IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661, p-ISSN: 2278-8727, Volume 28, Issue 1, Ser. 2 (Jan. – Feb. 2026), PP 16-28
www.iosrjournals.org

Advanced UAV Detection And Airspace Security Techniques In Military Environments

Ajlan Al-Ajlan
(Department Of Management Information Systems, College Of Business And Economics, Qassim University, Buraydah 51452, Saudi Arabia)

Abstract:
Background: *Small, fast drones are now cheap and easy to use, and they are being used in hostile military or other hostile settings. These drones can be armed or used to spy on people, and they represent a real threat to our military safety and equipment. It is very important that we have good automatic systems that can find these drones, no matter how hard they try to hide them.*
Materials and Methods: *Materials and Methods: This research investigates the efficacy of several supervised and unsupervised machine learning algorithms for classifying in-flight drones. The evaluated algorithms include linear regression, logistic regression, K-means clustering, random forests, decision trees, and naive Bayes classifiers. Model performance was rigorously assessed using standard evaluation techniques focused on minimizing classification errors, specifically false positives and false negatives.*
Results: *The study found that, when distinguishing between drone and non-drone items, the linear, logistic, and decision tree models performed best. These tools significantly reduce false calls and missed signs, making them very effective at spotting them.*
Conclusion: *The study shows that these machine learning tools, such as logistic regression and decision trees, can be used in real-world settings to fight. They can help make decisions independently, which will improve air defence. The work concludes with tips on developing better defence tools that can learn from new drone technology to protect against threats in today's wars.*

Key Words: *Machine Learning Algorithms, Model Evaluation Techniques, Drone Safety, Military, Drone Detection.*

Date of Submission: 21-01-2026 Date of Acceptance: 31-01-2026

I. Introduction

Over the last ten years, the technology of military drones has changed incredibly. Initially, drones were mainly used for spying, but now they can conduct precision strikes. Whatever their size, they are instrumental in providing aerial intelligence that can quickly lead to saving people's lives from unexpected dangers. Drones certainly help keep an eye on areas too dangerous for humans in ways that normal cameras cannot; nonetheless, they also create a whole realm of problems to be solved. Cybersecurity specialists reckon cyberterrorism is among the most significant threats military commanders face today. At the end of the day, drones are counted as one of the ultimate weapons ever devised in warfare [1, 2].

The enormous rise in unmanned aerial vehicles (UAVs), aka drones, in both military and non-military fields is creating a significant security problem. Drones can pose a hazard and may hit a bird, putting personnel at risk. Most current detection systems struggle to detect drones. Meanwhile, machine learning can significantly improve detection, and utilising radar, video, and audio data together can raise accuracy further. Still, real-time detection remains a problem. So, building robust UAV detection systems and bird-collision avoidance techniques is essential to keep the sky safe for flying [3, 4].

New studies on drone safety show that intelligent systems are vital for collision avoidance in the air. Machine learning methods, especially convolutional neural networks, not only improve the efficiency of object detection but also help address the problem of distinguishing between birds and drones [5, 6]. With the help of trajectory prediction models, unmanned aerial vehicles (UAVs) can predict the movement of birds, enabling real-time avoidance and ensuring that the flying machine's changed route does not violate mission objectives [6, 7]. This piece has solved the problem of preventing bird and drone collisions while keeping everyone safe.

Drones, or Unmanned Aerial Vehicles (UAVs), have become a popular tool for various civilian and military applications. However, they also bring about new risks of bird strikes. Bird strikes have been reported to occur more than 16, 000 times annually (Sun et al.). In fact, these incidents can cause more damage to drones, which are smaller and less robust, than to bigger, sturdier aircraft, according to [8, 9, 10].

Studies show that the impact of bird-drone collisions is quite different from that of birdplane strikes. Besides mechanical failures of the drone, there is also the risk of animal injury, and the situation may be complicated in the case of vital drone uses, such as the delivery of medical supplies and disaster relief operations [11, 12]. New solutions, such as machine learning algorithms and LiDAR sensing technologies, are being developed to forecast bird behaviour and enhance drone safety. Combining these studies and reports underscores the importance of recognising bird-drone collisions as a distinct safety issue, distinct from the usual cyber or military threats. Controlling this danger is a prerequisite not only for the safe integration of UAVs into the airspace but also for maintaining the balance of wildlife ecosystems [13, 14, 15].

This research aims to identify UAVs (Unmanned Aerial Vehicles) among a crowd of aerial objects. It is primarily dedicated to improving detection accuracy when models are trained on a massive collection of UAVs and other objects recorded under different environmental conditions. Additionally, machine learning and artificial intelligence are employed in experiments to develop sophisticated detection algorithms and to analyse flight patterns and sizes. Moreover, the system is installed and tested in simulated environments that replicate real-world scenarios, including UAV swarms. Hence, a system is devised that quickly gathers and processes data, thus enabling quick decision-making and maintaining high detection precision.

This paper presents machine learning as a tool to enhance drone security across multiple dimensions. Firstly, machine learning techniques improve drone detection and path prediction. Secondly, machine learning-powered detection systems can identify drones in a hostile environment where they are camouflaged. Thirdly, these systems can monitor multiple drones simultaneously, regardless of their type or size. Fourthly, the same technology helps identify objects suspected of being drones and neutralise their threat if necessary. This study highlighted the acute need to combine multiple sensors for drone detection, as single-sensor systems are unreliable under varying conditions (Carotenuto et al., 2017). Besides, the system can perform real-time signal processing and efficiently handle noisy data from uncontrolled environments. Last but not least, robust UAV detection systems will likely involve automatic target recognition features based on spectral, spatio-temporal, and other signatures.

This research paper is organised as follows: In Section 2, a review of relevant literature is presented to identify gaps in the topic. In Section 3, we describe our methods, including how we gathered data, the evaluation techniques used, and the machine learning algorithms employed. Section 4 presents and discusses the results and implications for airspace safety. Section 5 concludes with reflections and suggestions for further research.

II. Related Work

Previous Studies

Some recent studies have proposed different collision-avoidance strategies for swarm drones using distributed communication and repulsion vectors. Those methods, though quite successful in simulations, are hardly applicable in military airspace security as they depend heavily on precise communication and location awareness. This makes them susceptible to interference and GPS-denied environments. Hence, the plan is to create a multi-layered UAV detection and coordination framework for military applications, which will serve as the basis for the research. The idea is to improve collision avoidance and electronic countermeasures resilience while ensuring UAV platform scalability [13, 11].

