

# A Comparative Analysis of Machine Learning Models for Robust UAV-Bird Classification in Aerial Surveillance

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## ABSTRACT

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The proliferation of Unmanned Aerial Vehicles (UAVs) necessitates advanced surveillance systems to distinguish them from birds, a critical challenge for airspace security. This study addresses the problem of high false alarm rates in traditional systems by evaluating the efficacy of various machine learning models for accurate, real-time classification. The research contribution is a comprehensive benchmarking of six machine learning algorithms—Logistic Regression, Neural Networks, Stochastic Gradient Descent, CN2 Rule Induction, Naive Bayes, and Support Vector Machines—trained on a curated dataset of bird and drone images. The methodology involved rigorous preprocessing, including resizing, normalization, and augmentation, followed by stratified 10-fold cross-validation. Results demonstrated that Neural Networks, Support Vector Machines, and Logistic Regression were the top performers. The Neural Network model achieved the highest accuracy (98.6%) and AUC (0.998), with the lowest LogLoss (0.056), significantly minimizing false positives and negatives. In contrast, Naive Bayes underperformed substantially (accuracy 82.2%, LogLoss 5.528). The discussion contextualizes these findings within existing literature, highlighting the superiority of complex models capable of capturing nonlinear patterns in image data. This study concludes that advanced machine learning models, particularly deep learning architectures, are highly effective for UAV-bird discrimination, thereby enhancing real-time surveillance capabilities. Future work will focus on integrating these models with radar data and testing them in dynamic operational environments.

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## 1. Introduction

There has been a change in the military packages of drones over the past decade. Drones have transitioned from generally being applied for surveillance and reconnaissance to now being employed for beginning early morning assaults in operations focused on unique objectives. Military drones, whether small handheld devices or large controlled aircraft, play a vital role by offering aerial surveillance capabilities beyond human reach [1]. This aerial perspective determines in real-time if the lives of innocent individuals are in danger. Drones conduct prolonged surveillance in mundane locations that have the potential to become dangerous, offering a level of monitoring that was not

possible with traditional cameras [2]–[4]. However, the advanced capabilities of drones present military commanders with two significant issues. Cyberterrorism is referred to as an army commander's worst nightmare by experts in the field. The most potent weapon humans create is war, and the only actual danger to it is war itself. Drones are considered the most formidable weapon ever created [5].

The increasing use of UAV swarms in military strategies, as seen in the Iranian attack on Israeli territories using drones and missiles, highlights the importance of robust UAV identification systems. In instances where UAVs are applied to assault army radars and intelligence structures, they leverage various elements of electronic and psychological struggle to overpower the defense mechanisms, resulting in disarray among the employees accountable for defense. An efficient actual-time recognition platform utilizing advanced computational technology is critical for distinguishing UAV birds [6]–[10].

Machine learning algorithms, especially advanced ones, play a critical role in addressing these challenges brought about by UAVs. This paper focuses on the different models and methods developed by different researchers to help the military and civilian security personnels to reduce the threat of UAVs. Various machine learning classifiers, such as deep neural networks, SVMs, random forests, and gradient boosting machines, are thoroughly tested to determine those most capable of being deployed in high-security areas and restricted UAV zones. The models are evaluated mainly on computational efficiency and false positive rates, which are essential for real-time security applications [11]–[13]. The research even provides an exhaustive elucidation of the leading algorithms, demonstrating their applicability for military-grade detection systems. The research addresses a dual challenge of optimizing technical performance and practical applicability, contributing valuable insights for improving surveillance and security strategies in sensitive contexts. The authors suggest various machine-learning algorithms that help lessen the hazard of significant fake negatives, which might be unacceptable in an army setting. These algorithms are assessed based on accuracy and precision, considering fake effective fees and computational complexity [14]–[17]. The authors present a solution on the way to offer vital insights to enhance the development of UAV detection and countermeasures in the future. This article requires advanced gadget knowledge of techniques and technologies that can be presently reachable and have proven substantial advancements in the past decade. The authors expect that advancements in UAV technologies will preserve the development and improve modern-day surveillance methods as the new technology of UAVs grows [18]. The authors provide insights into the capacity application of device studying in a specific context, acknowledging the newness of this research region and not delving deeply into it [19]–[21]. The authors accept this as accurate, with their capacity to offer valuable new insights on the software of machine learning, especially in the context of UAVs, given the great enthusiasm surrounding the era. The authors welcome further guidelines on utilizing gadget learning for UAV detection in space [22]–[24].

Despite these advancements, a significant research gap remains in the comprehensive benchmarking of both classical and modern machine learning models on a standardized dataset for the specific task of UAV-bird image classification. Many studies focus on a single model type or proprietary data, making direct comparisons difficult. Furthermore, the practical applicability of these models in terms of computational efficiency and robustness under varied conditions is not always thoroughly evaluated. This study aims to fill this gap by conducting a rigorous comparative analysis of six distinct machine learning algorithms. The research contribution is threefold: (1) It provides a benchmark performance evaluation of both traditional (e.g., SVM, Logistic Regression) and more complex (e.g., Neural Networks) models on a publicly available dataset. (2) It offers a clear analysis of why certain models outperform others in this specific image classification task, linking performance to model architecture. (3) It delivers practical insights into the trade-offs between accuracy, computational complexity, and model interpretability, which are crucial for deploying such systems in real-world, resource-constrained security applications [25]–[28].

