

Beyond the Horizon: Real-Time UAV Detection Through Machine Learning Innovations

Más Allá del Horizonte: Detección en Tiempo Real de UAVs Mediante Innovaciones en Aprendizaje Automático

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ABSTRACT

As UAVs have become essential to military surveillance and operational strategies, our expertise addresses the increasing need for precise, real-time UAV deployment. The growth of UAVs raises several safety problems, necessitating systems capable of differentiating UAVs from non-UAVs, such as avian species. This study aims to identify a solution for the issue of quick aerial categorization across various situations without the need to rearrange devices, by analyzing and contrasting alternative models of advanced device mastery. We train and evaluate models utilizing extensive datasets, encompassing ANNs, SVMs, ensemble techniques, and RF-GBMs (Random Forests Gradient Boosting Machines). The models are assessed based on criteria that ascertain the feasibility of prospective real-time operations: accuracy, do-forget, and computational performance. Our findings indicate that Neural Networks significantly outperform birds, demonstrating remarkable precision in UAV recognition. This leads us to our main argument: Neural Networks significantly impact operational security and can substantially improve the distribution of defense resources. Our research indicates that machine learning is highly successful in real-time UAV recognition, significantly enhancing surveillance systems. Furthermore, it is advisable for military defenses to implement Neural Network systems to enhance decision-making capabilities and security operations. To remain competitive with increasingly agile and potentially covert drone designs, we anticipate advancements in UAV technology and recommend frequent model upgrades.

Keywords: Unmanned Aerial Vehicles (UAV); Real-Time Recognition; Surveillance; Security Operations; Image Recognition; Algorithm Performance.

RESUMEN

Los vehículos aéreos no tripulados (UAV) se han convertido en un elemento esencial de la vigilancia militar y las estrategias operativas, por lo que nuestros conocimientos abordan la creciente necesidad de desplegar UAV precisos y en tiempo real. El crecimiento de los UAV plantea varios problemas de seguridad, por lo que se necesitan sistemas capaces de diferenciar los UAV de los que no lo son, como las especies aviarias. Este estudio pretende identificar una solución para el problema de la rápida categorización aérea en diversas situaciones sin necesidad de reordenar los dispositivos, analizando y contrastando modelos alternativos de dominio avanzado de dispositivos. Entrenamos y evaluamos modelos utilizando amplios conjuntos de datos, que abarcan RNA, SVM, técnicas de ensemble y RF-GBM (Random Forests Gradient Boosting Machines). Los modelos se evalúan en función de criterios que determinan la viabilidad de posibles operaciones en tiempo real: precisión, olvido y rendimiento computacional. Nuestros resultados indican que las redes neuronales superan significativamente a las aves, demostrando una precisión notable en el reconocimiento de UAV.

Esto nos lleva a nuestro argumento principal: Las Redes Neuronales tienen un impacto significativo en la seguridad operativa y pueden mejorar sustancialmente la distribución de los recursos de defensa. Nuestra investigación indica que el aprendizaje automático tiene un gran éxito en el reconocimiento de UAV en tiempo real, mejorando significativamente los sistemas de vigilancia. Además, es aconsejable que las defensas militares implanten sistemas de Redes Neuronales para mejorar la capacidad de toma de decisiones y las operaciones de seguridad. Para seguir siendo competitivos frente a diseños de drones cada vez más ágiles y potencialmente encubiertos, nos anticipamos a los avances en la tecnología de los UAV y recomendamos actualizaciones frecuentes de los modelos.

Palabras clave: Vehículos Aéreos No Tripulados (UAV); Reconocimiento en Tiempo Real; Vigilancia; Operaciones de Seguridad; Reconocimiento de Imágenes; Rendimiento de Algoritmos.

INTRODUCTION

Military drone use has evolved during the past decade. Previously used for observation and reconnaissance, they now launch predawn target-specific strikes. Military drones, whether small portable or large-controlled aircraft, provide an eye in the sky humans cannot match. This airborne perspective decides whether innocent lives are at risk in real time. A drone may hover for hours in an uninteresting region that could turn hostile, providing surveillance that no camera could. However, drones' unparalleled capabilities present two major issues for military leaders. Cyberboffins call it cyberterrorism, an army commander's worst nightmare. Second, the most powerful weapon ever made, and only war threatens it. Most lethal weapon ever devised is drones.⁽¹⁾

The Iranian drone and missile storm on Israeli territory shows the strategic importance of robust UAV recognition systems as UAV swarms become increasingly widespread in warfare tactics. Cases where UAVs attack military radars and intelligence systems benefit from electronic and psychological warfare that overwhelms the defense apparatus and confuses the defense staff.