In recent years, some dramatic advances have been made in drone technology, as reflected in much of the research. Using a drone motion capture system built on principles of computer vision for real-time tracking, the researchers went beyond the limitations of a fixed-camera system, a significant drawback of the traditional method [14]. However, this is not a solution to the problem of security in military or restricted airspace; as such, military drone operations will require capabilities beyond those addressed by the study above. Another study [16] has successfully shown how drones have been used to conduct a bird survey in a very short time compared to the traditional survey method and with more accuracy; however, the study has not moved beyond passive observation and its integration of military features, for example, the case of threat detection, which is a very crucial aspect has been left out. This work aims to develop a UAV detection and airspace security framework suitable for military operations. The system, equipped with deep learning models and dynamic flight pattern recognition, will independently detect, track, and take appropriate action against unauthorised UAVs, thereby significantly improving airspace defence capabilities.

Study [17] details bio, inspired morphing mechanisms that help the flight efficiency of birds but fails to address important issues such as hiding from surveillance and interacting with radar systems, aspects that are very important in the military context. On the other hand, the article [18] uses a random forest classifier to identify aerial targets but it is not equipped to respond to threats in real time or to coordinate a swarm, thus this method is not very effective against UAVs that try to escape.

The work presented here is intended to combine intelligent detection algorithms, adaptive swarm coordination, and defensive behaviors, thus creating a unified system capable of handling changing threats in military airspace. Moreover, studies [19, 20] show that machine learning, especially the random forest model, can accurately (up to 86%) predict security risks at public events. Still, these studies are mostly about threats on the ground and thus they have limited use for the security of military airspace. Our project is aimed at closing this gap by applying sophisticated deep learning methods that combine data from radar and GPS. This method not only makes possible scalable detection and response to threats from unmanned aerial vehicles (UAVs) but also forms a flexible system for dealing with aerial threats.

Recently, many papers on UAV detection have used methods such as radar-based micro-Doppler analysis and deep learning classifiers to separate drones from other flying objects. In one paper [21], the authors, using a deep CNN combined with handcrafted features, online local binary patterns, and range and Doppler maps obtained from a radar system, achieved 96% UAV detection accuracy across different scenarios, including open space and cluttered environments. In another paper [22], the advantage of a convolutional neural network combined with an LSTM cell for UAV classification from a radar system is highlighted, achieving 98.1% accuracy in two-class scenarios. Given these research limitations, the study will focus on incorporating features of multimodal sensors, using distributed deep learning algorithms for on-the-fly classification, extending multi-class capability, and applying adaptive models to changing environments. The said methodology is aimed at military UAVs operating in fully or partly controlled airspace, where it is paramount to deliver the fastest and most accurate threat detection.

Recent advances in micro, Doppler signatures have made it possible to better distinguish drones from birds, which is crucial for surveillance. In one research [28], the authors used a convolutional neural network (CNN) on frequency-modulated continuous-wave (FMCW) radar data and obtained near-perfect accuracy. However, the method was limited to batch-based inference. Another work [24] used a 10 GHz radar along with Support Vector Machines (SVM) and Tensor Flow and got an accuracy of 96%. Still, the method could not be used for live scenarios. Both solutions are affected by major challenges like being sensitive to environmental conditions, losing accuracy with different movement patterns, depending on stationary setups, and focusing only on drones and birds. We intend to overcome these barriers by combining CNNs with LSTM attention mechanisms, implementing lightweight onboard models for UAVs, using multi-sensor fusion, and broadening the classification capabilities to include swarm detection and anomaly identification. Such an approach will make UAV surveillance systems of the future more scalable, real-time, and flexible.

Current drone detection research indicates that complex data poses a significant challenge, as it hampers performance and leads to overfitting, among other issues. Tools like Principal Component Analysis (PCA) and Autoencoders are helpful in data simplification, thus allowing machine learning models to work better. Among the birds in the sky, radars can detect drones with 100% accuracy; on the other hand, deep learning models achieve 83% accuracy and are therefore considered suitable for real-world use. Still, some drawbacks remain, namely complex methods, small datasets, and environmental changes that reduce accuracy [25, 26, 27]. In this paper, we confront the issues by proposing solutions such as the combination of radar and computer vision data, increasing the number of samples in the dataset to include different types of drones, and creating deep learning models that are not only efficient but also light and fit for military applications. With such systems, we can enhance UAV safety and strengthen airspace security in hostile environments.

Recent studies have uncovered UAV detection methods that have shown excellent results. One such method is a self-supervised ConvNeXt V2 framework that achieved over 81% accuracy, and another is Garuda's framework, which reached 94.5% accuracy at a 400-meter distance [29]. Some other studies suggest that bringing radar together with audio and video can make it more reliable [30, 31]. However, not all problems have been solved yet, for example, small datasets and high computing power requirements. Our framework should address these points by combining radar, vision, and audio, employing efficient models, and expanding datasets to improve UAV detection and, therefore, enhance airspace security in military environments.

Earlier research on avoiding aircraft collisions in the air can be grouped into four main areas. First, pertain to the visual detection methods (like CNNs and YOLO-based detectors), which show good accuracy; however, such methods often encounter problems due to changing lighting conditions and the presence of many unwanted objects in the background. Secondly, radar-based classification systems can detect even in very low visibility; however, they struggle to distinguish small UAVs from birds. Third, studies that focus on bird-detection differentiation show that ensemble methods can improve classification accuracy, but, on the flip side, they can become computationally intensive in real-time scenarios [6, 5]. Last but not least, machine learning, based prediction models are designed to make use of the concept of trajectory prediction and optimisation algorithms for creating a new route; however, such models are primarily dependent on the idea of perfect sensor inputs, and, in addition, they are only to some extent validated on complex real-world scenarios [12]. One significant gap is that few studies first efficiently differentiate between birds and drones, then consider predictive modelling and real-time path rerouting. Thus, our paper aims to fill this void by integrating visual machine learning classification with trajectory prediction and incorporating a lightweight avoidance algorithm that is optimised for UAV operations [6]. We used synthetic datasets and real-world video footage to train and test our system, and we applied transfer learning to fine-tune the models. The experiments were carried out using measures such as precision, recall, F1, score, and latency. We also ran a comparison of our solution with the state-of-the-art models to assess where we stand fairly. Although we have identified ethical issues such as privacy and surveillance, we primarily focus on the safety aspect of our work: eliminating the risk of ecological damage during flight.