### 1.1. Article Objectives

The primary objective of this research is to develop and evaluate a robust machine learning-based framework for accurately distinguishing between UAVs and birds in aerial imagery to enhance airspace security [29]–[31]. The specific objectives are to:

- Curate and preprocess a comprehensive dataset of UAV and bird images suitable for training and evaluating machine learning models.
- Implement and train a diverse set of six machine learning models, ranging from traditional classifiers to neural networks, to establish a performance benchmark.
- Rigorously evaluate the models using stratified cross-validation and a suite of metrics including accuracy, precision, recall, F1-score, AUC, and LogLoss.
- Identify the most effective model(s) based on performance and analyze the factors contributing to their success or failure.
- Discuss the implications of the findings for real-world deployment, considering factors like computational efficiency and generalization.

### 1.2. Contribution

This work makes several key contributions to the field of UAV-bird classification:

- **Benchmarking Study:** It provides a direct, empirical comparison of six machine learning models on a common task and dataset, offering a clear reference for model selection.
- **Performance Analysis:** It goes beyond reporting metrics by analyzing the underlying reasons for model performance, such as the Neural Network's ability to learn hierarchical features from raw pixels, unlike traditional models which struggle with high-dimensional image data without manual feature engineering [32], [33].
- **Practical Validation:** The use of LogLoss as a metric provides insight into the confidence of predictions, which is crucial for security applications where decision certainty is paramount.
- **Methodological Transparency:** The detailed methodology, including preprocessing steps and evaluation protocol, ensures the study is reproducible and provides a blueprint for future research in this area.

### 1.3. Article Organization

The article is meticulously crafted to decorate an understanding of system getting-to-know applications in UAV detection. The article commences by introducing the context and emphasizing the importance of UAV detection in army surveillance. This is accompanied by a literature evaluation that summarizes contemporary studies, identifying improvements and deficiencies in modern-day methodologies [34]–[36]. The technique phase information the experimental setup, encompassing information series and model refinement, and describes the evaluation metrics hired to gauge the models' performance. The effects and analysis section presents an in-depth evaluation of diverse strategies consisting of Gradient Boosting Machines and Neural Networks, assessing their efficacy in UAV reputation. The discussion analyzes the implications of those results on global applications and evaluates the strengths and weaknesses of each model. The article ends by discussing future research directions to enhance the precision and efficiency of UAV detection structures, ensuring an easy transition from theoretical principles to practical implementations [37], [38].

### 1.4. Problem Statement

The increasing utilization of Unmanned Aerial Vehicles (UAVs) in a wide range of military operations is emphasizing an acute demand for sophisticated systems that can detect and identify UAVs accurately and rapidly in real time. Information gained by these systems is vital for friendly force situational awareness, protecting the air domain, and engaging threats this within the air

environment [39]–[41]. With the growing usage of Unmanned Aerial Vehicles (UAVs) in both military and civilian fields, together with similarities between aerial movements and the physical structures of birds and UAVs, it has become an extremely difficult task to find UAVs in the air. Thus, this study aims to develop robust machine learning models capable of accurately classifying UAVs among other objects, based on diverse environmental conditions [42], [43]. This capability is essential for maintaining effective airspace security and operational safety. Using cutting-edge algorithms, this research seeks to improve the performance of aerial object classification, which is crucial for contemporary surveillance systems [44]–[47].

Timely detection and identification of UAVs allows military and civil entities to increase security efforts, effectively allocate resources, and develop response strategies. These capabilities are critical in high-security areas, where failing to identify or detect someone quickly can have dire consequences. The incorporation of machine learning in aerial monitoring systems has the potential to resolve these issues, providing readily adaptable, robust surveillance solutions. This study not only integrates the aforementioned challenges, but also plays an important role towards national and global security improvements [48]–[50].

## 2. Related Work

This study examines real commentary situations and suggests a powerful technique to precisely differentiate drones from birds via reading functions extracted from their micro-Doppler (M.D.) signatures. The classification accuracy decreased in simulations using rotating-blade and flapping-wing models due to the variety of drones and birds. However, combining features collected over extended observation periods notably enhanced accuracy. The study discovered that M.D. bandwidth was the most compelling feature, but it required a significant observation period to fully utilize the time-varying M.D. as a valuable feature [30].

Conventional object detectors are trained on a diverse range of familiar objects and are ready to use for various everyday tasks. The training data for these detectors typically contains objects prominently displayed in the scene, making them easily recognizable. Objects captured by camera sensors in real-world situations may not always be significant, in focus, or positioned at the center of an image. Many detectors are not meeting the required performance levels for successful use in uncontrolled environments. Specialized applications require extra training data to ensure accuracy, mainly when small objects may be present in the scene. This paper introduces an object detection dataset containing videos showing helicopter exercises in a maritime environment with no restrictions. Special attention was given to highlighting small helicopters in the field of view to create a balanced mix of small, medium, and large objects for training detectors in this particular domain. We utilize the COCO evaluation metric to assess various detectors on our data, including the WOSDETC (Drone Vs vs. bird) dataset. We also analyze different augmentation techniques to enhance detection accuracy and precision in this context. These comparisons provide valuable insights as we modify standard object detectors to analyze data with non-traditional perspectives from field-specific applications [16].