⁽²⁾ A viable, real-time recognition platform using powerful computational algorithms to discriminate UAV birds is needed.⁽³⁾

Research into improved machine learning algorithms is crucial. This article examines machine learning models and methods that can help military and civilian security professionals combat UAVs. To find the best machine learning methods for high-security zones and UAV-free areas, deep neural networks, Support Vector Machines (SVMs), random forests, and gradient boosting machines are compared. Computational efficiency and false positive rate are also examined in these machine learning models. The top real-time military detection models are detailed. Several machine learning methods reduce severe false negatives, which are not allowed in military settings. The accuracy, precision, recall, FP rate, and computational complexity of these methods are assessed. Here, the authors offer a solution that will provide essential insights for future UAV detection and countermeasure development. This essay calls for powerful machine learning methodologies and technology, which have advanced significantly in the recent decade. Since the "new era" of UAVs is rising, the authors expect our monitoring methods to improve. We offer our opinions on how machine learning might be utilized in a specific situation, but we recognize that this is a new area of research and did not explore it further. As the technology is exciting, the authors believe there is a chance to offer new insights on machine learning, especially in UAVs. The authors would like to know how they may utilize machine learning for UAV identification in space.⁽⁴⁾

Figure 1 illustrates the transition of UAVs from primarily surveillance and reconnaissance roles to executing targeted operations, emphasizing their dual nature as tools for aerial surveillance and potential security threats, along with the integration of machine learning and ethical considerations in their deployment.⁽⁵⁾

Problem Statement

Due to the growing usage of unmanned aerial vehicles (UAVs) in military programs, advanced structures that can detect UAVs in real time and with high precision are needed. Developing efficient device mastering models that can distinguish unmanned aerial vehicles (UAVs) from other entities, such as birds, in various environmental conditions is one of the most pressing challenges this study faces. This capacity benefits safety operations and reaction tactics in navy and civilian contexts where swift aerial object identification and category are essential for airspace security and operational protection. It also aids aerial object identification.⁽⁶⁾

Article Objectives

The research being conducted in this project is geared toward developing a method to improve navy surveillance operations' ability to discriminate UAV behaviours and appearances from those of birds. Which is very useful for optimizing the resource allocation and enhancing their response strategies as well valid points in order to protect its airspace. Objectives of the study. Advanced detection algorithms: Develop and optimize sophisticated sighted technologies that leverage machine learning & artificial intelligence to differentiate UAVs from birds.⁽⁷⁾ The algorithms provided insights on the different flight patterns, sizes and other dissimilar datasets by these systems. The second thing you might do is simply improve image recognition — picture popularity frameworks should be better at distinguishing UAVs against many natural backdrops. To do this we need to train these algorithms on large datasets of UAV and chook images from a range of environments. Third, reduce false positives and negatives: The goal is to require no alert (positive alarm) when birds are mistaken as UAVs or a missed detection occurs when a UAV operates but there is no positive report. The objective: Simplify video surveillance systems in high-security areas. Real-Time Processing — To design a rapid, real-time data processing and analysis platform for real time analytics in ever-changing environments Boots-on-the-Ground JButton Fifth, simulate system performance to optimize: Development of systems that are able to operate robustly in full-scale simulated global operational scenarios (including UAV swarms and electronic combat).⁽⁶⁾ Operational Integration Line of effort (LOE) to assess the technical and operational integration for advanced technology into established Army protection architectures, demonstrating how it will be employed without disruption. The goal is to enhance established military surveillance technologies used for national security and strategic defence.⁽⁸⁾