III. Methodology

Data Collection

The Kaggle dataset is an excellent resource for exploring how machine learning can be used to distinguish drones from other objects. It has really nice folders full of good photos from the camera. One folder contains pictures of various items collected via web scraping, which covers the real world well and makes the dataset more useful. On the other hand, a folder contains images of drones taken from a different dataset, providing a complete picture of both categories. Having such a wide variety of pictures is the main factor in creating strong, powerful machine learning models that can successfully recognise and separate drones from other objects in various situations [32.1].

In order to make our dataset uniform and suitable for training, we carried out several preprocessing steps. Initially, we scaled all the images so they had the same size, as consistent sizing is crucial for processing. Besides, we normalised pixel values to a range that allowed faster and more stable convergence during training. Moreover, we diversified our dataset by applying various image augmentation methods, such as rotation, zoom, and reflection. The rigorous efforts resulted in a model that generalises better and is more tolerant of changes likely to occur in real-world situations [33].

Machine Learning Algorithms

Linear Regression

Linear regression is a statistical method for estimating values (e.g., house prices) from one or more continuous variables. It describes how independent variables (things we can change) affect the dependent variable (the result that we want to predict) by drawing a straight line through the data points. The line is given by the equation $Y = a*X + b$. There are two main types of linear regression: simple linear regression, which considers only one independent variable, and multiple linear regression, which considers two or more independent variables for deeper analysis. Moreover, polynomial regression is capable of modelling more intricate, non-linear patterns in the data, thus allowing for better prediction and understanding [34].

Logistic Regression

Logistic regression is essentially a tool for forecasting binary results, e.g., "success" or "failure". It differs from regular regression in that it estimates the probability of an event occurring given the presence of one or more factors. The method converts the data fed to it into a probability score between 0 and 1, indicating the likelihood of the event; it can estimate a patient's risk of a particular disease by considering multiple symptoms. It is also known as logit regression and is widely used across fields such as medicine, banking, and sociology, where it describes how various variables are related and provides their probabilities [35].

K-Means

K-means is a well-known clustering technique widely used in data analysis. It enables grouping data points into clusters based on their similarities. Initially, you decide the number of clusters that you want, referred to as k. Following this, the algorithm designates each point to the closest cluster centre, thereby maintaining the similarity of points within the same cluster. This separates the data into distinct categories, facilitating analysis and decision-making [36].

Random Forest

Random Forest uses an ensemble of trees to combine multiple trees. A whole "forest" of trees is generated, where each tree is trained on a portion of the data and classifies objects based on different attributes. When there is a new object, each tree casts a vote for its class prediction, and the highest number of votes is the final class. Since this method improves the accuracy of the results and reduces the risk of overfitting, it is considered a powerful machine learning tool [37].

Decision Trees

The Decision Trees algorithm is a supervised machine learning method that serves both classification and regression purposes. It develops a tree-like model which determines a target variable by using straightforward and logical decision rules based on input features. Each node is a feature, and the branches show the possible outcomes. The model is very understandable, as the prediction is obtained by moving from the root to a leaf node [38].

Naïve Bayes Classifier

The Naive Bayes Classifier is one of the most widely applied supervised machine learning algorithms based on Bayes' Theorem. It computes the likelihood of a data point belonging to a particular class by assuming that its features are independent. This method is very efficient and is mainly used for text classification, spam filtering, and sentiment analysis [39].

Model Evaluation Techniques in Machine Learning

Evaluation metrics are indispensable instruments used to quantitatively measure the effectiveness of machine learning models. They not only help understand the model's accuracy, precision, recall, and other performance indicators but also focus on each model's ability and limitations. Consequently, this enables users to compare different algorithms and decide which one fits best for their requirements [40]. Here, we made use of these metrics to accurately classify images of objects and drones:

Classification Accuracy

Classification accuracy measures the percentage of correct predictions made by a machine learning model compared to the total number of predictions. This metric is easy to understand and ranges from 0 to 1. In scikit, learn, every estimator has a score method, and the default evaluation metric for classifiers is accuracy [41].

Confusion Matrix

Classification accuracy measures the percentage of correct predictions made by a machine learning model compared to the total number of predictions. This metric is easy to understand and ranges from 0 to 1. In scikit, learn, every estimator has a score method, and the default evaluation metric for classifiers is accuracy [41].

Area Under the Curve

The AUC (Area Under the Curve) metric measures how well the model can differentiate between two classes at different decision thresholds, which is extremely important in medical diagnostics to avoid misdiagnosis and improper treatment. On the other hand, the F1 score is a harmonic average of recall and precision; thus, it is extremely helpful for balancing between false positives and false negatives in high-risk situations where inaccurate decisions lead to distrust among users of automated systems [42].

LogLoss

LogLoss reflects how confident a predictive model is in its predictions and the implications of possible errors. This metric is of great importance in the medical field, as mistakes can have very grave consequences for patients. Together with other metrics, LogLoss is used for assessing the effectiveness of a model based on the machine learning technique and for grasping the seriousness of errors it can make [33].

K, S statistic

The K-S statistic is an important measure of how well a classification model distinguishes between positive and negative cases. A K, S value of 100 means that the model has achieved perfect separation, whereas a value of 0 means that the model cannot distinguish the two groups any better than a random selection. Usually, classification models produce K and S values ranging from 0 to 100, and higher values indicate better predictive power [43].

Gini Coefficient

The Gini coefficient is a measure that reflects how well a predictive model performs in classification tasks. It is calculated from the Area Under the Curve (AUC) of the ROC curve using the formula: Gini = 2 × AUC - 1. A Gini coefficient of over 60% indicates a good model. In this study, the calculated Gini coefficient was 92.7%, indicating that the model was very accurate in predicting [40].

A Schematic of the Processes

A key advantage is that the model-building process leverages several very capable libraries, especially the open-source Python Library Pandas. Since Pandas is a potent data processing and analysis tool, it is a must-have for any data scientist. Besides, Pandas provides highly efficient data structures, such as Series and DataFrames, which greatly simplify handling large datasets.

The next step is the implementation of automated machine learning (AutoML), which is a significant breakthrough in model building. AutoML not only simplifies the machine learning (ML) workflow but also democratises ML by making it accessible to people with limited experience through the automation of various stages. For experienced engineers, AutoML will take away the burden of performing mundane tasks over and over, so they can devote their time and creativity to developing better models and achieving superior results more efficiently. That is why a staggering combination of automation and expertise has produced a powerful synergy capable of generating innovative ideas in machine learning; it is equally suitable for both beginners and experts [38, 40, 44, 45].

