using evaluation metrics such as accuracy, precision, recall, F1 score, and Area Under the Curve (AUC) to determine their effectiveness in distinguishing UAVs from birds. Results demonstrate that kNN, AdaBoost, and CN2 Rule Induction are particularly effective, achieving high accuracy while minimizing false positives and false negatives. These models excel in reducing operational risks and enhancing surveillance efficiency, making them suitable for real-time security applications. The integration of these algorithms into existing surveillance systems offers robust classification capabilities and real-time decision-making under challenging conditions. Additionally, the study highlights future directions for research in computational performance optimization, algorithm development, and ethical considerations related to privacy and surveillance. The findings contribute to both the technical domain of machine learning in security and broader societal impacts, such as civil aviation safety and environmental monitoring.**

***Keywords*—*Unmanned Aerial Vehicles (UAVs); machine learning; image recognition; real-time processing; security; computer vision; image processing***

## I. Introduction

In the past decade, military applications of drones have undergone a significant transformation, expanding from surveillance and reconnaissance to more tactical roles, such as precision strikes on targeted objectives. Drones, whether small handheld units or large remotely piloted aircraft, provide invaluable aerial surveillance that extends beyond human capability. This real-time surveillance helps to identify potential threats, ensuring the safety of both civilians and military personnel [1]. Drones can monitor dangerous areas for extended periods, offering surveillance that surpasses traditional methods. However, while these capabilities are revolutionary, they also introduce critical challenges, particularly in security operations.

One significant concern is the threat posed by cyberterrorism, as drones—hailed as one of the most formidable weapons in modern warfare—can be exploited to breach defenses. For instance, the Iranian drone and missile attack on Israeli territories highlighted the need for robust UAV detection systems capable of distinguishing between drones and other aerial entities such as birds. In military contexts, adversarial tactics can include electronic warfare and psychological operations, which further complicate the identification process. Therefore, the development of efficient, real-time recognition platforms using advanced computational technologies is vital [2] [3].

This study explores the application of machine learning algorithms to address this challenge. We examine various models, including deep neural networks, Support Vector Machines (SVMs), random forests, and gradient boosting machines, to identify the most effective approach for high-security environments. The research primarily focuses on reducing false positives and negatives in UAV detection, a critical factor for maintaining operational integrity in military settings. The models are assessed based on accuracy, precision, computational performance, and suitability for real-time applications [4]. This article aims to provide key insights into improving UAV detection systems, offering practical applications that can enhance current military surveillance and security protocols. By leveraging machine learning advancements, this study contributes to the ongoing evolution of airspace control and UAV countermeasures.

### A. *Article Objectives*

This study aims to enhance the ability to differentiate Unmanned Aerial Vehicles (UAVs) from birds in military surveillance operations, with a focus on improving resource allocation, optimizing response strategies, and ensuring airspace security. The primary objectives are:

*1) Develop advanced detection algorithms:* Design and refine sophisticated machine learning algorithms capable of distinguishing between UAVs and birds by analyzing complex datasets based on flight patterns and physical characteristics.

*2) Enhance image recognition capabilities:* Improve image recognition accuracy for UAV detection against various

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natural backgrounds by training models on extensive datasets of UAV and bird images captured under diverse environmental conditions.

*3) Minimize false positives and negatives:* Reduce the rates of false alarms (misidentifying birds as UAVs) and missed detections (failing to identify UAVs) to streamline surveillance system performance in high-security zones.

*4) Implement real-time processing:* Create a system that processes and analyzes data in real time, enabling immediate and informed decision-making in dynamic, potentially adversarial environments.

*5) Evaluate system robustness in simulated environments:* Test the developed systems in simulated environments that mimic real-world conditions, including scenarios with UAV swarms and electronic warfare techniques.

*6) Assess operational integration:* Determine the feasibility and effectiveness of integrating the developed technologies into existing military security frameworks, ensuring seamless deployment and operational functionality.

Achieving these goals will significantly advance the technological capabilities of military surveillance, contributing to national security and strategic defense effectiveness [5].

### B. Contribution of the Article

This article contributes to military surveillance by improving UAV and bird differentiation systems. The key contributions are:

*1) Advancement in detection algorithms:* Introducing new machine learning algorithms for UAV and bird differentiation, focusing on pattern recognition and flight dynamics analysis to reduce misidentifications and improve threat assessment accuracy.

*2) Real-time data processing:* Enhancing real-time processing capabilities to allow rapid analysis and response in high-stakes environments, where timely decisions can critically impact military engagements.

*3) Reduction of false alarms:* Minimizing false positives and negatives to prevent unnecessary deployment of resources and reduce the risk of overlooking actual threats.

*4) Operational integration and testing:* Evaluating the systems in simulated environments, ensuring practical viability and seamless integration into existing military frameworks.

*5) Strategic implications and policy recommendations:* Offering strategic insights and policy recommendations for defense entities, with suggestions for deploying new technologies and updating current practices.

*6) Enhanced airspace security:* Improving UAV identification capabilities to strengthen airspace security, particularly in sensitive or high-security areas, mitigating threats like espionage and unauthorized surveillance [6].

### C. Article Organization

The article begins with an overview of the importance of UAV identification in military surveillance, followed by a literature review in Section II that highlights existing advancements and gaps in current methodologies. The methodology in Section III outlines the experimental setup, including data collection, model refinement, and evaluation metrics. The results and analysis in Section IV presents a comprehensive evaluation of methods such as neural networks and gradient-boosting machines, assessing their effectiveness in UAV recognition. Discussion is given in Section V. Finally, the article concludes in Section VI with a discussion on future research directions and recommendations for improving UAV detection systems in Section VII.

### D. Problem Statement

The growing use of UAVs in military operations underscores the need for advanced systems capable of accurately distinguishing UAVs from other entities, such as birds, in real time. This study focuses on developing machine learning models to improve UAV detection, which is crucial for enhancing airspace security and operational efficiency in both military and civilian settings.

## II. Related Work

Due to the increasing chance of drones being used for unlawful activities, the detection of drones has turned out to be especially significant inside the realm of security and surveillance. Artificial neural networks do not facilitate real-time object detection because multiple GPUs are necessary to train the models. Deep learning architectures aim to address this problem by creating convolutional neural networks (CNN) that can function in real-time with just one conventional GPU for training [7]. This paper employs appropriate deep-learning architectures for detecting drones and birds. This application utilizes YOLO (You Only Look Once) algorithms, which are one-stage approaches that examine an image just once using a single neural network. The community is skilled at stop-to-quit to output the bounding box, magnificence label, and detection probability without delay. The models are trained on a bespoke dataset comprising 664 drone pixels and 236 hen pictures. Simulation results indicate that YOLOv4 and YOLOv5 attained F1-ratings of 98% and 94%, respectively, with detection speeds of 54fps and 77fps. The fashions also tested mean average precision (mAP) values of 97.4% and 95%. YOLOv4 verified advanced overall performance in suggested Average Precision (mAP) compared to YOLOv5, whereas YOLOv5 exhibited faster detection speed than YOLOv4 [8].

Businesses, transportation, and military sports use drones. Advanced drone detection and identification systems are needed to protect the airspace. This paper accurately identified drones and birds in the air using radar and visible imaging. Using both drone detection and recognition systems was helpful. An average precision of 88.82% and accuracy of 71.43% makes this approach greener. Excellent performance is shown by the combined approach's 76.27% F1 score. Drone and chicken detection systems will benefit significantly from the findings. Better than similar works, the proposed algorithm [9].