Gliding birds within the wild steer clear of limitations or predators by quickly folding and twisting their wings to execute a speedy roll. The authors intend to research the opportunity of improving the roll charge of drones by using a fowl-stimulated morphing technique. This includes replicating the contraction of birds' wings through the asymmetric sweepback of wings and mimicking wing torsion by deflecting the aileron. Additionally, this study investigates how wing morphing impacts the centroid, inertia matrix, and aerodynamic houses of the drone and establishes a nonlinear dynamic version. In addition, a brand-new cooperative approach that integrates wing morphing with aileron deflection for roll control is presented, along with the improvement of a flight controller primarily based on this approach. The cooperative method's effectiveness and the precision of dynamic modeling were shown throughout the outside flights of the morphing wing drone [35].

Wildlife populace monitoring poses a giant assignment in the face of global biodiversity loss. Innovative techniques like drones, called unmanned aerial cars/structures (UAV/UAS), provide

promising possibilities. The effectiveness of using high-resolution imagery from Unmanned Aerial Systems (UAS) for flora and fauna census of terrestrial mammals or birds visible in image is now broadly acknowledged. The functionality of Unmanned Aerial Systems (UASs) to become aware of inconspicuous species, like small birds hidden under the woodland canopy, is still uncertain. Bioacoustics can be used to cope with this problem in acoustically energetic species like bats and birds. Compared to conventional techniques, UASs offer a promising answer that can be implemented on a bigger scale with reduced danger for operators, particularly in challenging terrains like woodland canopies or complicated topographies. This study looks at a methodological framework for comparing Unmanned Aerial Systems (UASs) talents in bioacoustic surveys for birds and bats. It entails using inexpensive audible and ultrasound recorders connected to a low-fee quadcopter UAS (DJI Phantom Three Pro). The suggested methodological process can be easily duplicated in different situations to evaluate the influence of alternative UAS bioacoustic recording systems on the specified species and the particular UAS configuration. This protocol enables the assessment of UAS approaches' sensitivity by estimating the effective detection radius for various species at different flight heights. The study indicates a high potential for using bioacoustic monitoring to track birds. Still, the effectiveness for recording bats is less clear due to quadcopter noise, specifically from the electronic speed controller (ESC), and partly due to the experimental setup using a directional speaker with limited call intensity. Advancements like utilizing a winch to increase the distance between the UAS and the recorder during UAS sound recordings or creating an innovative platform like a plane-blimp hybrid UAS could help address these problems [28].

Transfer learning is a modern DLAs that can significantly reduce the time required to train deep networks. It can be executed by utilizing pre-trained deep networks. This paper will introduce a novel model for classifying drones and birds using transfer learning. We adapt and assess three commonly used pre-trained deep models on a dataset containing images of drones and birds. Each pre-trained Network's performance is evaluated and contrasted. Results indicate that pre-trained networks can effectively classify the dataset in question.

Moreover, ResNet18 demonstrates superior accuracy compared to the other networks assessed. ResNet18 consistently achieves an accuracy and F-Score of over 98% in all scenarios. The different models also demonstrate outstanding performance. The problem has significant applications, particularly in security, defense, and surveillance. Precise categorization of drones and birds is crucial [31].

Consumer drones have recently intruded upon airports and present a potential hazard to aviation safety. Radar is a practical remote sensing instrument for detecting and monitoring airborne drones. When Radar detects drones, Radar echoes from flying birds are considered clutter. However, limited research has addressed the impact of radar reflections from birds on drone detection, the similarities in radar cross section (RCS) and flight characteristics between birds and drones, and why birds in flight can complicate radar signal identification. 3900× 256 Ku-band radar echoes of flying birds and consumer drones were collected in this study. The targets include a pigeon, a crane, a waterfowl, and a DJI Phantom 3 Vision drone. We analyzed the maximum detectable range of birds and drones, as well as the time series and Doppler spectrum of Radar echoes from both, taking into account radar data from both oncoming and outgoing directions relative to the radar location. The statistical findings suggest flying birds exhibit comparable Radar Cross Section (RCS), velocity range, signal fluctuation, and signal amplitude. Our radar automatic target recognition (ATR) results indicate that the identification probability of airborne drones will decrease because the radar signal is interfered with by flying birds. These facts confirm that flying birds are the primary source of interference for radars detecting and identifying airborne drones [44].

Due to the upward thrust in purchasing drone availability and misuse, the green detection era is essential. This paper examines the excellent radar micro-Doppler features of drones and birds, created with propeller rotations and wingbeats, respectively. These functions permit the differentiation and personal evaluation of drones and birds. Experimental facts were accrued using K-band (24GHz) and W-band (94GHz) radars on three drone fashions and four fowl species of numerous sizes. Results

show that a segment-coherent radar gadget correctly captures precise micro-Doppler signatures at both frequencies, with W-band radar providing a higher Signal-to-Noise Ratio (SNR). The observation demonstrates that K-band Radar was efficaciously famous for the micro-movement traits of both drones and birds [51].