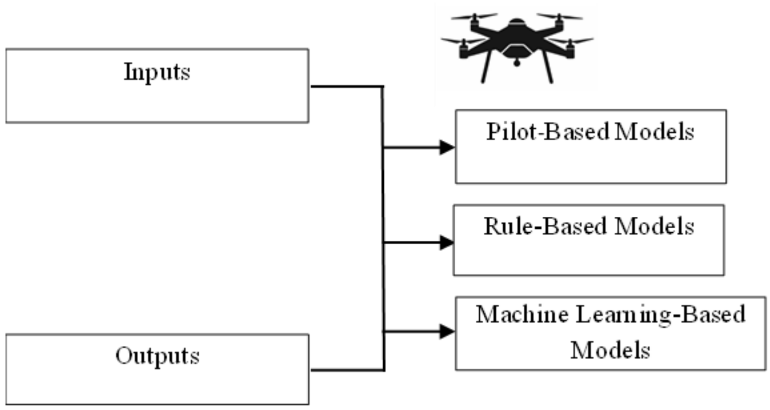

Figure no 1. Drone Safety Detections Models

The drone safety detection system starts by searching different databases to find the best routes to its destination, as shown in Figure 1. Once the best route is found, the system still needs to ensure the airspace is free of birds. It uses highly complex algorithms to identify these birds and avoid collisions. The drone stays on its path while continuously observing bird activity around it, ensuring it reaches its destination safely without any bird encounters.

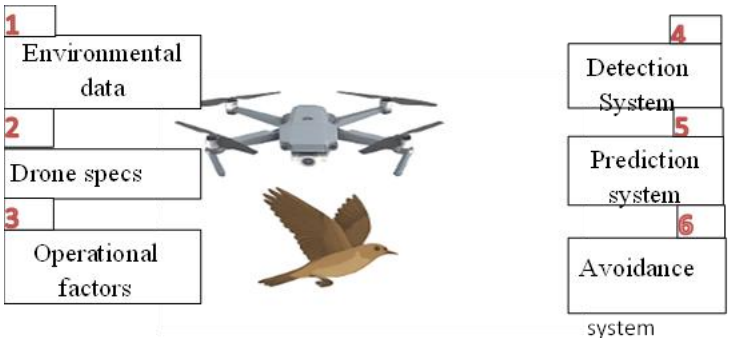

Figure no 2. A model for assessing drone safety in relation to birds, balancing safety and ecology.

Table 1 and Figure 2 show a well, thought, out set of criteria for assessing the safety of drones when interacting with birds. The purpose of this framework is to find a perfect balance between imposing strict safety requirements for drone operations and giving due consideration to the protection of birds and their natural habitats. It examines a range of elements like the possibilities of crashes, the ways birds react, and the influence on the environment. Ultimately, the goal is to make drones not only safe instruments for air navigation but also helpful allies in the preservation of nature.

Table no 1. A framework for evaluating drone safety in relation to birds, striking a balance between safety and ecological considerations.

Category	Details
Environmental data	Bird species, flock size, flight altitude, time of day, seasonal patterns, and weather conditions are essential for understanding bird behaviour and ecology.
Drone specs	Consider the following key factors: size, speed, manoeuvrability, sensor suite (cameras, LiDAR, radar), and battery endurance.
Operational factors	Flight information should include the following details: route, altitude, speed, mission type (such as hovering, transit, or delivery), and location (whether it's urban, rural, or near water).
Detection system	Performance metrics for machine learning models include precision, recall, and latency, as well as factors such as detection range and sensor accuracy.
Prediction system	The accuracy of machine learning trajectory forecasting is measured using metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), along with the forecast time horizon.
Avoidance system	Evasion success rates, minimum safe distances, and time-to-collision estimates are key factors in assessing safety.

Bird Detection Models and Drone Safety

First: Bird Detection Using Computer Vision Relies on drone-mounted cameras.
Models used: Machine Learning Algorithms to detect birds in images and videos in real time.
Outputs: Determine bird locations, speed, and direction. Basic Equation:

$$\frac{bird^s\ e}{j^s\ e\ \sum j} = (bird|x) \qquad (1)$$

Here, JS is the neural network's output for each class.

Second: Radar & Acoustic Sensors:

Radar waves reflect off small flying objects such as birds. Together with machine learning models, it can be used to identify a bird, another drone or any other object.

Model used: Deep Neural Networks take radar data as input and classify it.

$$b + softmax\ (W^T x = f(x) \qquad (2)$$

Third: Collision Prediction.

After we detect the bird, we predict whether a collision will occur by calculating the probability of a collision. For this, we take into account the speeds of the drone and the bird, as well as their relative path.

Equation:

d(t) is the distance between the drone and the bird. $_r u$ is the relative speed:

$$\frac{d(t)}{rU} = cT \qquad (3)$$

cT less a certain limit → we take escape or evasion action.

Fourth: Decision-Making System

If the system detects a risk of collision:

- Slows down
- Changes lane
- Stops mid-air

Mathematical model: We leverage an advanced machine learning algorithm, as detailed above, to uncover insights and drive accurate predictions, enhancing our analytical capabilities and ensuring the reliability of our results.

IV. Results

To assess the effectiveness of machine learning models in real-world settings, we review and validate their outputs. Such a procedure entails fitting the models to one dataset and evaluating them on another. Thus, we obtain valuable indicators of the model's performance, including Classification Accuracy, Confusion Matrix, Area Under the Curve, Logarithmic Loss, K-S Statistic, and Gini Coefficient. These indicators allow one to judge the model's predictive capability and its overall robustness. It's crucial to perform these analyses to detect overfitting, which occurs when a model performs very well on the training data but poorly on new data. Once overfitting is detected, developers can continue fine-tuning the model and eventually obtain a model that is well adjusted to and able to generalise from different data sets encountered in practice.

Analysis of Test Scores for Birds

Table 2 presents the performance of various systems using Machine Learning Evaluation Metrics for drones. Linear regression scored the highest, at 98, with logistic regression close behind at 96 and decision trees at 94. These results demonstrate how well the methods identified the correct bird types, as indicated by strong scores in key metrics such as the Confusion Matrix and Classification Accuracy.

Table no 2. Analysis of Test Scores for Birds

Metrics / Model	Classification Accuracy	Confusion Matrix	Area Under The Curve	Logarithmic Loss	K-S statistic	Gin coefficient	%
Linear Regression	1	1	0.99	0.97	0.93	0.96	98%
Logistic Regression	0.98	1	0.95	0.93	0.93	0.94	96%

K-Means	0.93	0.94	0.91	0.89	0.8	0.82	88%
Random Forest	0.94	0.94	0.93	0.91	0.85	0.87	91%
Decision Trees	0.96	0.98	0.92	0.93	0.91	0.92	94%
Naïve Bayes Classifier	0.95	0.97	0.94	0.9	0.9	0.9	93%
%	96%	97%	94%	92%	89%	90%	

The Naive Bayes Classifier, Random Forest, and K-Means models obtained mean values of 93, 91, and 88, respectively. The Logarithmic Loss, K-S statistic, and Gini coefficients for these models were 92, 90, and 89, respectively.