The examination was performed in northeastern Poland, where the Whooper Swan (Cygnus cygnus) breeds now and then. The Whooper Swan is shy and tends to conceal itself in emergent flowers. A drone was utilized to enhance the efficiency of studying its breeding success and offspring productivity. In 2022, the breeding density of Whooper Swans in the study area was 10 pairs per 100 square kilometers. There was no difference in the number of breeding birds detected at the start of the breeding season between the drone and ground methods. The breeding productivity of the sample of swans studied (N = 36) was 2.19 cygnets per breeding pair using the ground method but 3.71 per pair with the drone, showing a significant difference (p-value of the Wilcoxon test = 0.0148). In the conventional approach, 50% of the pairs successfully bred, while using the drone resulted in a 79% success rate. The birds either remained indifferent to the drone's presence or retreated slowly. The drone study on Whooper Swan breeding productivity was significantly quicker (9 minutes per site compared to 1-2 hours for a ground survey), more accurate, and less disruptive to the birds than a conventional survey [10].

Detecting objects like drones is difficult due to their size and agility, which can confuse machine learning models and lead to misclassification as birds or other objects. This study explores applying various deep-learning techniques to analyze real datasets collected from flying drones. A deep learning approach is suggested to reduce the complexity of such systems. The proposed paradigm combines the AdderNet deep learning paradigm and the SSD paradigm. The aim was to reduce complexity by decreasing the number of multiplication operations in the proposed system's filtering layers. Standard machine learning techniques like Support Vector Machines (SVM) are evaluated and contrasted with other deep learning systems. The datasets for training and testing were either complete or filtered to exclude images with small objects. The data types were either RGB or IR. Comparisons were conducted among all these types, and conclusions are provided [11].

Even advanced drones outperform birds with lightweight, adaptable wings and tails. 3D printing, servomotors, and composite materials enable more creative airplane designs inspired by bird flight, which may improve flight characteristics. By replacing control surfaces with rapidly changing wings, morphing technology improves aircraft aerodynamics and power efficiency. This paper introduces bio-inspired 3D-printed systems for unmanned aerial vehicle wings and tails that morph without flapping. The proposed wing uses a corrugated, flexible 3D-printed structure to expand and contract artificial feathers for sweep morphing. A flexible 3D-printed structure with circular corrugation is proposed for tail feather expansion. Various 3D-printing materials and intricate geometric components can achieve the proposed morphing deformations with minimal actuation forces. Testing prototypes showed that the chosen materials and actuators could achieve seagull-like morphing deformations [12].

The widespread availability of drones has opened up numerous new possibilities previously limited to a select few. Regrettably, this technology also brings countless adverse effects associated with illicit activities such as surveillance and smuggling. Sensitive areas should be equipped with sensors that can detect miniature drones from a long distance. Several techniques are present in this field, but each has notable disadvantages. This study introduces a new method for detecting small drones (<5 kg) using laser scanning and a technique to differentiate between UAVs and birds. Minimizing the false alarm rate in each drone monitoring equipment is a crucial challenge. The paper discusses the newly created sensor and its effectiveness in distinguishing between drones and birds. The concept relies on a straightforward analysis of the cross-polarization ratio of the optical echo produced by laser backscattering on the identified object. The experimental results indicate that the proposed method does not consistently ensure 100% discrimination efficiency but offers a distribution of confidence levels. However, because of the hardware's simplicity, this method appears to be a beneficial enhancement to the advanced anti-drone laser scanner [13].

To address security concerns, an algorithm is created to distinguish between airspace intruders, such as birds and drones, in unmanned aerial system (UAS) operations. The algorithm utilizes velocity data of detected intruders from Internet-of-Things platforms and a partial understanding of physical models. The identification problem is framed as a statistical hypothesis testing or detection problem, where inertial feedback-controlled objects under stochastic actuation must be differentiated based on speed data. The maximum a posteriori probability detector is derived and then simplified into an explicit computation using two points in the sample autocorrelation of the data. The simplified form facilitates the algorithm's computationally efficient implementation and enhances learning from stored data. The total probability of error of the detector is calculated and described. Simulations using synthesized data are shown to demonstrate and improve the formal analyses [14].

Detecting and tracking birds and drones accurately is crucial in different low-altitude airspace surveillance situations. Radar is the most suitable long-range surveillance technology for this issue, but it faces challenges in effectively differentiating between birds and drones. This paper examines birds' and drones' natural flight mechanics and behavioral patterns. A goal classification technique is suggested primarily based on extracting target motion characteristics from radar tracks. The random woodland version is selected for the goal type within the new function space. The proposed method confirms using real-time surveillance radar systems in airport regions. The results of classifying birds, quadcopter drones, and dynamic precipitations advise that the proposed method can reap high-class accuracy. The Gini significance descriptors in a random woodland model provide extra perception when evaluating movement traits and mining. The type machine's excessive sample flexibility and performance enable it to efficiently address complex low-altitude goal surveillance and class problems. Future studies will cope with the current technique's constraints and explore techniques capable of optimization [15].

This study examines the use of micro-Doppler spectrogram signatures of flying gadgets, like drones and birds, to help their remote identity. A 10-GHz non-stop wave radar device was custom-designed to accumulate measurements from numerous situations regarding distinct goals, which were then used to generate datasets for photo type. Time/pace spectrograms created for micro-Doppler evaluation of various drones and birds were utilized for target reputation and movement categorization with TensorFlow. The consequences indicated that aid vector machines (SVMs) did an accuracy of approximately 90% for drone length classification, around 96% for distinguishing between drones and birds, and more or less 85% for differentiating between individual drones and birds throughout five training. Various aspects of target detection were investigated, such as the terrain and actions of the target [16].

This study uses Long Short-Term Memory (LSTM) networks to explore a novel drone classifier. The classification time of a drone detection radar is crucial for its effectiveness as a real-time surveillance system. This work aims to create a classification framework with minimal latency for processing algorithm input data. Theoretical modeling was conducted on a rotary wing drone and a bird wing flapping to demonstrate the contrast in the patterns of their phase progressions. Subsequently, a dataset of 1D phase data was generated for supervised learning by utilizing 94 GHz experimental trial data consisting of 4800 sequences of drones, birds, noise, and clutter. A stacked LSTM network with optimized hyperparameters was created to mitigate potential overfitting compared to a basic LSTM model. An accuracy of 98.1% was achieved in validating the 2-class classification of drone and non-drone. The network successfully classified all sequences in a performance assessment using 30 unseen test data. This method has been determined to be approximately 10 times faster than a spectrogram-based classification model, as it eliminates the need for additional Fast Fourier Transform (FFT) operations [17].

Classifying multiple drones and birds based on micro-Doppler (MD) signatures is challenging due to potential contamination from multiple bird signatures and the similarity in MD signatures between different drones. This paper introduces three protocols and evaluates their classification accuracy for multiple drones and birds in an actual observation setting. The analysis is based on frequency-modulated continuous wave radar and a convolutional neural network classifier. By utilizing training data that consists of combinations of drone and bird movements in simulations involving rotating blades and flapping wings, our method achieved an accuracy of approximately 100% for majority vote classification. This outcome establishes our process as the most suitable for distinguishing between multiple drones and birds [18].

This paper explores the utilization of micro-Doppler signatures of drones and birds to detect and categorize them. Simulated assessment results are validated with data from a 10-GHz continuous wave (CW) radar system. Time/Velocity spectrograms created for micro-Doppler analysis of various drones and birds are employed for TensorFlow's target recognition and motion categorization. The Support Vector Machine (SVM) achieved 96% accuracy in distinguishing between drones and birds and 85% in distinguishing between individual drones and birds across five classes [19].