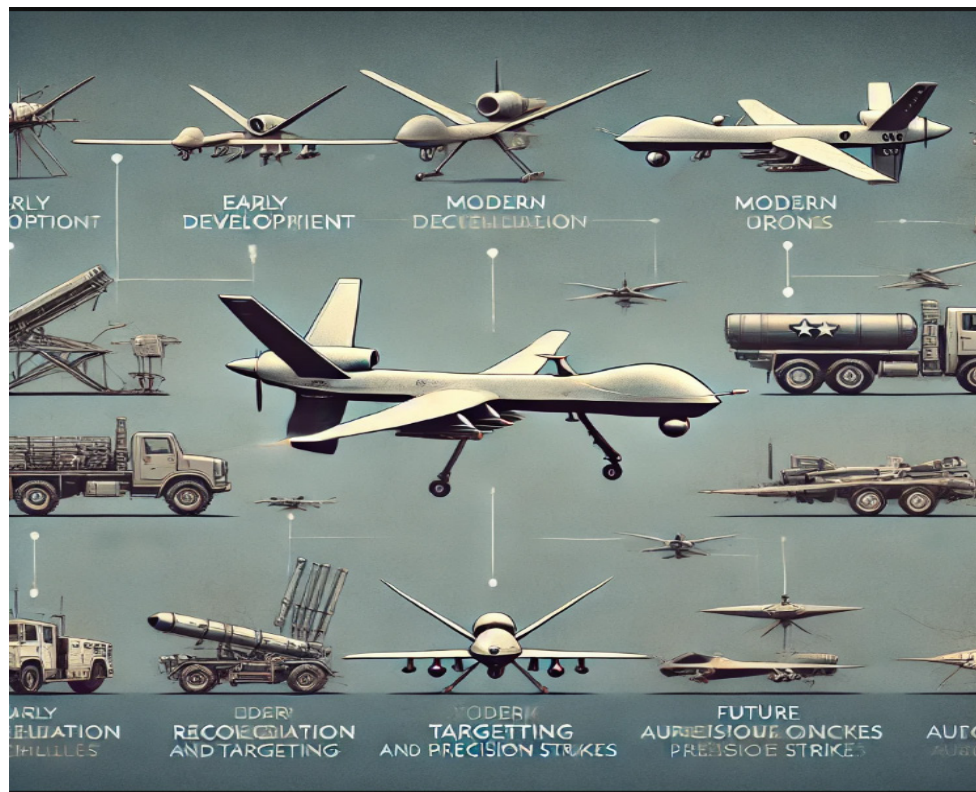


Figure 1. Evolution and Applications of Unmanned Aerial Vehicles (UAVs) in Military Operations (Created using DALL·E by OpenAI)

Contribution of the Article

This paper makes several important contributions to the generation of military surveillance, particularly in automatically distinguishing UAVs from birds. Strategically, this will redefine modern military operations given new detection and categorizing capabilities. The detection algorithm improvement is the main contribution of this text, where machine learning and AI algorithms are used to differentiate UAVs from birds.⁽⁹⁾ The research, via concentrating on advanced pattern recognition and flight dynamics offers you with an accurate basis to eliminate misidentifications in addition to enhance navy danger data. Second, they improved the manufacturing of surveillance by way of advancing within the processing expertise utilizing real-time data. While licking wounds, we have to research and respond aerial information to avoid busy demanding immoderate-stakes scenarios where fast reaction can intervene in army operations. This study reduces the unnecessary deployment of protecting things and the ability to overlook serious dangers by significantly lowering false positives and negatives. This helps maintain operational integrity and optimize navy asset allocation. Fourthly, operational Integration and Testing: The article details simulated testing techniques to ensure that the systems are theoretically sound and almost feasible.⁽¹⁰⁾ It also discusses catastrophic circumstances and solutions for integrating these technologies into current army systems, easing transitions and implementations. Fifth, strategic implications and policy suggestions: This study provides military and protection agencies with strategic insights and coverage tips beyond technology advances. This covered recommendations on new technology rollouts, enhancements in current processes and future research into UAV detection. VI: Enhanced airspace security: This study improves air space safety, in particular around sensitive or overprotected zones by boosting UAV detection. This feature protects against spying, interception and abilities to attack. This newsletter supports and informs the development of security features to counter state-of-the-art use of UAVs in army cases, ensuring that safety strategies evolve with technical threats.⁽¹¹⁾

Article Organization

The paper is carefully written to help UAV detecting system studying software users understand them. The introduction emphasizes UAV detection in navy surveillance to provide the scenario. The literature review analyzes current studies to identify improvements and shortcomings in modern approaches. Technique portion describes experimental setup, including information collection and version improvement, and assessment criteria used to evaluate model performance.⁽¹²⁾ In the effects and analysis section, Neural Networks and Gradient Boosting Machines are examined for UAV recognition. Discussion considers these effects on real-international packages and the pros and downsides of each variant. The article finishes with advice for future research to improve UAV detection system accuracy and performance, ensuring a seamless transition from theoretical frameworks to practical applications.⁽¹³⁾

Related work

The study introduces convolutional neural network-based drone classification. High-accuracy neural network-based categorization requires a large and diverse training dataset. The study's initial goal was to create a large collection of drone

and avian micro-Doppler spectrogram images in flight. Two datasets with identical RGB and grayscale photos were created. GoogLeNet was trained on RGB. The study trained architectures designed for the grayscale dataset. The dataset was divided into two categories: drone and non-drone. The first has four classifications (drone, bird, clutter, and noise). Validation took 20 % of the dataset during training. Unlabeled datasets were used to evaluate the models after training. The developed series network has 99,6 % and 94,4 % validation and testing accuracy for four classes and 99,3 % and 98,3 % for two classes. The GoogLeNet model had 99 % validation and testing accuracy across all scenarios.⁽¹⁴⁾

Target recognition with deep learning is cutting-edge. Deep knowing networks confront trustworthiness and dependability issues in radar target popularity. This letter offers an ICP-improved LSTM-SNN. It is related to conformal prediction in statistical concept and deep mastering and used to identify birds and drones using radar. The proposed method delivers drones and birds correct reputation effects by presenting confidence and trustworthiness for each identity. A self-confidence c language with the predicted parameter's true rate at a specific self-confidence level, such as 98 %, is also generated. The ICP improved LSTM-SNN approach was demonstrated using airport radar bird detection datasets.⁽¹⁵⁾