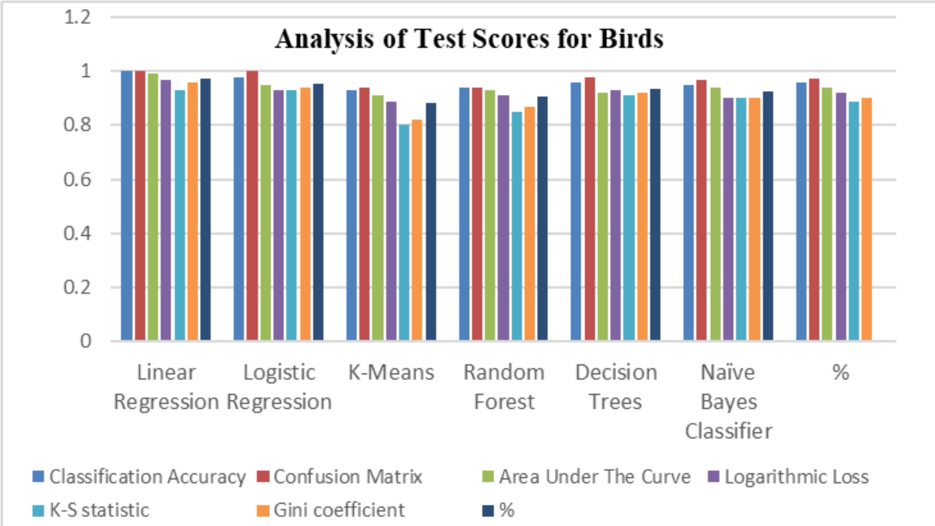

Figure no 3. Analysis of Test Scores for Birds

These outcomes reflect the challenges the models face in precisely identifying different bird species, which makes them unsure about their predictions. This situation serves as a reminder that one should always resort to sophisticated models and choose the right one according to the particular dataset's needs, as shown in Table 2 and Figure 3.

Analysis of Test Scores for Drones

Table 3 shows that Linear Regression, Logistic Regression, and Decision Trees topped the charts with scores of 99, 96, and 95, respectively, on primary metrics such as the Confusion Matrix and Classification Accuracy. These significant numbers indicate their strong ability to correctly classify and distinguish the various bird species in the dataset.

Table no 3. Analysis of Test Scores for Drones

Metrics / Model	Classification Accuracy	Confusion Matrix	Area Under The Curve	Logarithmic Loss	K-S statistic	Gin coefficient	%
Linear Regression	1	1	1	0.98	0.96	0.97	99%
Logistic Regression	1	1	0.96	0.95	0.92	0.94	96%
K-Means	0.93	0.95	0.91	0.89	0.81	0.85	89%
Random Forest	0.94	0.96	0.94	0.92	0.88	0.9	92%
Decision Trees	0.95	1	0.94	0.94	0.92	0.93	95%
Naïve Bayes Classifier	0.96	0.98	0.95	0.92	0.9	0.91	94%
%	96%	98%	95%	93%	90%	92%	

In contrast, the Naive Bayes Classifier, Random Forest, and K-Means models achieved average scores of 94, 92, and 89, respectively, while the Logarithmic Loss, Gini Coefficients, and K-S Statistics were 93, 92, and 90, respectively.

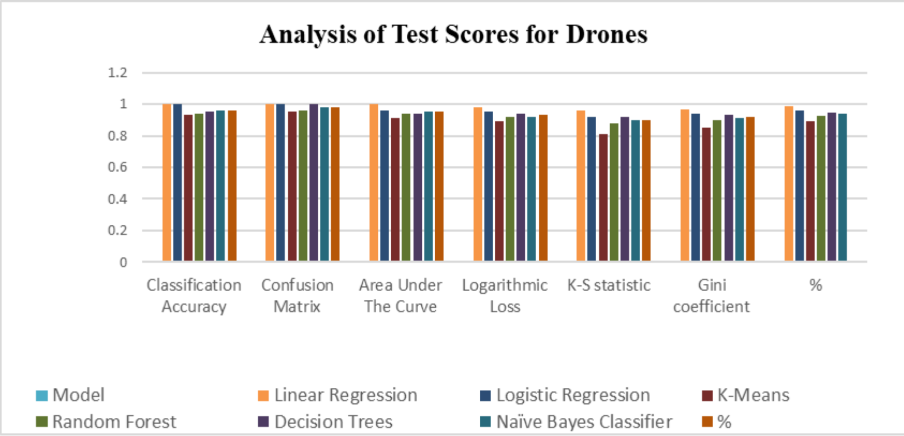

Figure no 4. Analysis of Test Scores for Drones

Test and Score Analyses for The Average Performance Over All Target Classes

Here, the analysis compares various models using UAV machine learning metrics. Linear regression, logistic regression, and decision trees have shown better results, with scores of 98, 96, and 94, respectively. These models lead the pack in the use of confusion matrices and classification accuracy metrics, which is a strong indication of their ability to classify bird species correctly, as evidenced by their high scores of 98, 96, and 95, respectively.

Table no 4. Analysis of Test Scores for Average Drones & Birds

Metrics / Model	Classification Accuracy	Confusion Matrix	Area Under The Curve	Logarithmic Loss	K-S statistic	Gin coefficient	%
Linear Regression	1	1	0.995	0.98	0.945	0.97	98%
Logistic Regression	0.99	1	0.955	0.94	0.925	0.94	96%
K-Means	0.93	0.95	0.91	0.89	0.81	0.84	89%
Random Forest	0.94	0.95	0.935	0.92	0.865	0.89	92%
Decision Trees	0.96	0.99	0.93	0.94	0.915	0.93	94%
Naïve Bayes Classifier	0.96	0.98	0.95	0.91	0.9	0.91	93%
%	96%	98%	95%	93%	89%	91%	

On the other hand, the Naive Bayes classifier, Random Forest, and K-means models only managed to score, on average, 93, 92, and 89, respectively; these models also reported performance measures of 93, 91, and 89, respectively. This points to significant problems in correctly classifying Average Drones and Birds. The results highlight the importance of selecting sophisticated models tailored to the task and dataset, as demonstrated in Table 4 and Figure 5.