The dangers of cannabis overuse are well known. Previous research has shown that the timing of alcohol and cigarette use strongly influences dependence. However, little research has been conducted on the adverse effects of short-term cannabis use. In this study, latent class analysis was employed to analyze data from cannabis-using college students. Participants were drawn from four universities across four different U.S. states, with a total sample size of 1,122 individuals. The study examined whether timing factors, such as the hour of the day and day of the week, could help classify cannabis use patterns. Additionally, it explored how these classifications related to cannabis use indicators (MUG), negative consequences (MACQ), and symptoms of cannabis use disorder (CUDIT-R). The MUG (Marijuana Use Grid) measures cannabis consumption in grams over one week during the past 30 days, displaying daily use (Monday through Sunday) across 4-hour intervals. We aggregated these intervals to represent cannabis consumption as a binary variable (0 = no consumption, 1 = consumption) for each day of the week. By summing the daily data, we converted cannabis use during each period into binary values. Using the Lo-Mendell-Rubin Likelihood Ratio Test (LRT) and other fit indices, we identified a 4-class solution with high classification accuracy (relative entropy = .905). The four classes were defined as follows: (1) daily, frequent morning use (N = 140.17, 12.5%); (2) daily, uncommon morning use (N = 241.02, 21.5%), with more than 88% of this class using cannabis every day of the week; (3) weekend, frequent morning use (N = 72.22, 6.4%); and (4) weekend, uncommon morning use (N = 668.59, 59.6%). Daily morning cannabis users reported the most negative consequences (M = 7.53 on the Marijuana Consequences Questionnaire) and the most symptoms of cannabis use disorder (M = 15.74 on the Cannabis Use Disorder Identification Test-Revised). In contrast, individuals who used cannabis exclusively on weekend mornings experienced fewer adverse effects (MACQ M = 2.24) and had lower cannabis use disorder symptoms (CUDIT-R M = 5.45). The classifications were primarily driven by cannabis use in the mornings and during the week. The time of day and day of the week significantly influenced cannabis-related harms. Further research is needed to explore how the timing of cannabis use—considering factors like frequency, quantity, type of product, and mode of consumption—affects cannabis-related outcomes [20].

This paper explores the millimeter-wave radar micro-Doppler characteristics of consumer drones and birds that can be used to differentiate targets by a classifier. The feature extraction methods were created by analyzing the micro-Doppler signature characteristics of in-flight targets detected using a frequency-modulated continuous wave (FMCW) radar. Three distinct drones (DJI Phantom 3 Standard, DJI Inspire 1, and DJI S900) and four birds of varying sizes (Northern Hawk Owl, Harris Hawk, Indian Eagle Owl, and Tawny Eagle) were utilized for feature extraction and classification. The data for all the targets was collected using a stationary W-band (94 GHz) FMCW radar. The extracted features were input into two distinct classifiers for training: linear discriminant and support vector machine (SVM). Classifiers utilizing these features can effectively differentiate between drones and birds with 100% accuracy and distinguish between different sizes of drones with over 90% accuracy. The results show that the suggested algorithm is highly appropriate for an automated target recognition method in a functional FMCW radar system for drone detection [21].

Drones are increasingly used for recreation, engineering, disaster management, logistics, and airport security. Despite their practical use, airport physical infrastructure security, safety, and surveillance raise concerns about malicious use. Many airports report unauthorized drone use disrupting airline operations. This study proposes deep learning to distinguish two drone and bird species. The suggested method outperforms literature-based detection systems in an image dataset test. Due to their resemblance in appearance and behavior, drones are often inappropriate for birds. The proposed method detects drones, distinguishes two types, and distinguishes birds. This study trained the network with 10,000 multirotor, helicopter, and bird drone images. As expected, the proposed deep learning method distinguishes drones and birds with 83% accuracy, 84% mAP, and 81% IoU. The average Recall, accuracy, and F1-score for the three classes were 84%, 83%, and 83% [22].

Reconnaissance drones are specifically designed to analyze data and interpret signals they intercept, allowing them to detect and pinpoint radar systems. However, identifying quasi-simultaneous arrival signals (QSAS) has become increasingly challenging in complex electromagnetic environments. To address this issue, we propose a framework for self-supervised deep representation learning. The framework consists of two phases: (1) Training an autoencoder: The ConvNeXt V2 model is trained to extract features from masked time-frequency images, enabling it to learn the unlabeled QSAS representation. The model reconstructs the corresponding signal in both the time and frequency domains. (2) Knowledge transfer: The model transfers the learned knowledge, where the encoder layers are kept fixed for downstream tasks. A linear layer is then fine-tuned to classify QSAS in few-shot scenarios. Experimental results demonstrate that the proposed algorithm achieves an average recognition accuracy exceeding 81% across a signal-to-noise ratio (SNR) range of -16 to 16 dB. Additionally, the new algorithm reduces testing time by approximately 11-fold and improves accuracy by up to 21.95% compared to existing CNN-based and Transformer-based neural networks [23].

Security cameras in a secure organization or facility transmit live video feeds to the server for security personnel to monitor. Traditional monitoring methods, such as human observation, are ineffective when a drone enters the facility beyond the range detectable by the monitor, which is live-streaming footage. A man can detect a drone at a distance of approximately 400 meters. Garuda's proposed solution utilizes a deep learning architecture trained on a specialized dataset containing visual images of drones and other aerial objects. The proposed model is designed to precisely identify the lines and edges of drones, enabling it to distinguish drones from birds, kites, and planes. The model can track drone movements such as approaching, receding, or moving laterally by analyzing the area covered by the drone in consecutive time intervals and determining the direction based on changes in the area size, indicating approaching or receding situations. Lateral movement is identified by comparing the drone's position coordinates at different intervals. The paper thoroughly compares different deep learning structures using two datasets. A software application has been developed to contain the drone detection model, capable of detecting, managing, and recording such events with a precision of 94.5% [24].

Authors: Michael Nentwich (project leader) and Delila Horvath from the Institute of Technology Assessment in Vienna, 2018. The concept of using drones for delivery is based on certain assumptions. To achieve this, numerous technical and regulatory challenges must be addressed. Given the significant impact on the airspace, previously used primarily by birds and occasionally helicopters, several standard technology assessment (TA) questions arise. Are there any safety concerns? Are there environmental risks? Can the technology be exploited by criminals or terrorists? Are we facing societal conflicts due to divergent interests? Is the current regulatory framework sufficient, or are new regulations needed? The vision of a drone-based delivery system is not without prerequisites. Many regulatory and technical hurdles must be overcome to make it a reality. Due to the significant impact of this technological development—since it will drastically change the airspace we inhabit, which has so far been used primarily by birds and the occasional helicopter, a series of typical technology assessment questions emerge. Are there safety concerns? Are there environmental hazards? Can the technology be misused for criminal or terrorist purposes? Does it hold the potential for societal conflict due to conflicting interests? Is the existing regulatory framework sufficient, or should new regulations be established [25]?

The proliferation of UAVs has rapidly increased in recent years. Drones are being used more frequently in both military and commercial settings. UAVs of different sizes, shapes, and types are utilized for various purposes, from leisure activities to specific missions. This progress has brought about difficulties and has been recognized as a possible cause of operational interruptions resulting in different security issues, such as risks to Critical Infrastructures (CI). Developing fully autonomous Anti-Unmanned Aerial Vehicle Defence Systems (AUDS) is more urgent now than ever. This paper introduces a comprehensive design and operational prototype of drone detection technology that uses Digital Image Processing (DIP) and Machine Learning (ML) to accurately detect, track, and classify drones to reduce or eliminate the threat they pose. The system utilizes a background-subtracted frame difference technique to detect moving objects, in conjunction with a Pan-Tilt tracking system controlled by a Raspberry Pi to track the detected object. Moving items are recognized using a Convolutional Neural Network (CNN) device known as the YOLO v4-tiny ML set of rules. The proposed gadget stands proud because of its precision, efficiency with cheaper sensing gadgets, and advanced overall performance in contrast to different options. Integrating the system with various systems, such as RADAR, may allow for appreciable decoration of detection technology, further simplifying operations. The proposed era was experimentally verified in diverse checks carried out in uncontrolled outside surroundings, demonstrating steady effectiveness in all situations and producing terrific results [26].

