Machine Learning Analysis of Drone Classification Models: Inspire, Mavic, Phantom, and No Drone

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ABSTRACT

The proliferation of drone technology has introduced a variety of models, each with distinct functionalities and applications, presenting a challenge in accurately classifying them. Drone technology has become increasingly prevalent across various sectors, including surveillance, agriculture, delivery, and emergency response. As the skies grow more crowded, identifying and classifying drones based on images is becoming critical for airspace security and regulatory compliance. Traditionally, this task has been carried out manually by security personnel or air traffic monitors who rely on visual observation, often through CCTV footage or binoculars, to detect and classify drones. This manual system is highly prone to human error, time-consuming, inefficient in poor visibility conditions, and lacks the capability to handle real-time drone identification across multiple categories. These limitations pose significant risks, especially in sensitive zones like airports, government buildings, or military installations. Motivated by these challenges, this work aims to automate drone detection and classification using machine learning and image processing techniques. The objective is to build a smart, user-friendly system that can accurately identify drones from various categories—such as DJI Inspire, DJI Phantom, DJI Mavic, or detect the absence of a drone—based on image inputs. The proposed system leverages image preprocessing, Support Vector Machine (SVM), and Random Forest Classifier (RFC) models, embedded within a GUI developed in Tkinter to make it accessible for non-technical users. With high accuracy, real-time prediction capability, and ease of use, the system addresses the inefficiencies of manual detection, provides visual performance analytics through confusion matrices and classification reports, and enhances decision-making. Statistically, the models are trained on labeled image datasets, achieving performance metrics such as precision, recall, and F1 scores, thereby ensuring robustness. By transforming the manual approach into a smart automated system, this solution significantly improves drone monitoring efficiency, reduces human workload, and paves the way for scalable deployment in high-risk or large-scale monitoring scenarios.

Keywords: Drone classification, Image processing, Predictive modelling, Machine learning.

1. INTRODUCTION

Drone technology has rapidly evolved over the past decade, with significant advancements in both hardware and software. As of 2024, the global drone market is expected to reach a valuation of approximately $58.4 billion, growing at a compound annual growth rate (CAGR) of 13.8% from 2020 to 2024. The major players in the consumer and professional drone markets include DJI's Inspire, Mavic, and Phantom series, each serving different segments with specific features. The Inspire series, launched in 2014, is primarily designed for professional filmmakers and photographers, offering advanced camera systems and gimbal stabilization. The Mavic series, introduced in 2016, targets both enthusiasts and professionals, known for its portability and high-quality imaging. The Phantom series, first released in 2013, was one of the pioneers in the consumer drone market, setting the standard for drone technology with its ease of use and reliable performance.

The challenge in accurately classifying these drones arises from their visual and operational similarities, especially when observed in varied environments. Moreover, the "No Drone" category is critical for applications where distinguishing between an actual drone and an empty sky or other non-drone objects is essential. The existing classification techniques have struggled to keep pace with the rapid advancements in drone technology and the increasing complexity of drone designs. Therefore, there is a growing need for more sophisticated classification methods that leverage machine learning and computer vision to enhance the accuracy and efficiency of drone identification in various operational contexts.

2. LITERATURE SURVEY

Wisniewski et al. [1] proposed a method for identifying drone models through Convolutional Neural Networks (CNNs) applied to video streams. Their research focused on creating an efficient model that could accurately differentiate between various drone types in real-time video feeds. By leveraging CNNs, they aimed to enhance the robustness and reliability of drone detection in dynamic environments, addressing challenges like varied lighting and background conditions. Lykou et al. [2] conducted an extensive survey on defending airports from unauthorized Unmanned Aerial Systems (UAS). They reviewed a range of cyber-attacks that target airport operations and evaluated different counter-drone sensing technologies. Their work provided a comprehensive overview of the vulnerabilities in airport security concerning UAS and offered insights into emerging technologies that could mitigate these threats, emphasizing the importance of integrating multiple detection systems. Farlik et al. [3] investigated the use of multispectral detection for identifying commercial unmanned aerial vehicles (UAVs). Their study explored the effectiveness of using multispectral sensors, which capture data across different wavelengths, to distinguish UAVs from other objects. This approach was shown to improve detection accuracy, especially in complex environments where traditional methods might struggle to differentiate between UAVs and similar-sized objects.