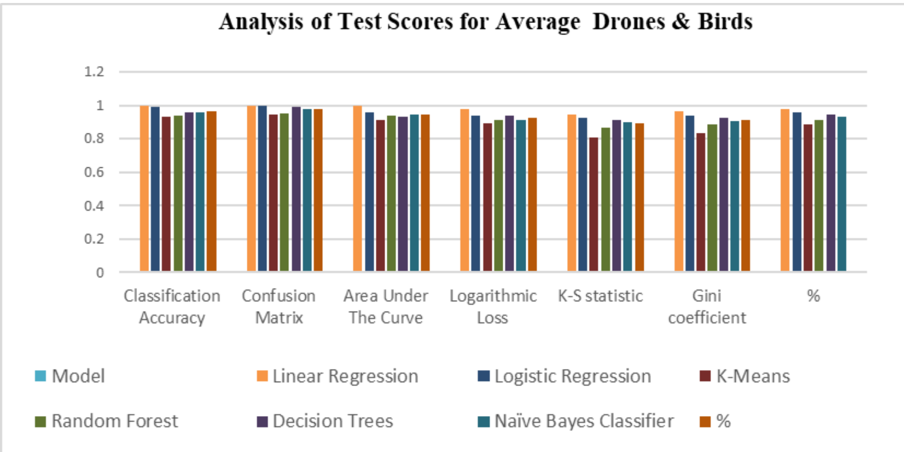

Figure no 5. Analysis of Test Scores for Average Drones & Birds

A Comprehensive Analysis of the Confusion Matrix

A Confusion Matrix Analysis helps in evaluating the performance of a classification model by showing the number of true positives, true negatives, false positives, and false negatives in a matrix form. Such a representation makes it easier to understand the model's prediction accuracy for different classes and also indicates areas of improvement.

The elements along the main diagonal of the matrix represent the correctly classified instances, whereas the elements away from the diagonal represent the incorrectly classified ones. Several important metrics can be computed from the confusion matrix, including precision (a measure of the correctness of optimistic predictions), recall (a measure of the ability to find all positive instances), and the F1 score (a balance between precision and recall). These performance measures are not only crucial in assessing the model's output but also in addressing any class imbalance issues, as they bring to light any prejudices and guide the tuning of parameters.

Table no 5. A Comprehensive Analysis of the Confusion Matrix for Machine Learning Algorithms for Birds & Drones

Expectation		
Machine Learning Algorithms	**Birds**	**Drones**
Linear Regression	5.85	-0.15
	-0.09	5.91
Logistic Regrssion	5.73	-0.27
	-0.23	5.77
K-Means	5.42	-0.58
	-0.52	5.48
Random Forest	5.44	-0.56
	-0.46	5.54
Decision Trees	5.62	-0.38
	-0.32	5.68
Naïve Bayes Classifier	5.56	-0.44
	-0.38	5.62

Table 5 compares the performance of several machine learning models for classifying targets as birds or drones. Linear regression, logistic regression, and decision tree models achieve excellent accuracy, with precision, recall, and overall accuracy rates up to 96%. On the other hand, the K-Means algorithm fails this test and achieves only 89% performance because it produces many false positives. Both the Naive Bayes and the Random Forest techniques yield average results, with prediction accuracy close to 93%. Thus, the first three models in the list are very efficient, but Naive Bayes and K-Means can also improve classification accuracy, as shown in Table 5 and Figure 6.

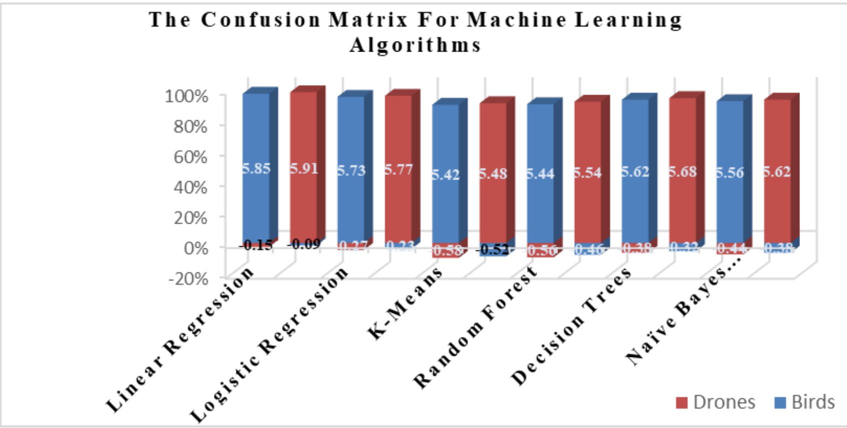

Figure no 6. A Comprehensive Analysis of the Confusion Matrix for Machine Learning Algorithms for Birds & Drones

V. Discussion

Drone detection and airspace security using UAVs are among the fields this paper advances, especially in military settings where misidentification could have fatal consequences. Hence, the detection systems used in military operations should not only be able to accurately identify drones but also assess their threat level instantaneously. In our study, we have experimented with various machine learning algorithms, including Linear Regression, Logistic Regression, K-Means Clustering, Random Forests, Decision Trees, and Naive Bayes Classifiers. Several of these models can distinguish drones from birds quite easily while also being very precise and efficient.

This study shows that these methods can be trusted even under nonideal conditions. These algorithms also work when faced with weather changes, varying visibility, and different types of ground. These factors are rarely considered in experiments, but are very important in defence in real scenarios. Hence, their resilience makes them basically a good fit for hostile airspace situations. It is very much the case that, on the one hand, too many false alarms can lead the military to waste resources and, on the other, the failure to detect a threat can lead to an attack on infrastructure or the loss of human lives. That is why minimising false positives and false negatives is essential.

Within military settings, precision and swiftness are above all essentials for quick decision-making. Our study reveals that algorithms such as Logistic Regression and Decision Trees are suitable for time-constrained environments because their hardware requirements are low. On the other hand, Random Forests, being more resource-hungry, offer better accuracy and versatility when dealing with bigger datasets. Hence, the highly efficient models can serve as initial filters, and the more complex ones can be applied to narrow down the findings.

The models evaluated demonstrate good performance; however, adding them to existing military surveillance systems would be a significant undertaking. These networks are equipped with a plethora of tools such as radar, camera, and sound detection devices. In order for machine learning to be successfully applied, compatibility, security from cyberattacks, and quick adaptability to changes in UAV technology must first be guaranteed. The introduction of stealth UAVs and swarm tactics makes detection even more challenging, thus underscoring the importance of having systems that can handle both individual and group threats from the air.