Summary A fluorescent sensor with more than one capability, based on coumarin and containing a di-2-picolylamine (DPA) organization (1), is brought. This probe can function as a fluorescent sensor for Co2 and Cu2 in an ON-OFF manner. The generated 1-Co(II) and 1-Cu(II) ensembles can then act as OFF-ON fluorescent sensors to differentiate between Zn2 and Cd2 and selectively locate sulphide anions in water through displacement. Specifically, Cu(II) can pass through the cellular membrane and be utilized for fluorescence imaging of S2− in living biological samples. The fluorescent sensors of the ON-OFF-ON type showed exceptional selectivity and sensitivity toward the objectives [27].

## III. Methodology

### A. Dataset Description

Inspecting the "Birds vs. Drone Dataset" on Kaggle, which Harsh Walia contributed. This dataset incorporates two folders that categorize snapshots of birds and drones [28]. These folders are essential for the author's academic device, as they assist in reading and differentiating between those two topics. The fowl pictures were received via net scraping, whilst the drone pix were obtained from another dataset. The folders incorporate extensive photos that constitute the subjects observed in natural sky backgrounds. These snapshots are essential for teaching the author's version [1]. Fig. 1 shows the process flow diagram.

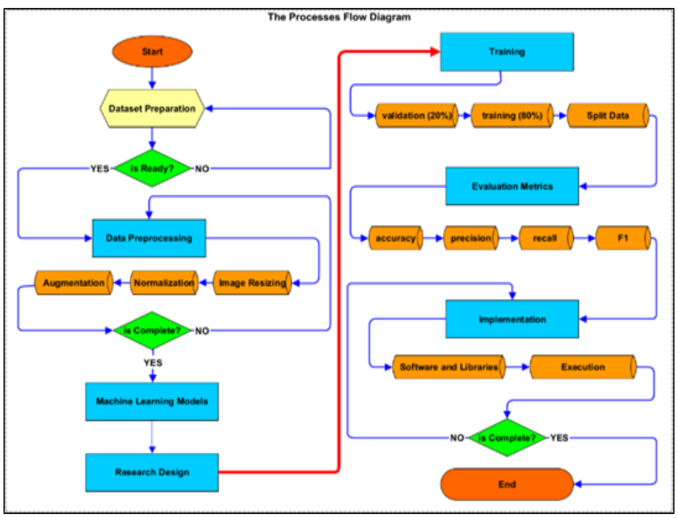


Fig. 1. The process flow diagram [29].

### B. Data Preprocessing

Considering the wide range of images in terms of background, orientation, and scale, we implemented the following preprocessing steps to ensure the dataset was standardized for optimal training [29]:

- Image Resizing: To maintain a consistent input size for the neural network, all images were adjusted to a uniform dimension of 224x224 pixels.
- Normalization: The pixel values of each image were adjusted to a range of 0 to 1, which helps to enhance the speed of convergence during the training process.
- Augmentation: To enhance the resilience of our model and avoid overfitting, we implemented image augmentation techniques, including rotation, zoom, and horizontal flipping.

### C. Machine Learning Models

Multiple machine learning models were utilized during the evaluation process to analyze their effectiveness in predicting the Bords and Drones Dataset [29]. We used the following models:

*1) K-Nearest Neighbors (KNN):* KNN is crucial for its simplicity and effectiveness in applications where relationships within the data are distance-based. It's precious in fields like recommendation systems and anomaly detection, where the closest neighbors often share more similarities or properties [30].

*2) AdaBoost (Adaptive Boosting):* AdaBoost is pivotal for enhancing the performance of weak classifiers, making it essential for scenarios where simple models must be combined to improve accuracy. It's widely used in applications requiring robust performance, such as face detection in images, due to its ability to focus iteratively on challenging cases [31].

*3) Constant model:* The constant model serves as a fundamental benchmark in machine learning, ensuring that any new model provides a meaningful improvement over the simplest possible approach. Establishing a baseline performance level that other, more sophisticated models must exceed to be considered adequate is crucial [32].

*4) CN2 rule induction:* CN2 Rule Induction is critical in settings where interpretability is as crucial as prediction accuracy, such as in medical or financial applications. Generate explicit if-then rules, which provide clear insights into decision processes and facilitate understanding and acceptance among users [33].

*5) Naive Bayes:* Naive Bayes is indispensable in text classification due to its efficiency and scalability, effectively handling large datasets with high-dimensional features. Its feature independence assumption simplifies calculations, making it a go-to method in spam detection and natural language processing [34].

*6) Support Vector Machine (SVM):* SVM's ability to find the optimal boundary between classes makes it extremely powerful for classification tasks, especially when the classes are well separable. Its application in bioinformatics, image recognition, and other areas where precision is critical underscores its importance. The kernel trick, which allows SVM to adapt to non-linear relationships, further enhances its applicability to a wide range of complex datasets [34].

### D. Research Design

The "Birds vs. Drone Dataset," created by Harsh Walia and made publicly available on Kaggle, is used to have a look. This dataset plays a crucial role in the author's investigating device studying-based aerial drone and fowl discrimination. Carefully organized into beautiful folders, it can take snapshots of birds and drones, respectively. The birds' pix were retrieved using an in-depth net scraping approach that changed into, in particular, engineered to capture various bird species in diverse flying positions and settings. This series aims to capture authentic, real-world variability. Contrarily, the drone photos are from an existing dataset and feature a range of drone styles, all set against a sky background. Because of this, you can rest assured that the dataset only shows cases where drones are in the air. Each folder contains a full-size quantity of pictures to train robust machine learning models, offering a broad range of visual records. A strong classifier capable of consistently differentiating among these training data in typical operational contexts requires images that are both varied and of high quality [35-37].

### E. Training

*1) Configuration:* A learning fee scheduler adjusted the model's parameters depending on when the validation loss plateaued; the model's batch size was 32, and the learning rate was 0.001.

*2) Environment:* Training was carried out on a GPU-enabled system to speed up the computation.

*3) Validation split:* Splitting the dataset into training (80%) and validation (20%) parts helped identify and prevent overfitting [38-40].

### F. Evaluation Metrics

The author's version was tested for overall performance using accuracy, precision, and remember metrics. This version's performance in accurately labeling photos as either birds or drones can be better understood with the help of these metrics [1], [3], [6], [28].

*1) AUC (Area Under the Curve):* AUC represents the ability of a model to discriminate between positive and negative classes across all possible classification thresholds. Its importance lies in its use as a single measure that summarizes the model's performance in prevalent and rare events. It makes it essential in medical diagnostics and other binary classification tasks where the choice of the decision threshold impacts outcomes significantly.

*2) CA (Classification Accuracy):* Classification Accuracy measures the overall effectiveness of a model in correctly identifying both positive and negative outcomes. It's a straightforward metric useful in evaluating models where class distributions are balanced, providing a quick snapshot of model efficacy in fields like educational testing and customer satisfaction analysis.

*3) F1 Score:* The F1 Score balances precision and Recall, which is crucial in scenarios where false positives and negatives have severe implications, such as in legal and financial domains. Its importance stems from providing a more realistic measure of a model's performance when dealing with imbalanced datasets, where the cost of errors can be high.