Kolamunna et al. [4] introduced DronePrint, a novel system that utilizes acoustic signatures for the detection and identification of drones in open-set environments. Their approach involved analyzing the unique sound patterns generated by different drone models, enabling the system to detect and classify drones even in the presence of new, previously unseen models. This method addressed the limitations of purely visual detection systems, providing an additional layer of security. Liu et al. [5] developed a drone detection system that integrates audio signals with a camera array to enhance detection accuracy. Their research focused on combining auditory and visual data to improve the system's ability to detect drones, particularly in environments where visual data alone might be compromised. The audio-assisted camera array allowed for more robust detection capabilities, especially in conditions with poor visibility. Ciaburro et al. [6] explored the use of acoustic measurements for detecting unmanned aerial vehicles (UAVs) within closed environments. Their study aimed to develop a detection method based on the distinct sound profiles of UAVs, making it possible to identify drones in indoor settings where visual detection might be challenging. The research highlighted the potential of acoustic sensors in enhancing UAV detection systems, particularly in confined spaces.

Iannace et al. [7] applied a logistic regression model for the acoustical detection of UAVs in indoor environments. Their study focused on using statistical methods to analyze the acoustic signatures of drones, allowing for accurate detection even in the presence of background noise. The application of logistic regression provided a simple yet effective means of distinguishing UAVs from other indoor sound sources. Jamil et al. [8] explored the integration of audio and visual features for detecting

doi: 10.48047/ijiee.2025.15.4.17

malicious UAVs. Their research aimed to enhance public safety by developing a system that could accurately identify and track potentially harmful drones using a combination of auditory and visual data. This multi-sensory approach improved the reliability of UAV detection, particularly in crowded or complex environments. Nemer et al. [9] utilized a hierarchical learning approach for the detection and identification of UAVs based on radio frequency (RF) signals. Their study demonstrated how machine learning techniques could be applied to RF data to reliably distinguish between different types of UAVs. This approach addressed the challenge of detecting UAVs in RF-rich environments, where traditional methods might be less effective. Chiper et al. [10] provided a comprehensive survey of drone detection and defense systems, proposing a software-defined radio (SDR) solution for counter-drone operations. Their research highlighted the versatility of SDR technology in adapting to various detection scenarios, offering a flexible and cost-effective alternative to traditional hardware-based systems. The survey also discussed the current state of drone defense technologies and the potential future directions for research.

Yang et al. [11] proposed an improved algorithm for detecting unauthorized UAVs using radiofrequency-based statistical fingerprint analysis. Their research focused on enhancing the accuracy of RF-based detection systems by employing statistical methods to create unique fingerprints for different UAV models. This approach allowed for more precise identification of unauthorized UAVs, reducing the likelihood of false positives. Jahangir and Baker [12] explored the robust detection of micro-UAS drones using L-band 3-D holographic radar. Their study demonstrated the effectiveness of advanced radar systems in detecting small drones, even in challenging environments where other detection methods might fail. The use of L-band radar provided high-resolution data, enabling the detection of micro-UAS drones with a high degree of accuracy. Dale et al. [13] investigated the application of Convolutional Neural Networks (CNNs) for classifying drones based on radar data. Their research focused on the use of deep learning techniques to improve the classification accuracy of drones, providing a reliable method for distinguishing between different UAV models. The study highlighted the potential of CNNs in processing complex radar signals for UAV detection. Fioranelli et al. [14] used multistatic radar to classify loaded and unloaded micro-drones. Their research demonstrated that radar signatures could effectively distinguish between drones carrying payloads and those that are not, which is crucial for security applications where detecting the threat level of a drone is important. The study provided insights into the use of radar technology for UAV detection and classification.