Future research should focus on developing hybrid detection models that integrate radar signals, computer vision, acoustic data, and radio communications. The combination of these fields will not only increase the accuracy but also make the system more resistant to tricks like drones mimicking birds. Furthermore, using data reduction methods such as Principal Component Analysis (PCA) or autoencoders can help optimise performance by reducing noise and increasing processing speed, which is essential for real-time applications.

This paper confirms that machine learning has great potential to enhance UAV detection and, consequently, secure the airspace. There are still some issues to be addressed, mainly in system integration, dataset generalisation, and scalability; however, the suggested frameworks and next steps in this line of research provide an excellent basis for further innovation. In the future, it is expected that mixing various techniques and making detection systems flexible will be the surest way to keep the airspace safe for both military and civilian use.

Our results not only confirm but also build on the previous research on UAV detection. Publications exploring radar-based detection systems reported that drone-versus-bird classification flights powered by radar have achieved near-perfect accuracy in challenging scenarios. Nonetheless, high costs and usage limitations are among the barriers to deploying radar solutions. On the other hand, we have developed machine-learning methods that can be easily embedded in existing sensor networks, making them adaptable not only to military forces with abundant resources but also to those with scarce resources.

Studies developing deep learning models for pictorial identification have achieved precision rates of 83% to 94.5%, underscoring the potential of computer vision techniques. On the other hand, these models generally need vast amounts of data and enough computational power, which may hamper their use in military applications demanding instant results [22, 24]. Compared to that, we have shown through our research that less complicated models, e.g., Logistic Regression and Decision Trees, can deliver a high level of precision with fewer computational resources, and hence they are better suited for real-time operations where quick decision-making is of paramount importance.

VI. Conclusion

This research aligns with the military airspace security area, where the primary focus is on how machine learning algorithms can be effectively used to detect unmanned aerial vehicles (UAVs) and distinguish them from birds and other aerial objects. Our experiments reveal that algorithms such as Logistic Regression, Decision Trees, and Linear Regression can pinpoint UAVs with high accuracy while requiring less computational power. This feature of theirs makes them a perfect fit for the military operations in the real world, where it is very important to be quick and accurate.

Moreover, a detailed analysis of our results relative to prior work was conducted, and the main benefit of our method was emphasised: reliable detection can be achieved without costly infrastructure, massive datasets, or resource-intensive computational models. This clever approach makes our research a highly pragmatic and scalable solution for the air defence systems of the future, especially when it is crucial to combine resource efficiency with high accuracy.

Furthermore, the paper emphasises the importance of developing hybrid detection systems that combine radar, computer vision, and audio technology by taking advantage of their individual features. On top of that, the next step in research should focus on validating these systems in real-world environments, as well as on developing lightweight models capable of keeping pace with novel UAVs and the evolving tactics of adversaries.

In summary, this study significantly enhances the UAV detection techniques currently in use, offering immediate practical benefits. Moreover, it provides a sturdy base for the creation of adaptive, multi-layer airspace security systems. Such highly advanced systems will be crucial for military and civilian protection against threats posed by advanced, hostile UAV technologies.

Acknowledgment

The author acknowledges the Qassim University Graduate Studies Deanship for its crucial assistance in developing our paper.

Data Availability Statement

The data used in this paper are available from well-known, recognised online repositories that host research datasets. Next to the names of these repositories, which are presented here, you will also see the unique accession numbers that will help locate and reference them easily:
https://www.kaggle.com/datasets/ajlan2010/drone-and-bird