*4) Precision (Prec.):* Precision assesses the model's accuracy in predicting positive labels, which is essential in situations where the consequences of false positives are more severe than false negatives, such as in spam detection or during the preliminary stages of drug approval processes, ensuring resources are used efficiently and safely.

*5) Recall:* Recall is essential when missing a positive occurrence (false negative) is unacceptable, such as in fraud detection or disease screening. It ensures that the most critical cases are identified, even at the expense of making more errors on the negative side (false positives).

*6) LogLoss (Logarithmic Loss):* LogLoss provides insight into the certainty of a model's predictions, emphasizing the consequences of being wrong, not just whether it is incorrect. This metric is paramount in fields like healthcare and risk assessment, where understanding the probability of outcomes influences decision-making processes significantly, ensuring decisions are informed and minimizing risk.

These metrics collectively provide a comprehensive assessment framework for machine learning models, facilitating informed decision-making in various applications by highlighting aspects of model performance related to the specific costs of prediction errors.

### G. Implementation

The model was implemented using Python, utilizing TensorFlow and Keras to construct and train the neural network. Supplementary libraries were utilized alongside NumPy and Matplotlib for data manipulation and visualization. The script was completed through iterative processes, adjusting parameters and configurations based on the performance observed in the validation set.

## IV. Results

### A. Test and Score Analyses

Test and Score analyses are critical for assessing the generalization abilities of gadget learning models. This is executed by educating them on a selected training set and comparing their performance on a separate trying-out set. This approach evaluates critical metrics like accuracy, precision, consider, F1 score, and place underneath the ROC curve (AUC) to benefit intensive know-how of the model's overall performance in predicting consequences, its capacity to become aware of relevant times efficiently, and its universal accuracy. Performing these analyses is vital for figuring out overfitting, a scenario wherein a version performs well on education records but poorly on new, unseen facts. This lets developers regulate the model to decorate its practicality and resilience through iterative optimization.

*1) Test and score analyses for target class birds:* Table I compares the performance of various system studying models and the usage of stratified 10-fold pass-validation for classifying “Birds”. Models like kNN, AdaBoost, and CN2 Rule Induction excel with best scores across AUC, CA, F1, Precision, and Recall, indicating their tremendous ability to categorize and differentiate birds as they should be inside the dataset. However, CN2 has a moderate LogLoss, indicating minor prediction uncertainty. The SVM model demonstrates high efficiency with nearly perfect metrics and a very low LogLoss, suggesting effective generalization with minor imperfections. In contrast, Naïve Bayes shows moderate performance with the highest LogLoss, reflecting significant prediction uncertainty. At the same time, the Constant model, used as a baseline, performs poorly, substantiating its inadequacy beyond a control comparison. These results highlight the effectiveness of using advanced models over simpler ones and the critical role of choosing the suitable model based on specific task requirements and dataset characteristics, as shown in Table I and Fig. 2.

2) *Test and score analyses for target class drones:* Table II provides a comparative performance analysis of several machine learning models for drone classification using stratified 10-fold cross-validation, showcasing a range of outcomes. The kNN, AdaBoost, and CN2 Rule Induction models excel with perfect scores across all metrics (AUC, CA, F1, Precision, Recall), indicating flawless classification abilities. However, CN2 has a slight LogLoss of 0.086, suggesting minimal uncertainty. The SVM model also performs robustly with nearly perfect metrics and a low LogLoss of 0.055, signaling strong but not absolute precision. In contrast, Naive Bayes shows moderate effectiveness with an AUC of 0.868 and significant prediction uncertainty (LogLoss of 5.139), reflecting its limitations in reliability for this task. The Constant model, used as a baseline, predictably underperforms with the lowest scores except in Recall, where it identifies all instances as drones, leading to many false positives. This analysis highlights the superiority of kNN, AdaBoost, and CN2 for drone detection in terms of accuracy and reliability compared to the other models, as shown in Table II and Fig. 3.

TABLE I. THE TEST AND SCORE ANALYSES FOR THE KNN, ADABOOST, CN2, SVM, NAÏVE BAYES, AND CONSTANT MODELS FOR THE TARGET CLASS: BIRDS

| Model | AUC | CA | F1 | Prec | Recall | LogLoss |
|---|---|---|---|---|---|---|
| kNN | 1 | 1 | 1 | 1 | 1 | 0 |
| AdaBoost | 1 | 1 | 1 | 1 | 1 | 0 |
| CN2 Rule Induction | 1 | 1 | 1 | 1 | 1 | 0.086 |
| SVM | 0.998 | 0.979 | 0.979 | 0.969 | 0.99 | 0.055 |
| Naïve Bayes | 0.884 | 0.838 | 0.843 | 0.808 | 0.881 | 5.139 |
| Constant | 0.5 | 0.507 | 0 | 0 | 0 | 0.693 |

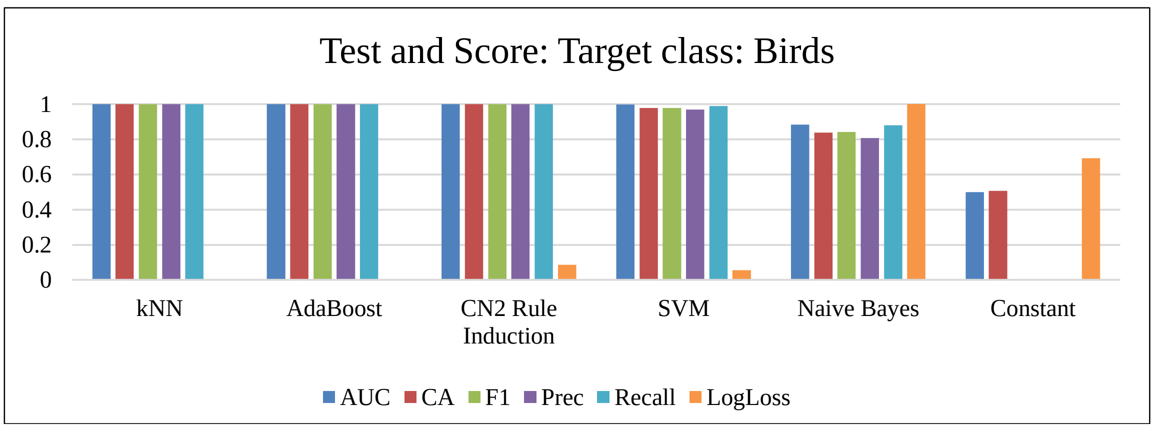


Fig. 2. The test and score analyses for the KNN, AdaBoost, CN2, SVM, Naïve Bayes, and Constant models for the target class: Birds.