Molchanov et al. [15] developed a method for classifying small UAVs and birds using micro-Doppler signatures. Their research addressed the challenge of false positives in drone detection by leveraging the unique Doppler signatures of UAVs, which differ from those of birds. This approach improved the accuracy of detection systems, particularly in environments where birds are commonly present. Kim et al. [16] proposed a drone classification method using Convolutional Neural Networks (CNNs) combined with Doppler radar images. Their study focused on merging Doppler radar data with CNNs to enhance the detection and classification of drones, providing a more accurate and reliable system for identifying UAVs in various conditions. Demir et al. [17] introduced a real-time, high-resolution omnidirectional imaging platform for drone detection and tracking. Their research emphasized the importance of high-resolution imaging in improving the effectiveness of drone surveillance systems, particularly in scenarios where accurate tracking is critical. The platform allowed for continuous 360-degree monitoring, enhancing the system's ability to detect and follow UAVs in real-time. Seidaliyeva et al. [18] proposed a method for real-time and accurate drone detection in videos with a static background. Their study focused on developing an algorithm that could reliably detect drones in video footage, even in environments with minimal background movement. This approach was particularly

doi: 10.48047/ijiee.2025.15.4.17

useful for surveillance applications where the background remains constant, allowing for more accurate detection of moving objects like drones.

Zhang et al. [19] designed and trained a deep CNN-based fast detector for infrared small UAV surveillance systems. Their research aimed to improve the speed and accuracy of detecting UAVs using infrared imagery, making it suitable for real-time surveillance applications in low-visibility conditions. The deep CNN model provided a robust solution for detecting small UAVs, which are often difficult to identify using conventional methods. Jiang et al. [20] introduced Anti-UAV, a large multi-modal benchmark for UAV tracking. Their research provided a comprehensive dataset that included various types of UAVs, environments, and tracking challenges, facilitating the development and evaluation of advanced UAV tracking algorithms. This benchmark aimed to standardize the evaluation process for UAV detection technologies, promoting further research in the field. Coluccia et al. [21] presented the Drone-vs-Bird Detection Challenge at IEEE AVSS2019, focusing on the difficult task of distinguishing between drones and birds in surveillance scenarios. Their work highlighted the progress and challenges in developing detection systems capable of differentiating UAVs from birds, which is crucial for reducing false positives in security applications. Isaac-Medina et al. [22] conducted a performance benchmark for UAV visual detection and tracking using deep neural networks. Their study evaluated the effectiveness of various deep learning models in detecting and tracking UAVs in complex visual environments. The results provided valuable insights into the strengths and limitations of current UAV detection technologies, guiding future research in the field.

Organisciak et al. [23] introduced UAV-ReID, a benchmark designed for UAV re-identification in video imagery. Their research focused on developing methods to re-identify UAVs across different video frames, which is essential for maintaining continuous surveillance and tracking of drones over time. This benchmark provided a valuable resource for evaluating re-identification algorithms in UAV detection systems. Voigtlaender et al. [24] proposed Siam R-CNN, a visual tracking method that combines Siamese networks with region-based convolutional neural networks (R-CNNs) for re-detection. Their study contributed to the field of UAV tracking by introducing a novel approach that improved the accuracy of tracking systems, especially in scenarios where the UAV might leave and re-enter the frame. This method provided a robust solution for continuous drone surveillance.