Since the “humanitarian drone” emerged, drones have become a controversial public interest technology that has garnered media attention. Drones could revolutionize humanitarian sector health supply logistics, but routine drone delivery is currently unproven. A 2019 Malawi field study employed drones to deliver medical supplies to inaccessible places. In low-resource settings, drones have two benefits. The research uses a real-world case study and an ethical viewpoint to examine the effects of systemic change in health supply chains. Finally, rigorous analysis and systematic advice for appropriate medical cargo drone evaluation are needed.⁽¹⁶⁾

Lower-end consumer drones have already made their way into airports, contributing to a growing safety risk. Aerial drones can be detected and tracked using radar. One such clutter while identifying drones in bird radar echoes. Nonetheless, radar reflections from birds may impact drone detection differently; few studies have investigated the effects of bird RCS and flight attributes on drones sufficiently shared by drones themselves or explained why performing as a decoy in flying birds can impair identification for drone to be detected using radar signal. We collected 3900×256 Ku-band radar echoes from birds and consumer drones in this study. They go after pigeons, cranes, ducks and even DJI Phantom 3 Vision drones. The radar data were analyzed considering the maximum detectable range of birds and drones, as well as their radar echoes' time series and Doppler spectrum at this distance for both upwind direction (oncoming) in reference to the sounder position, downwind dir... The results obtained statistically is that when birds are flying, all the average of Radar Cross Section (RCS), velocity range and signal fluctuation like amplitudes with have too much equivalent. Since birds are known to distort the radar signals, his models demonstrate that it is difficult for airborne drones detected in detected using Automatic Target Recognition (ATR) of radars. This data suggests that the general source of radar interference for aerial drones is flying birds.⁽¹⁷⁾

Efficiency must be key in airborne drone detection systems, as the development of cheap drones has also enabled their abuse. This paper compares drone and bird radar micro-Doppler attributes. Both drones and birds produce micro-Doppler signatures due to the rotation of their propeller blades or wingbeats. These characteristics can distinguish a drone from bird and treat separately. Here, we provide and discuss experimental micro-Doppler signatures of drones and birds. The data for this study were collected by K-band (24,9 GHz) and W-band (89,0 – 94,40 GHz) radar observations conducted over the North Atlantic during the ChArMEx / EMERGEx campaign implemented as a part of SOP1A/TACTO in June-July, 2012~ [Koffi et al., 2006], metis-data; AMMA-CATCH campaigns. We used three drone types to survey four bird species with different sizes. The results demonstrate that a phase coherent radar system is able to precisely gather micro-Doppler signals of flying targets at K- and W-band frequencies. When comparing the two signatures at both frequencies (lower figure), it is evident that W-band radar micro-Doppler return has a better SNR. K-band radar returns show micro-motions of drone and avian in the Micro-Doppler features.⁽¹⁸⁾

The technology has even started to federate for ecological study as researchers hunt ever-reliant and isolated wildlife using drones. We need best practices suggestions as well in the impact studies at no time. Researchers examined how drone colour, approach speed and flight trajectory influenced mallard (*Anas platyrhynchos*) responses neared semi-captive individuals; a Hesco barrier-like blinds), wild greater flamingos (*Phoenicopterus roseus* but see Study Specific Problem section for details of conventionally exposed regimes has relocated drop pond sanctuary also modified study thermal dyes to assess strategy sampling from these birds] or when stationary in coastal wetland with common greenshanks (*Tringa nebularia*); false positives species quantified fidelity avoid geographical unknown situations). The authors did not achieve unaffected birds in 80 % The other drone approach flights with quaternopter drones were within 4 m (n =.INSTANCE) of unaltered individuals (withIdentifier). We found that drone speed, color and the number of flights did not change bird behavior, but birds responded more to any drones approaching from above. Distance: launch your Drone 100 meters away from birds and respect species-specific approach distances. His project is the drone wildlife study ever. Subsequent research should assess the impacts of drones on multiple organisms and compare these physiological stress markers within groups in exposure level by group size and reproductive status.⁽¹⁹⁾

METHOD

Dataset Info

Harsh Walia's Kaggle “Birds vs. Drone Dataset” was used in this investigation. Bird and drone photographs are separated into two folders in the dataset to train the machine learning model to distinguish between them. The drone photographs came from another dataset, while the bird images came from web scraping. Each folder offers a large number of photographs of subjects against natural sky backgrounds for model training.⁽²⁰⁾

Preprocessing Data

Due to image backdrop, orientation, and scale diversity, numerous preprocessing processes were used to standardize the dataset for effective training. To maintain neural network input size consistency, all images were scaled to 224x224 pixels. Normalizing image pixel values to 0–1 speeds training convergence. Rotation, zoom, and horizontal flipping were used to strengthen the model and prevent overfitting.⁽²¹⁾