TABLE II. THE TEST AND SCORE ANALYSES FOR THE KNN, ADABOOST, CN2, SVM, NAÏVE BAYES, AND CONSTANT MODELS FOR THE TARGET CLASS: DRONES

| Model | AUC | CA | F1 | Prec | Recall | LogLoss |
|---|---|---|---|---|---|---|
| kNN | 1 | 1 | 1 | 1 | 1 | 0 |
| AdaBoost | 1 | 1 | 1 | 1 | 1 | 0 |
| CN2 Rule Induction | 1 | 1 | 1 | 1 | 1 | 0.086 |
| SVM | 0.998 | 0.979 | 0.979 | 0.99 | 0.969 | 0.055 |
| Naive Bayes | 0.868 | 0.838 | 0.833 | 0.873 | 0.796 | 5.139 |
| Constant | 0.5 | 0.507 | 0.673 | 0.507 | 1 | 0.693 |

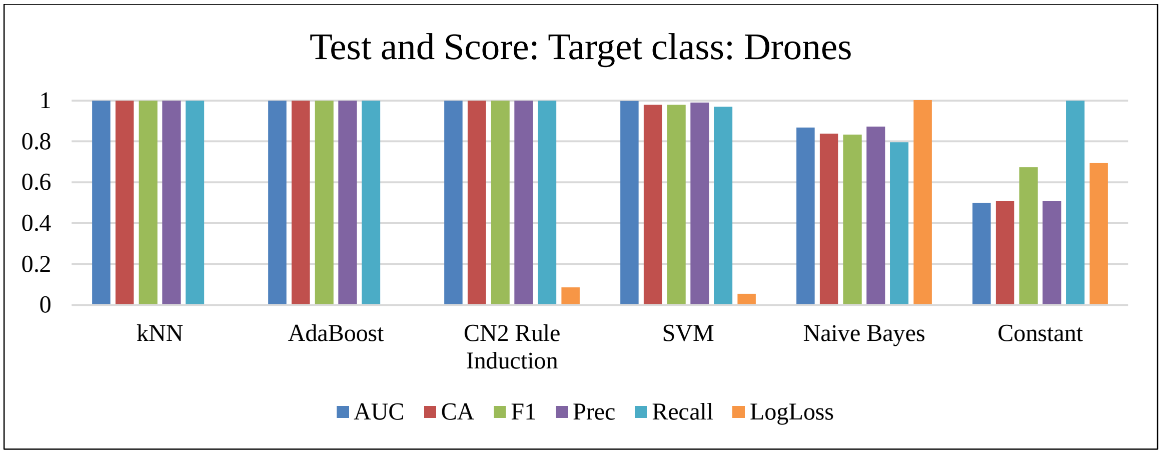


Fig. 3. The test and score analyses for the KNN, AdaBoost, CN2, SVM, Naïve Bayes, and Constant models for the target class: Drones.

*3) Test and score analyses for the average performance over all target classes:* Table III provides performance metrics for several machine learning models evaluated through stratified 10-fold cross-validation across various classes, revealing distinct levels of effectiveness. The kNN, AdaBoost, and CN2 Rule Induction models excel with perfect scores across all metrics (AUC, CA, F1, Precision, Recall), suggesting flawless classification capabilities; CN2 Rule Induction shows a negligible LogLoss of 0.086, indicating minimal uncertainty. The SVM model also performs exceptionally with nearly perfect metrics and a low LogLoss of 0.055, demonstrating high accuracy and confidence in predictions. In contrast, the Naive Bayes model shows moderate performance with lower scores and a high LogLoss of 5.139, indicating significant predictive uncertainty. The Constant model, used primarily as a baseline, exhibits poor effectiveness with the lowest scores across most metrics, substantiating its limited utility beyond providing a comparative benchmark. This analysis underscores the superiority of kNN, AdaBoost, CN2 Rule Induction, and SVM in achieving reliable and accurate class predictions across diverse datasets, as shown in Table III and Fig. 4.

TABLE III. THE TEST AND SCORE ANALYSES FOR THE TARGET CLASS: AVERAGE OVER CLASSES FOR THE KNN, ADABOOST, CN2, SVM, NAÏVE BAYES, AND CONSTANT MODELS

| Model | AUC | CA | F1 | Prec | Recall | LogLoss |
|---|---|---|---|---|---|---|
| kNN | 1 | 1 | 1 | 1 | 1 | 0 |
| AdaBoost | 1 | 1 | 1 | 1 | 1 | 0 |
| CN2 Rule Induction | 1 | 1 | 1 | 1 | 1 | 0.086 |
| SVM | 0.998 | 0.979 | 0.979 | 0.98 | 0.979 | 0.055 |
| Naive Bayes | 0.868 | 0.838 | 0.838 | 0.841 | 0.838 | 5.139 |
| Constant | 0.5 | 0.507 | 0.341 | 0.257 | 0.507 | 0.693 |

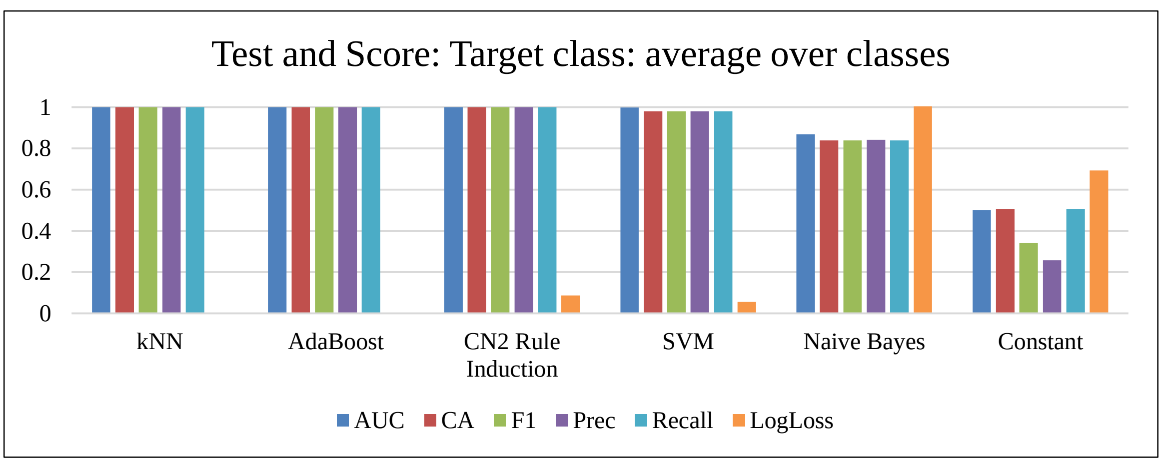


Fig. 4. The test and score analyses for the KNN, AdaBoost, CN2, SVM, Naïve Bayes, and Constant models for the target class: Average over classes.

## B. Confusion Matrix Analyses

Confusion Matrix Analyses provide a complete evaluation of a classification version's overall performance by presenting the counts of real positives, real negatives, false positives, and fake negatives in a matrix format. This analysis helps to visualize the accuracy of a version in predicting one-of-a-kind lessons, taking into consideration a more profound expertise of its predictive competencies and weaknesses. The most critical diagonal of the matrix indicates the range of accurate predictions, even as the off-diagonal elements imply the errors. Key derived metrics such as precision (the accuracy of superb predictions), remember (the version's capacity to discover all the excellent samples), and F1-rating (a harmonic implication of precision and remember) can be calculated from the confusion matrix. These metrics are crucial for diagnosing the overall performance of a model past easy accuracy, particularly in cases in which training is imbalanced, assisting in picking out whether a model is biased toward one magnificence and offering insights necessary for further refining the version's parameters.

Table IV confusion matrix showcases the performance of various machine learning models in classifying entities into two categories: Birds and Drones. kNN, AdaBoost, and CN2 Rule Induction excel with perfect classification accuracy, correctly identifying all Birds and Drones without misclassifications, achieving 100% precision, Recall, and accuracy. In stark contrast, the Constant model, used as a baseline, misclassifies all instances, highlighting its inadequacy for practical use with a recall of 1 for Drones due to predicting everything as Drones and a very low precision. Naive Bayes and SVM show moderate to high performance, with Naive Bayes misclassifying many birds and drones. SVM makes a few errors but still maintains high accuracy overall. These results indicate that while kNN, AdaBoost, and CN2 Rule Induction are highly effective for this task, Naive Bayes and SVM, although robust, exhibit potential areas for improvement in classification accuracy, as shown in Table IV and Fig. 5.