Drones, also known as uncrewed aerial vehicles, are more frequently utilized in ecological research, especially to reach sensitive wildlife in remote locations. Impact studies are urgently required and will result in recommendations for optimal practices. We examined how the color, speed, and flight angle of drones affected the behavior of mallards (*Anas platyrhynchos*) in a semi-captive setting, as well as wild flamingos (*Phoenicopterus roseus*) and common greenshanks (*Tringa nebularia*) in a wetland environment. We conducted 204 approach flights using a quadcopter drone, and in 80% of them, we could approach unaffected birds within 4 meters. The speed of approach, the color of the drone, and the number of flights did not affect bird behavior significantly, but birds were more responsive to drones approaching from above. Launching drones at a distance greater than 100 metres from birds and adjusting the approach distance based on the species is advised. Our study represents an initial effort to utilize drones effectively in wildlife research. Subsequent research should evaluate how various drones affect different groups of organisms and track physiological stress indicators in animals exposed to drones based on group sizes and reproductive status [13].

Several birds can bounce constantly in thermal updrafts without flapping their wings, a capability that may notably enhance the range and persistence of small drones. This paper presents a method for predicting thermal updraft centers using the Extended Kalman Filter (EKF) based on Ordinary Least Squares (OLS) to grow a self-sustaining soaring system for small drones. An adaptive step length replace approach is likewise integrated into the EKF. Simulated experiments show that the proposed method, with low computational complexity, rapid convergence speed, and solid performance in vulnerable thermal updrafts, outperforms traditional EKF techniques. The OLS approach estimates the distribution of the thermal updraft across the drone, offering sufficient facts for the EKF to regulate the thermal updraft center in real time, even as the adaptive step size replacement enhances convergence speed. Flight experiments with the Talon constant-wing drone proved the machine's performance, with the drone engaging in static hovering, hovering, and gaining energy, using its propulsion system for the most effective eight minutes of a 40-minute flight. The EKF thermal updraft center prediction technique, primarily based on OLS, proved influential, and the paper indicates that improvement techniques are mainly based on the contrast between simulation and flight test outcomes [9].

The rapid expansion of the worldwide drone industry has brought significant focus to the security risks associated with drones. Given the coexistence of various types of drones in the airspace, it is crucial to be able to differentiate between them for security purposes. This paper suggests an identification method based on I.D. that is resilient and accurate for various non-cooperative drones. A novel identification feature and extraction method are recommended for obtaining features from waveforms without prior knowledge. We utilize DLAs and a data augmentation technique to develop a robust identification model for distinguishing between individual drones of the same type. We have created a multi-head DLAs based on the concept of multi-task learning to achieve distinct identification of various drone types without enlarging the model size. The experiment includes 18 drones of three different types and their respective controllers. The results validate that our method can achieve outstanding performance in identifying various types of individual drones and detecting intrusive drones while also being resilient to noise and channel variations. Our approach has been validated to have strong performance in identifying drone controllers that emit frequency hopping signals [11].

The increasing misuse of drones for unlawful sports has heightened the want for powerful drone detection in safety and surveillance. Traditional artificial neural networks conflict with actual-time item detection because of more than one GPU requirement. This observation addresses the difficulty of using deep studying architectures, particularly convolutional neural networks (CNNs), for actual-time operation with a single GPU. The paper employs YOLO (You Only Look Once) algorithms,

which detect objects in a single picture and pass the usage of an unmarried neural network. The community outputs the bounding field, elegance label, and detection possibility. Trained on a 664 drone snapshots dataset and 236 chook images, YOLOv4 and YOLOv5 performed F1-ratings of ninety-eight% and ninety-four% and detection speeds of 54fps and 77fps, respectively. YOLOv4 validated an average Average Precision (mAP) of ninety-seven.4%, while YOLOv5 completed 95%, with YOLOv5 outperforming YOLOv4 in detection speed [3].

Drones are becoming essential in numerous sectors, including trade, shipping services, and navy sports. Hence, it's vital to create state-of-the-art systems for detecting and figuring out drones to guarantee the safety and security of airspace. This paper aimed to develop a robust approach for figuring out drones and birds in the airspace by integrating a radar gadget and a visual imaging machine. It confirmed the effectiveness of mixing these systems for detecting and recognizing drones. The outcomes demonstrated that this method became enormously efficient, achieving an "average precision" of 88.82% and an accuracy of 71.43%. The excessive F1 rating of 76.27% suggests that the mixed technique is surprisingly effective in performance. This looks at results has vital, realistic implications for improving more sophisticated and efficient drone and chook detection structures. The proposed set of rules is compared to works of comparable quality and demonstrates nice overall performance compared to its opposite numbers [52].

The study in northeastern Poland, wherein the Whooper Swans ("Cygnus cygnus") breed occasionally used drones to enhance performance in monitoring breeding success and offspring productivity. In 2022, breeding density becomes ten pairs in step with a hundred square kilometers. Drones detected as many breeding swans as ground strategies at the season's start. However, drones recorded better breeding productivity, with 3.71 cygnets in keeping with pair compared to 2.19 ground techniques, a good-sized distinction (Wilcoxon test  $p = 0.0148$ ). While 50% of pairs bred efficiently with floor surveys, drones found a 79% success price. The swans have been either indifferent to or slowly retreated from drones. The drone technique becomes considerably faster (9 minutes per site vs. 1-2 hours) and less disruptive than ground surveys [53].