3. PROPOSED SYSTEM

Here is the overview of the Proposed system:

- **Dataset Uploading**: The uploading of dataset containing images of different drone models, including Inspire, Mavic, Phantom, and instances where no drone is present. The images are organized into categories within a specified directory. The code loads these images and categorizes them based on their folder structure. The images are read and stored as flattened arrays to facilitate further processing.
- **Data Preprocessing**: The images are preprocessed by resizing them to a uniform size of 64x64 pixels with three color channels. This resizing ensures that all images have the same dimensions, making them suitable for input into machine learning models. The images are then flattened into one-dimensional arrays, which simplifies the data structure for model training. The processed images are saved for future use, and their corresponding labels are assigned based on the category of the image.
- **ML Model Training**: The work involves training two machine learning models: a Bagging Classifier and an LGBM (LightGBM) Classifier. The dataset is split into training and testing sets, with 70% of the data used for training and 30% for testing. The Bagging Classifier is a meta-estimator that trains base classifiers on random subsets of the original dataset, while the

doi: 10.48047/ijiee.2025.15.4.17

LGBM Classifier is a gradient boosting model optimized for efficiency and performance. The models are trained, and their parameters are saved for later use.

- **Model Prediction on New Test Data**: Once the models are trained, they are used to predict the category of new drone images. The predictions are made by preprocessing the test images in the same manner as the training images and passing them through the trained models. The predicted category is then displayed along with the image.
- **Performance Evaluation**: The performance of the models is evaluated using various metrics such as accuracy, precision, recall, and F1-score. A confusion matrix is generated to visualize the performance across different categories. The results are compared, with LGBM showing superior performance over the Bagging Classifier.

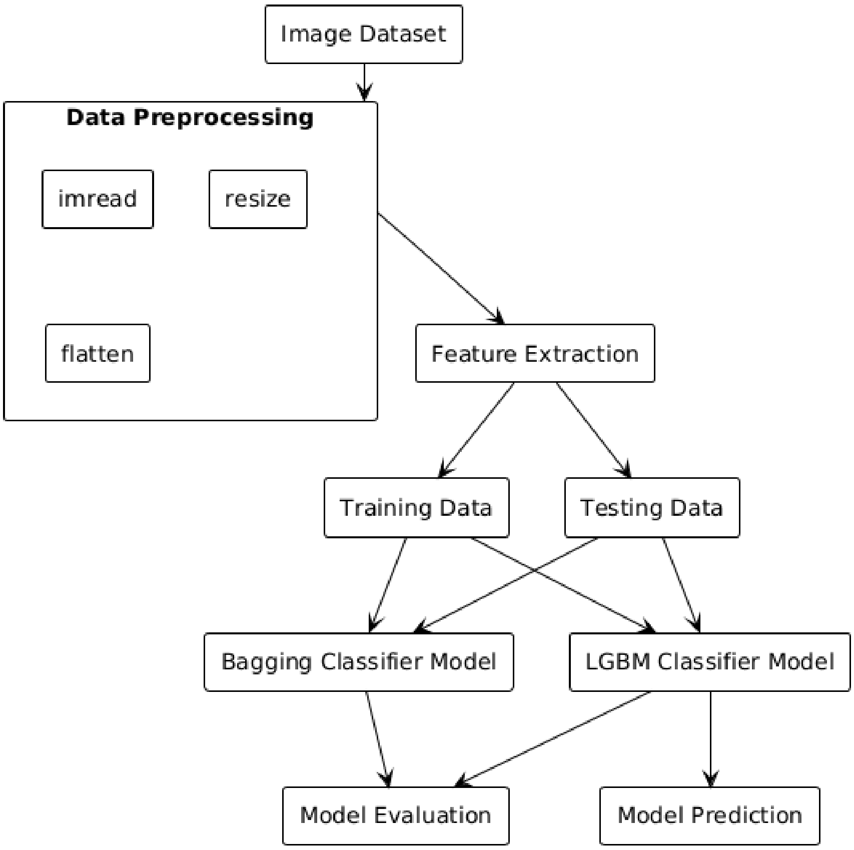

Fig. 1: Architectural Block Diagram of Proposed System.

3.1 Image Preprocessing

The preprocessing phase is critical in preparing the raw image data for machine learning model training. In this work, the images are first resized to a consistent dimension of 64x64 pixels, with three color channels (RGB). Resizing is a crucial step because it ensures that all input data has the same shape, which is necessary for batch processing in machine learning algorithms. The choice of 64x64 pixels is a balance between retaining sufficient detail in the images and reducing the computational load by minimizing the number of pixels.