TABLE IV. THE CONFUSION MATRIX ANALYSES FOR THE MODELS KNN, ADABOOST, CN2, SVM, NAÏVE BAYES, AND CONSTANT

| | | | **Predicted** | |
|---|---|---|---|---|
| | | | **Birds** | **Drones** |
| Actual | KNN | Birds | 286 | 0 |
| | | Drones | 0 | 294 |
| | AdaBoost | Birds | 286 | 0 |
| | | Drones | 0 | 294 |
| | Constant | Birds | 0 | 286 |
| | | Drones | 0 | 294 |
| | CN2 Rule Induction | Birds | 286 | 0 |
| | | Drones | 0 | 294 |
| | Naive Bayes | Birds | 252 | 34 |
| | | Drones | 60 | 234 |
| | SVM | Birds | 283 | 3 |
| | | Drones | 9 | 285 |

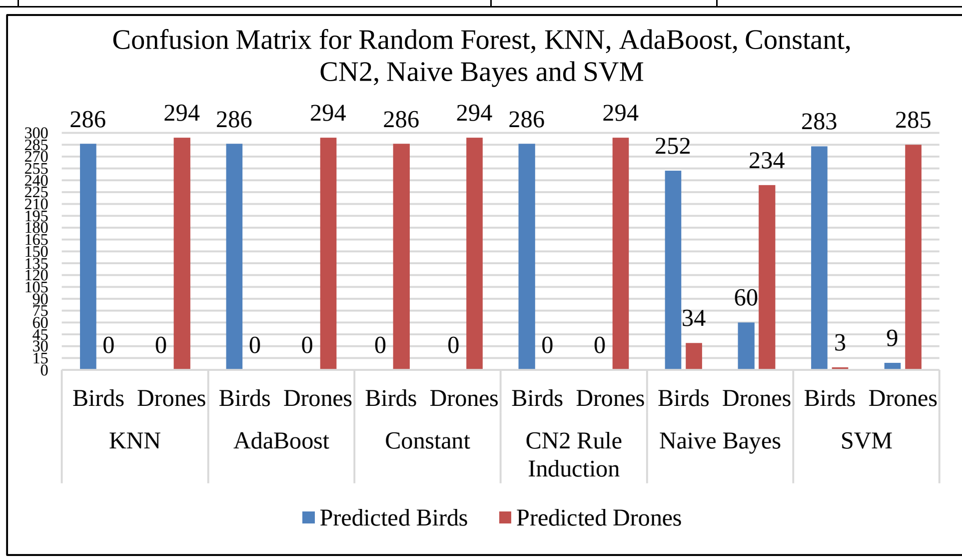


Fig. 5. The confusion matrix analyses of the KNN, AdaBoost, CN2, SVM, Naïve Bayes, and Constant models for the target class: Birds and drones.

### C. ROC Analyses

ROC analysis is a statistical method utilized in educational discussions to assess the diagnostic performance of binary classifiers. An ROC curve is a graph that shows how properly a classifier performs by evaluating the True Positive Rate (TPR) with the False Positive Rate (FPR) at one of a kind threshold degrees without considering class distribution or error rates. The location under the ROC curve (AUC) is a metric that quantifies a classifier's potential to differentiate between two instructions, with a better AUC indicating better performance. ROC assessment is highly precious for assessing overall performance across all types of thresholds, presenting an independent degree of impartiality regarding precise decision criteria. This analytical device is essential for comparing exclusive classifiers, supplying a clean visualization of their strengths and weaknesses in numerous operational eventualities. It is a fundamental component in the discipline of gadgets getting to know for developing fashions with better choice-making competencies.

*1) ROC analyses for target class birds:* The ROC (Receiver Operating Characteristic) curve evaluation within the Fig. 6 evaluates several systems, getting to know models for classifying "Birds," highlighting their performance underneath situations where false positives and false negatives are equally costly. The kNN and AdaBoost models showcase superior performance, with their ROC curves nearing the top left corner, indicating first-rate sensitivity and minimum fake fantastic charges, which are ideal for precision-crucial applications. CN2 Rule Induction additionally indicates brilliant effects, closely matching the primary fashions, suggesting its effectiveness in complicated sample reputation. Although slightly below the top performers, the SVM model maintains robust discrimination capabilities. In contrast, Naive Bayes displays moderate performance with a noticeable distance from the ideal curve, indicating potential issues with precision in distinguishing similar classes. The Constant model, represented by the diagonal line, serves as a baseline, performing at a chance level, thereby underscoring the advanced discriminative power of the specialized algorithms compared to a non-discriminative approach.

*2) ROC analyses for target class drones:* As shown in Fig. 7, the ROC curve analysis for drone classification reveals that the kNN and AdaBoost models exhibit exceptional performance, with their curves closely approaching the top left corner, indicative of high sensitivity and minimal false positives, making them highly effective for applications where precision is paramount due to high costs associated with misclassifications. CN2 Rule Induction also demonstrates robust capabilities, with its curve nearly matching the leaders, indicating its suitability for complex pattern recognition tasks. In contrast, the SVM model, though showing good performance, has a slightly less optimal curve, suggesting a few more false positives under certain thresholds. Naive Bayes significantly underperform relative to other models, as its curve is closer to the diagonal, indicating a higher rate of false positives, which may not be ideal in high-stakes scenarios. The Constant model, aligning with the diagonal, serves as a non-discriminative baseline, highlighting the necessity and effectiveness of the more sophisticated models in accurately classifying drones to avoid costly errors.

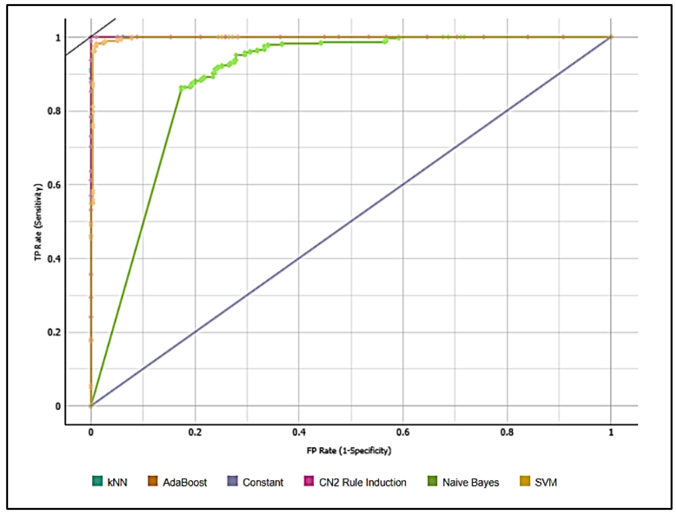


Fig. 6. The ROC Analyses for the KNN, AdaBoost, CN2, SVM, Naïve Bayes, and Constant models for the target class: Birds.

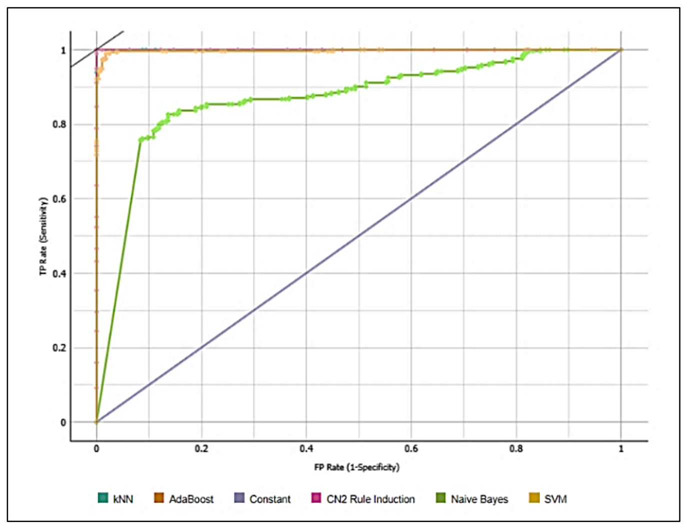


Fig. 7. The ROC analyses for the KNN, AdaBoost, CN2, SVM, Naïve Bayes, and Constant Models for the target class: Drones.