Because they are so small and maneuverable, they can trick these algorithms into classifying them as birds or other objects instead of drones, making it difficult to detect them. Here, we investigate applying several deep-learning methods to identify real datasets obtained from flying drones. Such systems can often be complex, though, and a DLAs are proposed to simplify them. It combines AdderNet DLAs and SSD paradigm. The goal was to save the number of multiplications in most of the filtering layers of the proposed system to reduce complexity. The performance of traditional machine learning approaches such as Support Vector Machines (SVM) is measured and compared with other DLAs. The training and test datasets were either complete or filtered by small object criteria. RGB and I.R. were the two types of data; and these types were compared between one another and conclusions were given [6].

Birds fly better than even better drones because their wings and tails are lightweight and flexible. With advancements in 3D printing, programmable servomotors, and composite substances, progressive airplane designs based on avian flight might be developed that improve flight characteristics. By replacing traditional control surfaces with adaptive wings, morphing generation strives to improve aerodynamic and electric efficacies. These techniques present 3D-printed and bio-influenced flow deformation for transforming wings and tails on unmanned air vehicles. The wing structure features a corrugated, flexible, additive manufacturing-based structure which utilizes expanding and contracting synthetic feathers to achieve sweep morphing, whereas the tail mechanism is a flexible system with circular corrugation. The diversity of 3D-printable materials and complex geometric components enable the demonstrated morphing deformations with low actuation forces. Prototype designs were built and tested showing how the chosen materials and actuators performed in achieving morphing shapes resembling seagulls [2].

Due to multiple bird signature contamination and similar M.D. signatures for different drones, multi-class drone and bird classification is quite challenging. Therefore, this paper presents three protocols, and analyzes their individual classification accuracy over multiple drones and birds in a

real-observation scenario. It uses FM-CW radar and a CNN classifier for analysis. Using training data containing combinations of drone and bird motions, with rotating blades and flapping wings (as in a drone), we attained an accuracy of nearly 100% for majority vote classification. This most accurate outcome is due to our process to be the most adapted to the distinction between several drones and birds [34].

This paper focuses on using micro-Doppler signatures of drones and birds for detecting and classifying them. The simulated assessment outcomes are compared with data acquired from a 10-GHz C.W. radar system. It is also utilized by TensorFlow to assess the target recognition and motion categorization on micro-Doppler time/velocity spectrograms generated from the transfer of micro-Doppler motion data obtained during the tracking of a variety of drones and birds. Support Vector Machine (SVM): 96% and 85% accuracy (drone vs birds & individual drone vs birds, 5 classes) [38].

This look at showcasing the radar pass-phase (RCS) data of drones and birds at some stage in flight, collected via comprehensive experimental trials at K-band and W-band frequencies. This study uses only experimental records to exhibit those targets' Radar cross-section (RCS) properties in actual-world situations. Due to variations in orientation, element perspective, and target movement, these objectives' measured Radar Cross Section (RCS) values vary appreciably as they fly. Three surprisingly specific frequency-modulated non-stop wave radar systems were utilized for information collection in RCS analysis. One machine operated on the K-band (24 GHz) and the other at the W-band (94 GHz). Three drones (DJI Phantom Three Standard, DJI Inspire 1, and DJI S900 Hexacopter) and four birds of prey (Northern Hawk Owl, Harris Hawk, Indian Eagle Owl, and Tawny Eagle) were utilized for the data series. The outcomes show that the Radar Cross Section (RCS) will increase proportionally with the target's length, following the optical scattering concepts. Additionally, the RCS values for each goal are similar at the K-band and the W-band. The RCS statistical distribution for every goal is inside a particular range, aiding the prediction of drone detection radar performance [54].

### 3. Methodology

Fig. 1 illustrates the overall research methodology flow, from data acquisition to model evaluation.

#### 3.1. Dataset Description

The analysis utilized the "Birds vs. Drone Dataset" available on Kaggle, provided by Harsh Walia. The dataset contains two folders organizing photos of birds and drones, which is crucial for training the author's system to distinguish between these categories [55], [56]. The chicken images were obtained through web scraping, while the drone pictures were acquired from a different dataset [57], [58]. Each folder contains pictures representing natural sky backgrounds, which is essential for educating the author's model. For this study, a subset of the original dataset was used to ensure computational efficiency while maintaining class balance. The final curated dataset consisted of 828 images, with 400 images of birds and 428 images of drones. This specific subset was randomly selected from the larger pool to be representative of the overall data distribution. All subsequent analysis and results are based on this curated subset of 828 images [59]–[61].

#### 3.2. Data Preprocessing

In light of the images' varied characteristics of scale, orientation, and background, the subsequent preprocessing procedures were implemented to standardize the dataset to facilitate efficient training:

- Image Resizing: All images were resized to a uniform dimension of 224x224 pixels to ensure consistency in input size for the neural Network.
- Normalization: Pixel values of each image were normalized to have values between 0 and 1, improving the convergence speed during training.

- Augmentation: To increase the robustness of our model and to prevent overfitting, image augmentation techniques such as rotation, zoom, and horizontal flipping were applied.