Models of machine learning

Several machine learning models were tested for Birds vs. Drones prediction. Logistic Regression, a logistic function-based binary classification model, is used. Non-parametric supervised learning algorithm Decision Trees predict target variables by inferring basic decision rules from data attributes. Random Forest improves predicted accuracy by training several decision trees. A differentiable loss function is optimized via Gradient Boosting, another sequential model-building machine learning method. Deep learning techniques rely on neural networks, which capture non-linear data correlations using layers of interconnected nodes. Finally, Stochastic Gradient Descent (SGD) calculates gradients using a single sample or small batch, improving performance for huge datasets while fitting classifiers under convex loss functions as shown in figure 2.⁽²²⁾

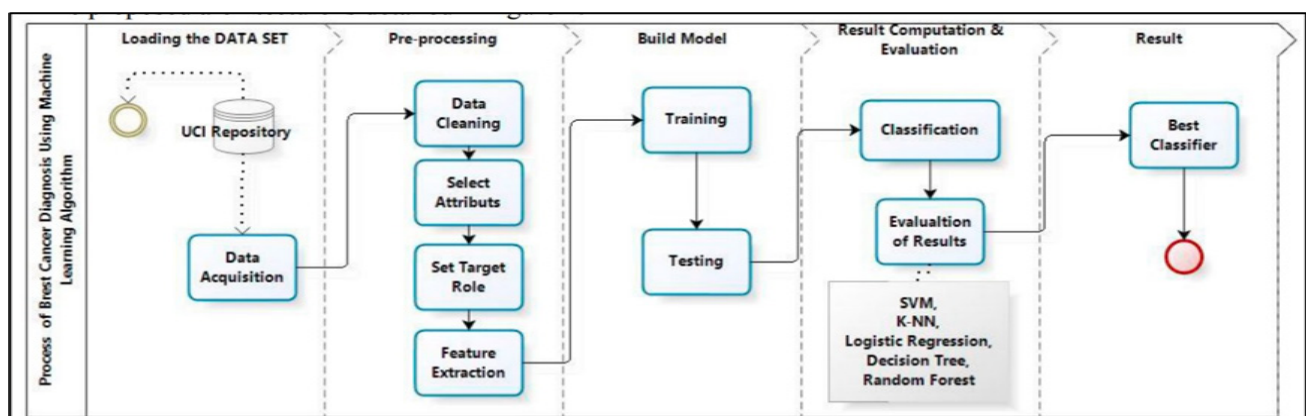


Figure 2. The Processes Flow Diagram

RESULTS

Confusion Matrix Analyses

System mastering uses confusion matrix analysis to evaluate class fashion performance. This table, with dimensions “Actual” and “Predicted,” visualizes rule performance. The matrix compares target values to model predictions, resulting in four effects: genuine positives (TP), proper negatives (TN), fake positives (FP), and false negatives. True positives and actual negatives are observations successfully predicted by the version; false positives and negatives are errors.⁽²³⁾ The confusion matrix inspires more exact measurements like accuracy, precision, memory, and F1 score. Accuracy counts the percentage of correct forecasts, precision measures fantastic predictions, take into account evaluates the version’s ability to find positive times, and the F1 rating balances precision and recall. These metrics give a more detailed understanding of model performance than accuracy, especially in datasets with uneven class distributions as shown in figure 3.⁽²⁴⁾

Bar chart in figure 2 shows confusion matrices of six machine learning models’ true and false predictions for ‘Birds’ and ‘Drones.’ Number of predictions is shown by bar height. For ‘Birds,’ the blue bars show true positives (properly predicted birds) and the little orange segments at the base represent false negatives (drones). For ‘Drones,’ blue segments represent false positives (drones predicted as birds) while orange bars show actual negatives. The Neural Network model has the most true positives and negatives and the lowest false negatives and positives, indicating the best predicting accuracy. The Tree model makes more erroneous predictions than the others, suggesting it is less reliable. Gradient Boosting, Logistic Regression, Stochastic Gradient Descent, and Random Forest yield balanced results with few incorrect predictions. The Neural Network has excellent accuracy in classifying ‘Birds’ and ‘Drones.’⁽²⁵⁾

ROC Analyses

In academia, Receiver Operating Characteristic (ROC) analysis is a powerful statistical method for assessing binary classifier diagnostics. Plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings, a ROC curve shows a classifier’s performance independent of class distribution or error rates. AUC, a unique statistic below the ROC curve, measures the classifier’s ability to distinguish between the two lessons, with a higher AUC indicating better performance. ROC evaluation is particularly good in providing version performance across all class thresholds, giving it a strong degree that is independent of any choice criterion. This analytical tool is essential for comparing classifiers and visualizing their strengths and weaknesses in different operational situations. It is also a key tool in device mastering for developing models with optimized decision-making skills.⁽²⁶⁾