References

[1]. E. Hetelekides, Et Al., "Early Birds And Night Owls: Distinguishing Profiles Of Cannabis Use Habits By Use Times With Latent Class Analysis," Vol. 6(1), Pp.79-98, 2022.
[2]. M. Nentwich And D. M. Hórvath, "Delivery Drones From A Technology Assessment Perspective," Overv. Report, No.2018-01, Viennaita, 2018.
[3]. M. S. Alzboon, Et Al., "Pushing The Envelope: Investigating The Potential And Limitations Of Chatgpt And Artificial Intelligence In Advancing Computer Science Research", 3rd International Conference On Emerging Smart Technologies And Applications (Esmarta), Pp 1-6, 2023.
[4]. M. S. Alzboon, Et Al., "Early Diagnosis Of Diabetes: A Comparison Of Machine Learning Methods," Int. J. Online Biomed. Eng., Vol. 19, No. 15, Pp. 144–165, 2023.
[5]. S Heimbs, Et Al., Comparison Of Drone Collision And Bird Strike On Aircraft Radome Using Experimental And Simulation Methods. Procs Of The International Conference On Impact Loading Of Structures And Materials (Icilsm 2022), Trondheim, Norway, 2022.
[6]. A. K. Jha, "Bird Strike Damage And Analysis Of Uav's Airframe." International Journal Of Lightweight Materials And Manufacture, Vol. 2, No. 4, 2019, Pp. 390–397. Elsevier.
[7]. Saqib, S. M. "Ensemble Technique For Birds And Drones Prediction." Peerj Computer Science, Vol. 10, 2024, E2341.
[8]. Sun, H., Y. Wang, X. Cai, P. Wang, Z. Huang, D. Li, Y. Shao, And S. Wang. Airbirds: A Large-Scale Challenging Dataset For Bird Strike Prevention In Real-World Airports. Arxiv, 2023, Https://Arxiv.Org/Abs/2304.11662.
[9]. S. A. Alomari, Et Al., "Toward Achieving Self-Resource Discovery In Distributed Systems Based On Distributed Quadtree," J. Theor. Appl. Inf. Technol., Vol. 98, No. 20, Pp. 3088–3099, 2020.
[10]. M. S. Alzboon, Et Al., "A Comparative Study Of Machine Learning Techniques For Early Prediction Of Diabetes," Sensors, Pp. 1–12, 2023.
[11]. X. Lu, "Simulation Of Airborne Collision Between A Drone And An Aircraft Structure." International Journal Of Impact Engineering, Vol. 155, 2021, P. 103913. Elsevier.
[12]. P. Seoane, "Assessment Of Lidar-Based Sensing Technologies In Bird Detection For Uav Collision Avoidance." Drones, Vol. 9, No. 1, 2024, P. 13. Mdpi.
[13]. D. Marek, "Collision Avoidance Mechanism For Swarms Of Drones, "Sensors, Vol. 25, P. 1141, 2025.
[14]. M. Capture Autonomous Drone. Journal Of Information Systems Engineering And Management. Vol. 10. Pp. 929-933, 2025.
[15]. M. S. Alzboon, Et Al., "A Comparative Study Of Machine Learning Techniques For Early Prediction Of Prostate Cancer," In 2023 Ieee 10th International Conference On Communications And Networking, Comnet 2023 - Proceedings, Pp. 1–12, 2023.
[16]. M. Kassab Et Al., "A Lower Complexity Deep Learning Method For Drone Detection," Sensors, Vol. 23, No. 14, P. 6251, 2023.
[17]. P. L. Bishay Et Al., "3d-Printed Bio-Inspired Mechanisms For Bird-Like Morphing Drones," Appl. Sci., Vol. 13, No. 21, P. 11814, 2023.
[18]. A. Sikora And D. Marchowski, "The Use Of Drones To Study The Breeding Productivity Of Whooper Swan Cygnus Cygnus," Eur. Zool. J., Vol. 90, No. 1, Pp. 193–200, 2023.
[19]. Chen, Y.; Et Al., Large-Group Activity Security Risk Assessment And Risk Early Warning Based On A Random Forest Algorithm. Pattern Recognit. Lett. , 144, 1–5, 2021.
[20]. J. Liu Et Al., "Classification Of Bird And Drone Targets Based On Motion Characteristics And Random Forest Model Using Surveillance Radar Data," Ieee Access, Vol. 9, Pp. 160135–160144, 2021.
[21]. R. M. Narayanan, Et Al., "Classification And Discrimination Of Birds And Small Drones Using Radar Micro-Doppler Spectrogram Images †," Signals, Vol. 4, No. 2, Pp. 337–358, 2023.
[22]. M. A. Bell, S. Rahman, And D. A. Robertson, "Fast Classification Of Drones And Birds With An Lstm Network Applied To 1d Phase Data," 2023.
[23]. S.-W. Yoon Et Al., "Efficient Protocol To Use Fmcw Radar And Cnn To Distinguish Micro-Doppler Signatures Of Multiple Drones And Birds," Ieee Access, Vol. 10, Pp. 26033–26044, 2022.
[24]. B. Tsang, R. M. Narayanan, And R. Bharadwaj, "Experimental Analysis Of Micro-Doppler Characteristics Of Drones And Birds For Classification Purposes," In Defence + Commercial Sensing, P. 24, 2022.
[25]. Ajibade, Et Al., "The Impact Of Dimensionality Reduction Techniques On Machine Learning Algorithm Efficiency". 2024.
[26]. S. Rahman And D. A. Robertson, "Millimetre-Wave Radar Micro-Doppler Feature Extraction Of Consumer Drones And Birds For Target Discrimination," In Defence + Commercial Sensing, P. 28, 2019.
[27]. F. Samadzadegan, Et Al., "Detection And Recognition Of Drones Based On A Deep Convolutional Neural Network Using Visible Imagery," Aerospace, Vol. 9, No. 1, 2022.
[28]. L. Guo, Et Al., "Self-Supervised Representation Learning For Quasi-Simultaneous Arrival Signal Identification Based On Reconnaissance Drones," Drones, Vol. 7, No. 7, 2023.
[29]. S. S. Selvi, Et Al., "Garuda: Third Eye For Detecting And Tracking Drones,", Sensors, Vol. 11, No. 1, Pp. 32–43, 2023

[30]. I. Alla Et Al., "From Sound To Sight: Audio-Visual Fusion And Deep Learning For Drone Detection," In Proceedings Of The 17th Acm Conference On Security And Privacy In Wireless And Mobile Networks (Wisec' 24), Pp. 123–133, 2024.

[31]. D. S. Omkar, Et Al., "Detection, Tracking And Classification Of Rogue Drones Using Computer Vision," Int. J. Eng. Appl. Sci. Technol., Vol. 7, No. 3, Pp. 11–19, 2022.

[32]. M. S. Alzboon, Et Al., "The Two Sides Of Ai In Cybersecurity: Opportunities And Challenges", Vol. 14, No. 2, Pp. 78–91, 2023.

[33]. S. Al Tal, Et Al., "The Modern Hosting Computing Systems For Small And Medium Businesses," Acad. Entrepreneur. J., Vol. 25, No. 4, Pp. 1–7, 2022.

[34]. M., Ramchandra & C., Pallavi." Simple Linear Regression, Book Chapter: Predictive Analytics With Sas And R., 2025.

[35]. C. Thomas. "Logistic Regression", Chapter Book: Applied Statistics And Multivariate Data Analysis For Business And Economics, 2025.

[36]. P. Shazia & Y. Miin-Shen. "Lasso-Based K-Means++ Clustering". Electronics. Vol. 14, Pp. 1429, 2025

[37]. C. Nayma, Et Al. "A Proactive Approach For Random Forest". Applied Intelligence. Vol. 15, Pp. 10, 2025.

[38]. D. Kerven, Et Al. " Construction Of Decision Trees And Acyclic Decision Graphs From Decision Rule Systems", Chapter Book: Decision Trees Versus Systems Of Decision Rules, 2024.

[39]. L. Wang, "Spam Email Detection Using Naïve Bayes Classifier", Itm Web Of Journal, Vol. 70, Pp. 145-157, 2025.

[40]. M. Nielsen, "Improving The Way Neural Networks Learn, Neural Networks And Deep Learning, Chapter 3, 2019.

[41]. A. András, Et Al. "The Effect Of Processing Techniques On The Classification Accuracy Of Brain-Computer Interface Systems". Brain Sciences. Vol.14. Pp. 1272, 2024.

[42]. M. Alzboon, "Semantic Text Analysis On Social Networks And Data Processing: Review And Future Directions," Inf. Sci. Lett., Vol. 11, No. 5, Pp. 1371–1384, 2022.

[43]. Raschka, Et Al., "Machine Learning In Python: Main Developments And Technology Trends In Data Science, Machine Learning, And Artificial Intelligence. Information, Vol. 11(4), Pp. 193, 2020.

[44]. I. Alla Et Al., "From Sound To Sight: Audio-Visual Fusion And Deep Learning For Drone Detection," In Proceedings Of The 17th Acm Conference On Security And Privacy In Wireless And Mobile Networks (Wisec' 24), Pp. 123–133, 2024.

[45]. S. Sethu Selvi, Et Al., "A Deep Learning Approach To Classify Drones And Birds", Ieee 2nd Mysore Sub Section International Conference (Mysurucon), Mysuru, India, Pp. 1-5, 2022.