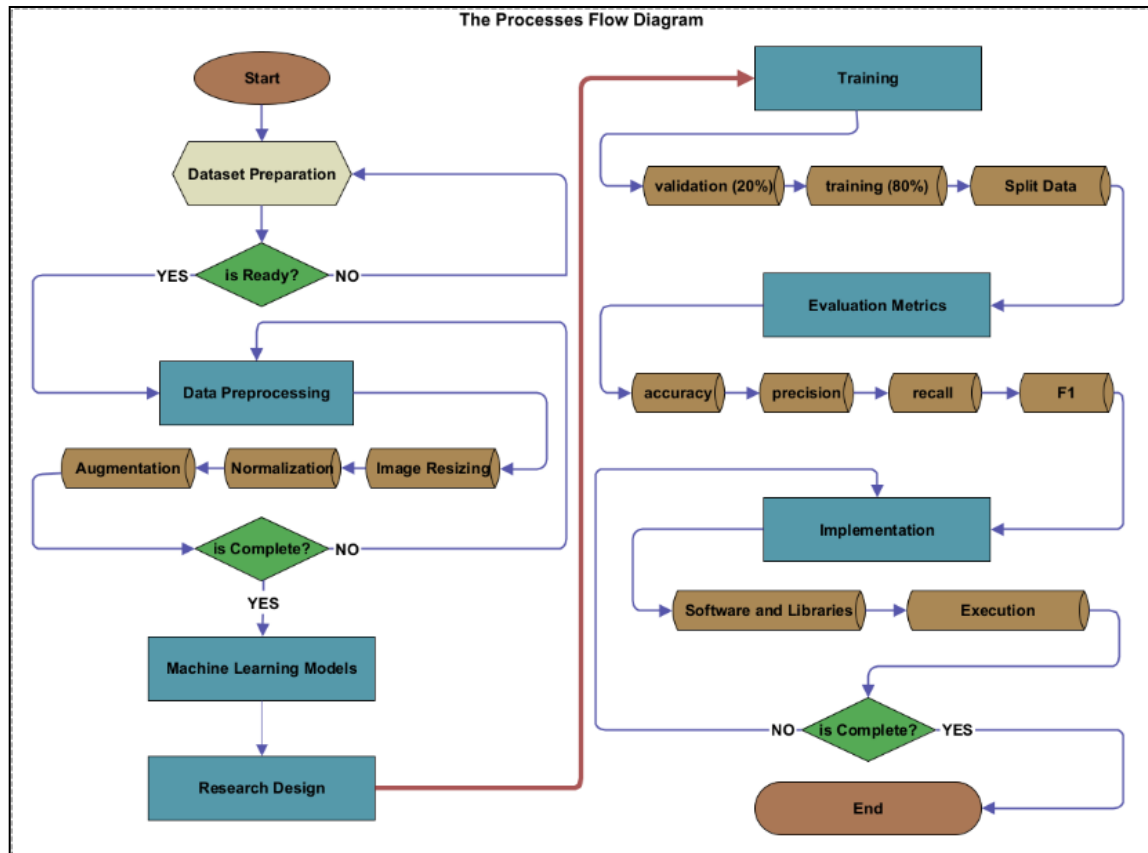


Fig. 1. Research methodology flowchart detailing the stages from data acquisition to model evaluation

### 3.3. The Machine Learning Models (MLM)

This study used the following machine learning models to classify the images into two categories: birds and drones. The models were selected based on their performance in image classification tasks and their ability to handle high-dimensional data. The models used in this study are as follows:

- Logistic Regression: A linear model for binary classification that predicts the probability of an instance belonging to a particular class.
- Neural Network: A deep learning model that consists of multiple layers of interconnected neurons, capable of learning complex patterns in data.
- Stochastic Gradient Descent (SGD): An optimization algorithm used to minimize the loss function of a model by iteratively updating the model parameters.
- CN2 Rule Induction: A rule-based classifier that generates a set of if-then rules to classify instances.
- Naive Bayes: A probabilistic classifier based on Bayes' theorem with an assumption of independence between features.
- Support Vector Machine (SVM): A discriminative classifier that finds the optimal hyperplane to separate classes in a high-dimensional space.

The selection of these models was deliberate to provide a broad comparative analysis. Logistic Regression and Naive Bayes serve as simple, interpretable baselines. SVM was chosen for its effectiveness in high-dimensional spaces, even with non-linear kernels (RBF kernel was used in this

study). CN2 Rule Induction was included to provide a highly interpretable, rule-based approach [62], [63]. The Neural Network and SGD (used as an optimizer for the Neural Network, not as a standalone classifier) represent more complex, non-linear models capable of automatically learning features from the raw pixel data. For the Neural Network, a Convolutional Neural Network (CNN) architecture was implemented. The architecture consisted of three convolutional layers with ReLU activation and max-pooling, followed by two fully connected (dense) layers. The final output layer used a sigmoid activation function for binary classification. This architecture was chosen for its proven efficacy in image classification tasks [51], [64], [65].