For a classification project, figure 4 shows a ROC (Receiver Operating Characteristic) curve evaluation of six machine learning

models: Random Forest, Tree, Gradient Boosting, Logistic Regression, Neural Network, and Stochastic Gradient Descent. The Neural Network model outperforms the rest, followed by Gradient Boosting and Logistic Regression models, which also have good predictive abilities. The ROC curves show the True Positive Rate (TPR) versus False Positive Rate (FPR) for each model. Random Forest and Stochastic Gradient Descent models perform well but do not fit the best models. In contrast, the Tree model, whose curve is farthest from the pinnacle-left nook, performs worse, showing lower category accuracy. The curves suggest that the Neural Network version, with its superior curve function, may have the best spot beneath the curve (AUC), indicating its ability to parent between target classes.⁽²⁷⁾

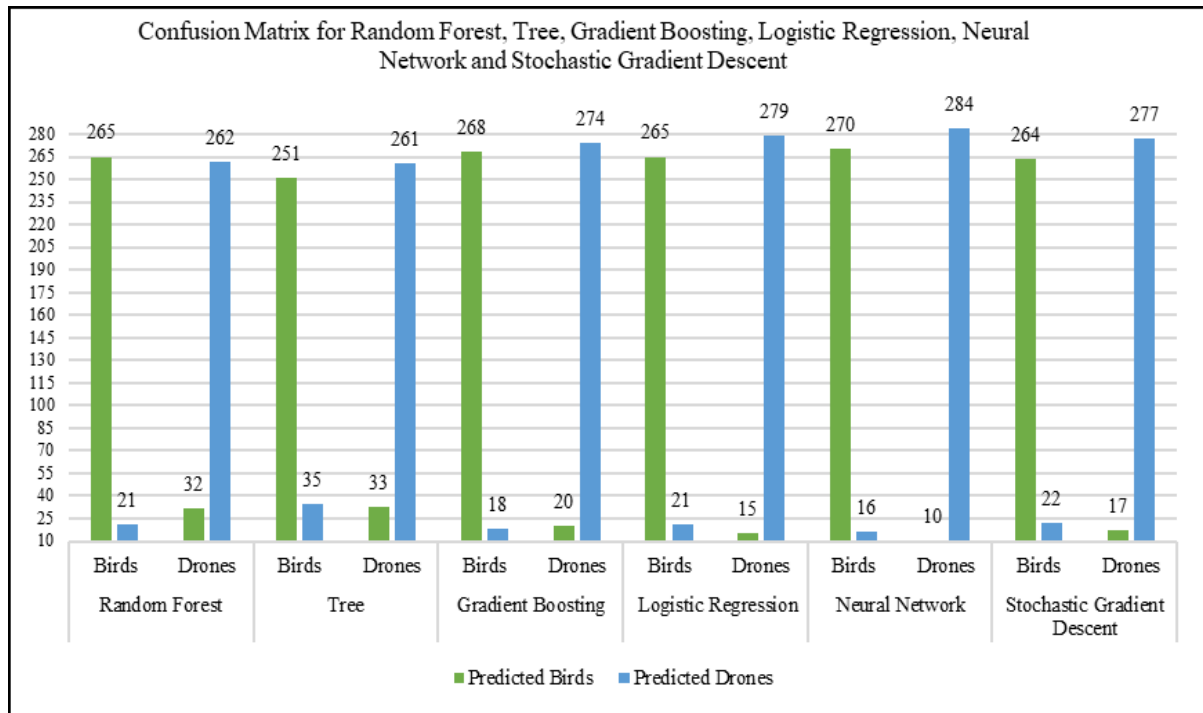


Figure 3. Illustrate The Confusion Matrix for Random Forest, Tree, Gradient Boosting, Logistic Regression, Neural Network and Stochastic Gradient Descent for the Birds and Drones Classes