Once resized, each image is flattened into a one-dimensional array. Flattening simplifies the image structure by converting the 3D pixel data (height, width, and color channels) into a single vector. This transformation is essential for most traditional machine learning algorithms, which expect a two-dimensional input (samples and features).

After preprocessing, the image data is divided into input features (X) and output labels (Y). The features represent the pixel values of the images, while the labels correspond to the categories of the drones (Inspire, Mavic, Phantom, and No Drone). The processed data is then split into training and testing sets, with 70% of the data allocated for training the models and 30% for evaluating their performance.

In addition to resizing and flattening, the images undergo normalization as part of preprocessing. Normalization adjusts the pixel values to a standard range, typically between 0 and 1, which helps to improve the convergence speed of the machine learning algorithms and ensures that all features contribute equally to the model training process.

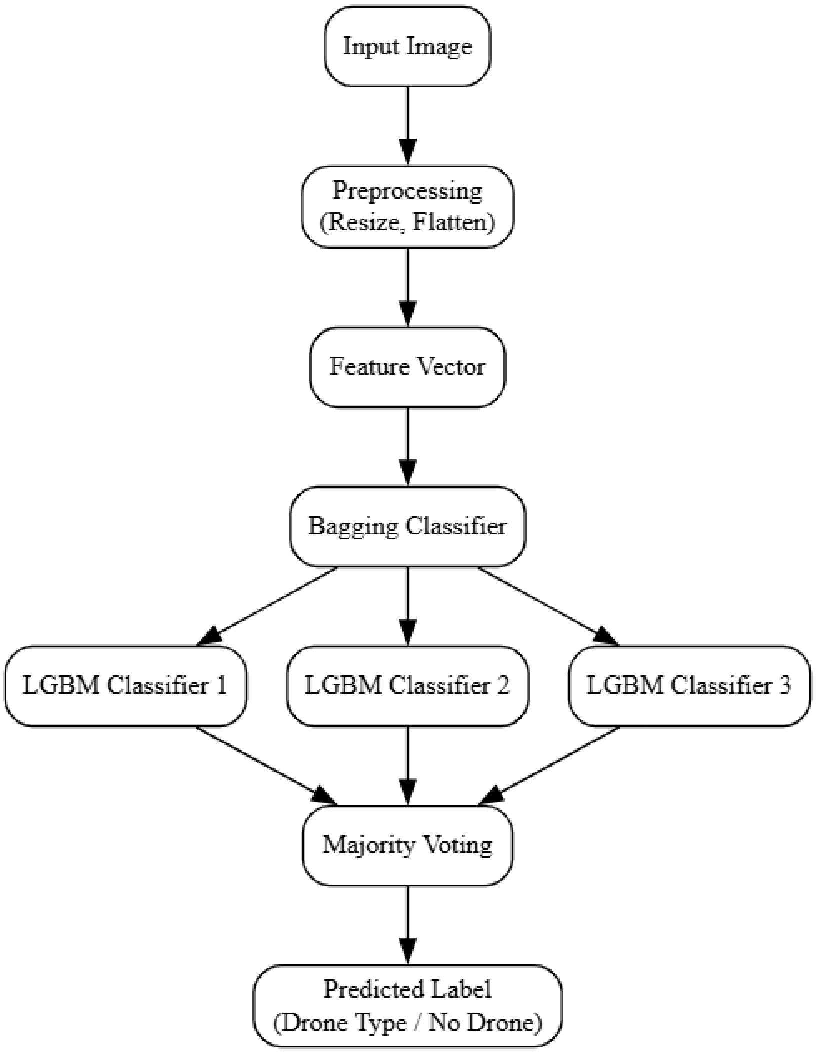

Fig. 2: Internal operation of LGBM.