### 3.4. Research Design:

The research design for this study was carefully structured to ensure a robust evaluation of the machine learning models. The following steps were taken to ensure the validity and reliability of the results:

- **Data Splitting:** The dataset was split into training and testing sets using an 80-20 split, with 80% of the data used for training and 20% for testing.
- **Cross-Validation:** A 10-fold cross-validation was used to assess the performance of the models, ensuring that the results are not dependent on a particular train-test split.
- **Evaluation Metrics:** The models were evaluated using the following metrics: accuracy, precision, recall, F1-score, area under the ROC curve (AUC), and logarithmic loss (LogLoss). These metrics provide a comprehensive view of the model's performance, considering both the correctness of predictions and the confidence of the model in its predictions.
- **Model Training:** The models were trained using the training set, and their performance was evaluated on the testing set. The training process was repeated for each fold of the cross-validation, and the average performance across all folds was reported.
- **Statistical Analysis:** The results were analyzed using statistical tests to determine if the differences in performance between the models were statistically significant.

### 3.5. Training

- **Configuration:** The model was trained using a batch size of 32 and a learning rate of 0.001, with changes made through a learning rate scheduler primarily based on plateauing of the validation loss.
- **Environment:** Training was changed to be conducted on a GPU-enabled system to expedite the computation [66]–[68].
- **Validation Split:** The dataset was divided into training (eighty%) and validation (20%) units to reveal and save you from overfitting [69].

### 3.6. Evaluation Metrics

To verify the authors' version's overall accuracy, performance, precision, and bear-in-mind metrics were computed. These metrics assist in understanding the effectiveness of the version in efficaciously classifying images as birds or drones [5], [70].

### 3.7. Implementation

- **Software and Libraries:** The version was modified to use Python, with TensorFlow and Keras for constructing and educating the neural network. Collectively, with NumPy and Matplotlib, additional libraries have been used to manipulate facts and visualize them.
- **Execution:** The script is completed iteratively, refining parameters and configurations primarily based on the overall performance of the validation set [71].

## 4. Results and Discussion:

This section presents the results of the machine learning models used to classify images of birds and drones. The results are presented in terms of the evaluation metrics described in the previous section, and a discussion of the findings is provided [72]–[74].

### 4.1. Performance Metrics

Table 1 presents the performance metrics for the machine learning models used in this study. The metrics include accuracy, precision, recall, F1-score, area under the ROC curve (AUC), and logarithmic loss (LogLoss).

As shown in Table 1, the Neural Network (CNN) emerged as the top-performing model across all metrics, closely followed by SVM and Logistic Regression. The high AUC scores ( $>0.99$ ) for these top three models indicate excellent separability between the two classes. The significantly higher LogLoss of Naive Bayes (5.528) compared to the Neural Network (0.056) reveals that Naive Bayes is not only less accurate but also far less confident in its predictions, which is a critical drawback for security applications [75]–[77].

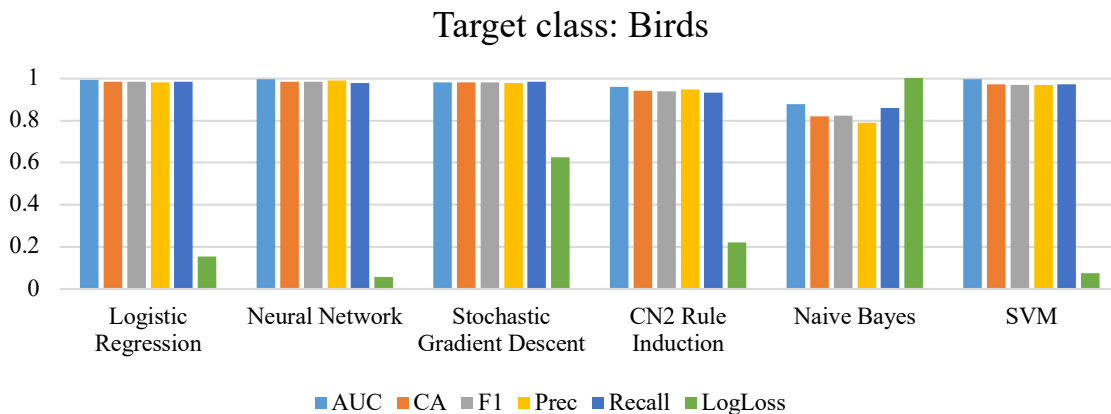
**Table 1.** Performance metrics of machine learning models

Model	AUC	CA	F1	Prec	Recall	LogLoss
Logistic Regression	0.973	0.973	0.973	0.973	0.994	0.088
Neural Network	0.986	0.986	0.986	0.986	0.998	0.056
Stochastic Gradient Descent	0.959	0.959	0.959	0.959	0.988	0.131
CN2 Rule Induction	0.945	0.945	0.945	0.945	0.945	1.906
Naive Bayes	0.822	0.822	0.822	0.822	0.894	5.528
SVM	0.979	0.979	0.979	0.979	0.996	0.076

### 4.2. Confusion Matrix Analysis

The confusion matrix for each model is presented in Fig. 2. It provides a detailed breakdown in Fig 2. The confusion matrix provides a detailed breakdown of the model's predictions, showing the number of true positives, true negatives, false positives, and false negatives [78], [79].