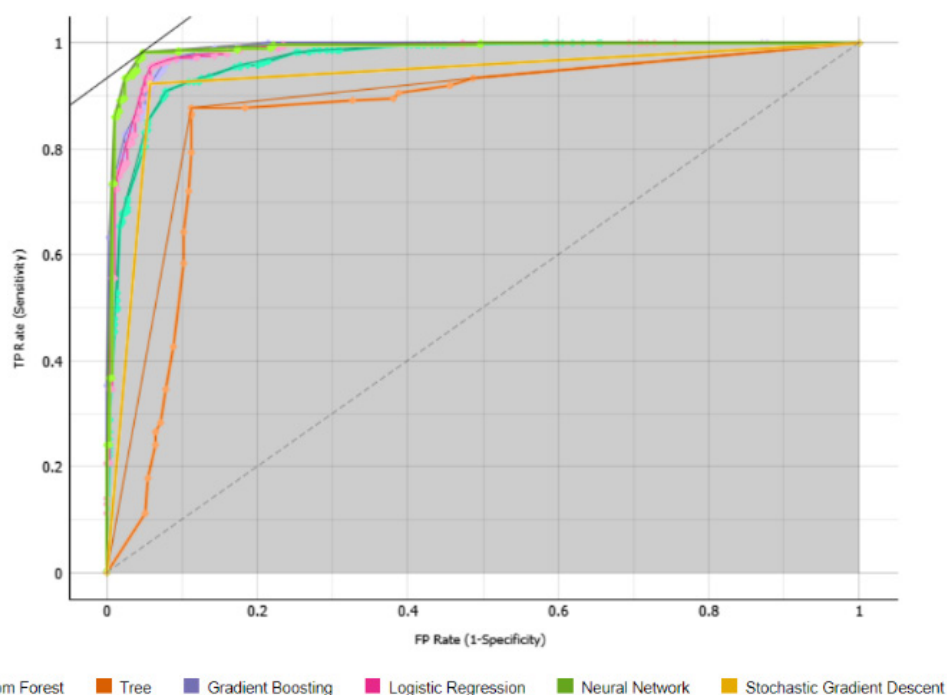


Figure 4. Illustrate the ROC Analyses for Random Forest, Tree, Gradient Boosting, Logistic Regression, Neural Network and Stochastic Gradient Descent for the Birds Class

The ROC curve in figure 5 compares the true positive rate (TPR) against the false positive rate (FPR) for several machine learning models. This plot shows ROC curves for Random Forest, Tree, Gradient Boosting, Logistic Regression, Neural Network, and Stochastic Gradient Descent. The Neural Network model's curve is closest to the top-left corner, showing a greater TPR and lower FPR, indicating better performance. Gradient Boosting and Logistic Regression also detect positives well with curves around the upper left. Although slightly below the other models, the Random Forest model performs well. The Tree model performs worse with its curve closer to the diagonal line that symbolizes a random chance. The Stochastic Gradient Descent curve is further from the top-left corner but still performs well. This image shows that the Neural Network model is likely the best classifier, especially for distinguishing the positive class with few false positives.⁽²⁸⁾

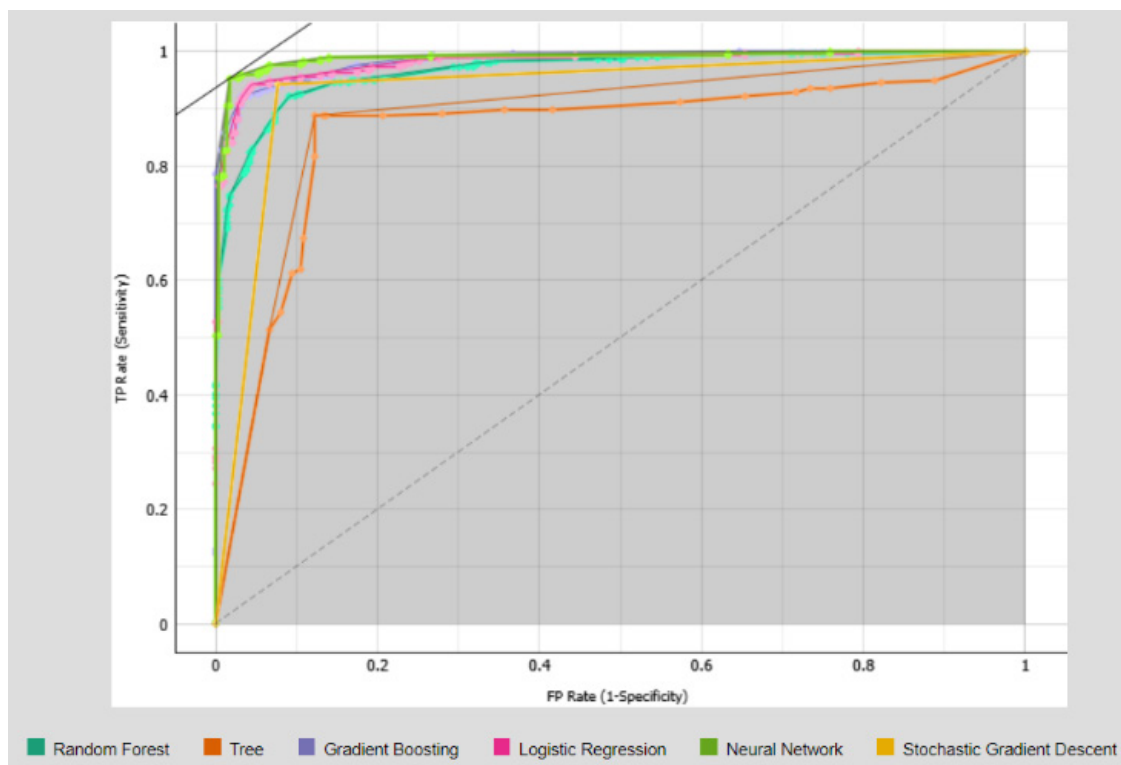


Figure 5. Illustrate the ROC Analyses for Random Forest, Tree, Gradient Boosting, Logistic Regression, Neural Network and Stochastic Gradient Descent for the Drones Class