## V. Discussion

The "Discussion" section of the item titled "Advances in AI-Based Classification: Differentiating between Unmanned Aerial Vehicles and Birds in Flight" centers on evaluating the realistic implications, demanding situations, and future guidelines advised via the study's findings. The look at, through its rigorous assessment of various system learning fashions, which include kNN, AdaBoost, CN2 Rule Induction, and SVM, demonstrates their effectiveness in as it should be distinguishing UAVs from birds—a critical functionality for enhancing safety features in each military and civilian domain names.

This discussion emphasizes the precision with which these fashions operate, highlighting their capability to reduce false positives and negatives seriously. Such accuracy is vital in real-time safety contexts where the value of errors is exceedingly excessive. It also addresses the combination challenges of those advanced algorithms in present surveillance frameworks. The adaptability of these fashions across exceptional environmental situations is vital, as well as factors like variable lighting fixtures, weather adjustments, and diverse landscapes that might affect detection accuracy.

Moreover, the dialogue explores the computational efficiency of those algorithms, noting the significance of processing speed for real-time applications and the ability for further optimization to deal with larger, more complicated datasets without compromising performance. There is also an acknowledgment of the need for ongoing development to keep pace with the evolving abilities of UAV technology and the corresponding security requirements.

Ethical concerns form an essential part of the discourse, mainly the stability among protection enhancements and the capability for infringement on privacy rights. The deployment of such technology must be managed cautiously to avoid abuse that might cause massive societal and moral dilemmas.

The phase concludes by proposing future research guidelines. It indicates exploring hybrid models that could combine the strengths of numerous present approaches to enhance accuracy and performance. Additionally, there is a call for empirical checking out those models in operational situations to validate their effectiveness in international situations and to refine their talents primarily based on stay facts.

Overall, this discussion synthesizes the study's contributions to the field of airspace security but also outlines a roadmap for destiny technological and strategic improvements in UAV detection and classification, ensuring that safety features evolve in tandem with rising aerial threats.

## VI. Conclusion

The study titled "Skywatch: Advanced Machine Learning Techniques for Distinguishing UAVs from Birds in Airspace Security" represents a significant advancement in the application of machine learning for enhancing airspace security. By employing a variety of advanced algorithms, including kNN, AdaBoost, CN2 Rule Induction, and SVM, the research has demonstrated high accuracy in differentiating UAVs from birds, which is crucial for both military operations and civilian airspace protection.

The results indicate that these models achieve a high level of accuracy and effectively reduce false positives and negatives—key factors in real-time surveillance and threat detection. This capability ensures rapid and reliable responses in dynamic and potentially adversarial environments. Furthermore, the integration of these machine learning models into existing surveillance systems has proven to significantly enhance national security measures.

However, the study also acknowledges certain limitations. First, while the machine learning models demonstrated strong performance, the evolving sophistication of UAV technologies presents a continuous challenge. Future UAVs may exhibit more complex flight behaviors and features, potentially reducing the efficacy of the current models. Thus, there is a need for ongoing refinement and adaptation of these algorithms to keep pace with advancements in UAV technology. Second, the environmental diversity in real-world scenarios poses a limitation. The models were tested under controlled or simulated conditions, and their performance may vary when exposed to a wider range of environmental factors, such as extreme weather, varying light conditions, and densely populated areas. Further testing in diverse, real-world settings is essential to fully validate the practical applicability of these systems.

Additionally, the study highlights ethical and privacy concerns related to the deployment of UAV detection systems in civilian contexts. The potential misuse of these technologies underscores the importance of establishing clear regulatory frameworks to ensure responsible and transparent usage.

Looking forward, the research suggests exploring hybrid machine learning models that combine the strengths of various algorithms to achieve even greater accuracy and efficiency. Testing these models in real-world scenarios will be crucial for refining their capabilities and ensuring their practical deployment.

In conclusion, this study offers significant contributions to the fields of machine learning and security technology, providing valuable insights and practical solutions for improving airspace security in an era where UAV technology is rapidly advancing. The findings not only enhance current security protocols but also pave the way for future innovations in aerial threat detection and management.

## VII. Future Work and Improvements

While this study has made significant advancements in distinguishing UAVs from birds using machine learning algorithms, there are several areas that warrant further investigation to enhance the robustness and applicability of the models.

*1) Addressing model scalability and complexity:* One major limitation is the scalability of the models in increasingly complex environments. As UAV technologies continue to evolve, particularly with the introduction of more sophisticated designs and swarming behaviors, the current models may struggle to accurately classify these newer types. Future research should focus on developing more scalable algorithms that can adapt to new types of UAVs and handle increasingly complex data inputs. This may involve the exploration of hybrid models or deep learning techniques that can capture more nuanced patterns in flight behavior.

*2) Environmental adaptability:* Another area for improvement lies in enhancing the adaptability of these models to diverse and unpredictable environmental conditions. While the current study evaluated the models under controlled conditions, real-world environments often present challenges such as adverse weather, poor lighting, and background clutter that could affect detection accuracy. Further work is needed to test and refine the models in a broader range of real-world scenarios. Techniques such as transfer learning and domain adaptation could be explored to make the models more resilient across different environmental conditions.

*3) Integration with multi-sensor data:* Future research could also explore the integration of multi-sensor data to enhance detection accuracy. Combining optical imagery with other forms of data, such as radar or infrared signals, could provide a more comprehensive input for the models, helping to distinguish UAVs from birds with even greater precision. Investigating how to optimally fuse data from multiple sensors in real time would be a valuable next step.

*4) Real-time performance enhancements:* While this study demonstrates the feasibility of real-time UAV detection, there is still room for improving the speed and computational efficiency of the models, particularly in high-stakes environments. Real-time systems require low-latency performance, which may necessitate further algorithmic optimizations or the use of specialized hardware such as GPUs or edge computing devices to ensure faster processing times without sacrificing accuracy.

*5) Mitigating ethical and privacy concerns:* Ethical and privacy concerns regarding the use of UAV detection systems in civilian settings remain an important topic for future research. There is a need for guidelines and frameworks that govern the deployment of these technologies to avoid misuse and ensure transparency. Future work should also address how these systems can be designed to respect privacy while still providing the necessary security benefits.

*6) Long-term model maintenance and adaptability:* Machine learning models must be regularly updated to maintain their effectiveness as the nature of threats evolves. This study does not delve into long-term maintenance strategies for the algorithms. Developing methods for automatic retraining of the models with new data, without compromising their performance, will be essential to ensure continued effectiveness in rapidly changing operational contexts.

*7) Potential for cross-domain applications:* Beyond military and civilian airspace security, the techniques developed in this study could be adapted for other domains such as environmental monitoring, wildlife protection, or even urban management systems. Future work should explore the feasibility of transferring these models to other fields where UAVs or flying objects are involved, potentially opening up new applications for the technology.

By addressing these limitations and pursuing these future directions, this research can evolve to become a more comprehensive solution, capable of adapting to the complexities of real-world scenarios while balancing the technological and ethical challenges of UAV detection.

## Data Availability Statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://www.kaggle.com/datasets/saidulkabir/vcug-vur-dataset

## Conflict of Interest

The authors declare that the research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

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