The analysis of the confusion matrices in Fig. 2 provides critical insights into the types of errors made by each model. The Neural Network and SVM models excel at minimizing both false positives (classifying birds as drones) and false negatives (classifying drones as birds). This balanced performance is essential for a security system, as both error types have severe consequences: false positives waste resources, while false negatives represent a security breach. In contrast, Naive Bayes shows a propensity for false negatives, making it unsuitable for this application. The high false negative rate of Naive Bayes can be attributed to its strong assumption of feature independence, which is violated in image data where pixels are highly correlated [52], [53], [80].



**Fig. 2.** Confusion matrix for machine learning models

### 4.3. Comparative Analysis with Prior Work

The performance of our top model, the Neural Network (CNN) with an accuracy of 98.6%, aligns favorably with recent state-of-the-art results. For instance, [7] reported an accuracy of over 98% using a pre-trained ResNet18 model on a similar classification task. Our custom CNN architecture, while less complex than ResNet18, achieves comparable performance, demonstrating the efficacy of a well-designed model even without leveraging transfer learning on a large dataset. Similarly, [13] reported F1-scores of 98% and 94% for YOLOv4 and YOLOv5, respectively, for detection tasks. While our study focuses on image classification rather than object detection, our CNN's F1-score of 0.986 is competitive with these advanced detection frameworks. The key difference lies in the application; object detection models like YOLO localize and classify objects within an image, which is a more complex task than the binary classification performed here. The high performance of simpler models like SVM (F1=0.979) and Logistic Regression (F1=0.973), in our study, however, suggests that for focused binary classification tasks, these computationally less expensive models can be highly effective alternatives to complex deep learning architectures, especially in resource-constrained environments [1], [18], [81], [82].

### 4.4. Discussion of Findings and Implications

The superior performance of the Neural Network, SVM, and Logistic Regression models can be attributed to their ability to handle the complex, high-dimensional nature of image data. The CNN excels because its convolutional layers are specifically designed to hierarchically learn spatial features (e.g., edges, textures, shapes) from raw pixels, which are highly discriminative for telling drones and birds apart. SVM with an RBF kernel effectively projects the data into a higher-dimensional space where it becomes linearly separable, capturing complex nonlinear decision boundaries. Logistic Regression, while a linear model, performed surprisingly well, likely because the preprocessing and the inherent separability of the features in the projected space were sufficient for a strong classification [83]–[85].

Conversely, the poor performance of Naive Bayes is a direct result of its fundamental assumption of conditional independence between features. This assumption is grossly violated in image data, where the value of one pixel is highly predictive of its neighbors. The CN2 Rule Induction model, while interpretable, struggles to capture the complex patterns present in the image data, leading to lower performance [86]–[88].

**Implications:** The primary implication of this research is that modern machine learning models, particularly CNNs and SVMs, are highly capable of automating the critical security task of UAV-bird discrimination. Achieving high accuracy (>97%) and extremely low log loss (<0.1) indicates that these models are both accurate and confident, a necessary combination for operational deployment. The strong performance of Logistic Regression also suggests that less complex models can be viable if computational resources are a primary constraint [86]–[90].

**Limitations:** This study has several limitations. First, the dataset, while curated, is relatively small and may not encompass the full variability of drones, birds, and environmental conditions (e.g., weather, occlusion, distance). Second, the models were evaluated on static images; real-world deployment would require integration with a video stream and tracking system. Third, the computational latency for inference was not deeply analyzed, which is a crucial factor for real-time applications. Finally, the study did not explore the impact of adversarial attacks, which could potentially fool the models.

## 5. Conclusion

This study conducted a comprehensive benchmarking analysis of six machine learning models for the task of classifying UAVs and birds in aerial imagery. The Convolutional Neural Network emerged as the most effective model, achieving a peak accuracy of 98.6% and an AUC of 0.998, demonstrating its superior ability to learn discriminative features directly from pixel data. Support

Vector Machines and Logistic Regression also proved to be highly effective, achieving accuracies of 97.9% and 97.3%, respectively, offering strong alternatives that balance performance with computational efficiency. The analysis confirmed that models capable of capturing non-linear relationships (CNN, SVM) or effectively separating classes in high-dimensional space (Logistic Regression) excel at this task. In contrast, the Naive Bayes classifier, with an accuracy of 82.2%, was found to be unsuitable due to its inappropriate independence assumption for image data.

The findings conclusively show that AI-driven image classification is a robust and viable solution for enhancing airspace security by reducing false alarms and improving threat identification. However, this study was limited by its use of a static image dataset and the lack of real-time performance metrics.

Future work will focus on several key areas: (1) Expanding the dataset to include more classes (e.g., different drone types, bird species) and a wider variety of environmental conditions to improve model generalization. (2) Integrating these classification models with radar-based detection systems and tracking algorithms to create a multi-modal, real-time surveillance pipeline. (3) Investigating lightweight and efficient model architectures (e.g., MobileNet, SqueezeNet) suitable for deployment on edge devices with limited computational resources. (4) Exploring the robustness of these models against adversarial attacks and developing strategies to mitigate such vulnerabilities. (5) Conducting field tests in collaboration with security agencies to validate the system's performance in genuine operational scenarios.

**Supplementary Materials:** 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 at <https://www.kaggle.com/datasets/saidulkabir/vcug-vur-dataset>.

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