DISCUSSION

The rise of Unmanned Aerial Vehicles (UAVs) in military surveillance presents both new operational capabilities and security risks. This paradox highlights the need for advanced real-time recognition systems, which our work develops and compares machine learning models to meet. In national defense and security, distinguishing UAVs from similar-sized, non-threatening items like birds is crucial. This research addresses this difficulty. Neural Networks outperformed other models in precision, recall, and computing efficiency, which are crucial for real-time military applications. Neural Networks' superiority, especially in AUC values, makes them ideal for deployment in sensitive navy scenarios with small error margins and high misidentification costs. Their accuracy in identifying positives and negatives makes them a reliable foundation for future surveillance systems that can detect quickly and accurately.^(29,30,31)

Gradient Boosting and Logistic Regression models also showed strong predictive abilities. With high Recall scores, these models are well-equipped for situations that need a compromise between speed and precision and limited processing resources. The findings suggest a multi-tiered detection approach using the reliable Random Forest as an initial filter and the balanced Stochastic Gradient Descent for accuracy and velocity-stressed events to enhance protection mechanisms. The Tree model's trailing performance highlights the complexity of real-time UAV popularity and the need for robust, nimble algorithms to analyze various environmental styles and data. This study shows the power of system studying in UAV reputation, however it has limits. The effectiveness of modern trends in different environments and against stealth-designed UAVs is still being studied. UAV technologies are continually evolving, therefore model adaptation is needed to stay up with emerging risks.^(32,33,34) Future research will improve these models' real-time processing capabilities to ensure they work seamlessly with military technologies and can adapt to increasingly sophisticated UAV designs. As the technological arms race grows, machine learning models must keep up to ensure a secure and responsive defense posture.^(35,36,37)

In summary, the research recommends strategic integration of Neural Network-based airspace monitoring and UAV recognition systems into military defenses. It lays the groundwork for a safer future where machine learning's complex digital skills defend against UAV misuse. This research is not only a testimonial to present capabilities but also a demand for constant awareness and proactive preparation against growing aerial threats.⁽³⁸⁾

CONCLUSION

In conclusion, this research Article's key conclusions are substantial and useful for improving military surveillance operations. This study evaluated various machine learning models under real-time data processing and environmental variability. With its powerful computational architecture, the Neural Network model distinguished UAVs from natural phenomena like birds with unparalleled accuracy, enhancing airspace security.

The study found that while Gradient Boosting and Logistic Regression models were also predictive, the Neural Network consistently outperformed them in key performance metrics like AUC, CA, F1 Score, and Recall. This higher performance suggests integrating Neural Network-based technologies into army defenses, which could improve chance evaluation and defense asset allocation, improving operational efficacy.

Deploying these complex models is not without challenges. The research emphasizes the need to develop these machine learning models as UAV technology advances in stealth and operational agility. Maintaining a strong defense posture requires models to develop with UAV designs.

In conclusion, the article emphasizes the need for real-world operational testing and model adaption to new airborne threats, as well as a commitment to research in this field. This research advances military surveillance capabilities and establishes the standard for defending global airspaces from the multiple risks posed by unchecked UAV technology.

FINANCING

Currently, there are no available financing sources designated for this project. This absence of financial support underscores the need for strategic planning to identify potential funding avenues that could facilitate the successful implementation and advancement of the initiative.

CONFLICT OF INTEREST

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

AUTHORSHIP CONTRIBUTION

Conceptualization: Muhyeeddin Alqaraleh, Mowafaq Salem Alzboon, Mohammad Subhi Al-Batah.

Data curation: Muhyeeddin Alqaraleh, Mowafaq Salem Alzboon, Mohammad Subhi Al-Batah.

Formal analysis: Muhyeeddin Alqaraleh, Mowafaq Salem Alzboon, Mohammad Subhi Al-Batah.

Research: Muhyeeddin Alqaraleh, Mowafaq Salem Alzboon, Mohammad Subhi Al-Batah.

Methodology: Muhyeeddin Alqaraleh, Mowafaq Salem Alzboon, Mohammad Subhi Al-Batah.

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Writing - proofreading and editing: Muhyeeddin Alqaraleh, Mowafaq Salem Alzboon, Mohammad Subhi Al-Batah.

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