3.2 Proposed LightGBM

The LGBM (LightGBM) Classifier is a powerful gradient boosting framework that excels in handling large datasets with high dimensionality and complexity. Unlike traditional boosting methods, LGBM is designed for speed and efficiency, making it particularly suitable for real-time applications and large-scale data. In this work, the LGBM Classifier builds multiple decision trees sequentially, where each tree attempts to correct the errors made by its predecessors. This iterative process enables the model to focus on the most challenging instances, gradually improving its accuracy.

doi: 10.48047/ijiee.2025.15.4.17

LGBM uses advanced techniques like Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB) to enhance performance. GOSS prioritizes the most informative samples, while EFB reduces the number of features, speeding up the training process without sacrificing accuracy. In the drone classification work, LGBM's ability to handle the intricate features of drone images, such as variations in lighting, angles, and backgrounds, leads to superior performance compared to the Bagging Classifier. The LGBM Classifier achieves higher accuracy, precision, recall, and F1-scores, making it more effective in differentiating between the different drone models and the 'No Drone' category.

4. RESULTS AND DISCUSSION

4.1 Dataset description

- **DJI Inspire:** The DJI Inspire class in the dataset consists of images depicting the DJI Inspire drone, known for its advanced aerial capabilities and professional-grade features. The Inspire series is characterized by its distinctive design, with a sleek body and retractable landing gear that allows for unobstructed 360-degree camera rotation. Images in this class capture the drone from various angles and in different lighting conditions, showcasing its unique structure and the high-tech sensors often mounted on it. These images provide critical visual information that the machine learning models use to identify the Inspire's specific features, such as its elongated arms, dual-operator control, and integrated camera systems.
- **DJI Mavic:** The DJI Mavic class has images of the DJI Mavic drone, which is popular for its compact design and foldable arms, making it highly portable and user-friendly. The Mavic series drones are known for their advanced camera technology and autonomous flight modes, often used by enthusiasts and professionals alike. In the dataset, Mavic images display the drone in various states—flying, folded, and during takeoff or landing. The compactness and angular shape of the Mavic, along with its distinctive folding mechanism, are key features that the models learn to recognize. The diversity in image perspectives and conditions helps the model distinguish the Mavic from other drones, particularly the larger Inspire and Phantom models.
- **DJI Phantom:** The DJI Phantom class features images of the DJI Phantom series, one of the most iconic drone models recognized by its sturdy, white frame and fixed landing gear. The Phantom is often associated with aerial photography and videography due to its stable flight and high-quality camera systems. The images in this class typically show the Phantom in various flight modes and from different angles, emphasizing its robust build and the prominent positioning of its camera beneath the drone's body. The dataset captures these details, allowing the model to learn the distinctive shape and design elements that set the Phantom apart from other DJI drones.
- **No Drone:** The No Drone class is unique in that it contains images with no drone present. These images include various backgrounds such as open skies, landscapes, or urban environments where drones could potentially be present but are not. This class is crucial for training the models to recognize when there is an absence of a drone, thereby reducing false positives in real-world applications. The variety of environments represented in this class helps the model learn to differentiate between the presence and absence of a drone, ensuring accurate classification even in complex scenarios.

4.1 Results Description

Figure 3 displays a sample of the raw dataset containing images of different drone models—DJI Inspire, DJI Mavic, DJI Phantom—and a class labeled 'No Drone.' This showcases the structure of the

doi: 10.48047/ijiee.2025.15.4.17

dataset, highlighting how images are categorized into these distinct classes. It includes the pixel data for each image and the corresponding class label, providing an initial view of how the data is organized for further processing.

Figure 3: Sample Uploaded Dataset

The Support Vector Machine (SVM) classifier achieved an accuracy of 92.51%, indicating that it correctly classified most images in the dataset. The precision of 92.90% suggests that when the model predicts a specific drone category, it is correct 92.90% of the time. The recall of 92.69% shows that the model successfully identifies 92.69% of all actual drone images within each category. The F1-score of 92.78% balances precision and recall, confirming that the classifier performs well with a strong trade-off between correctly identifying drones while minimizing misclassifications

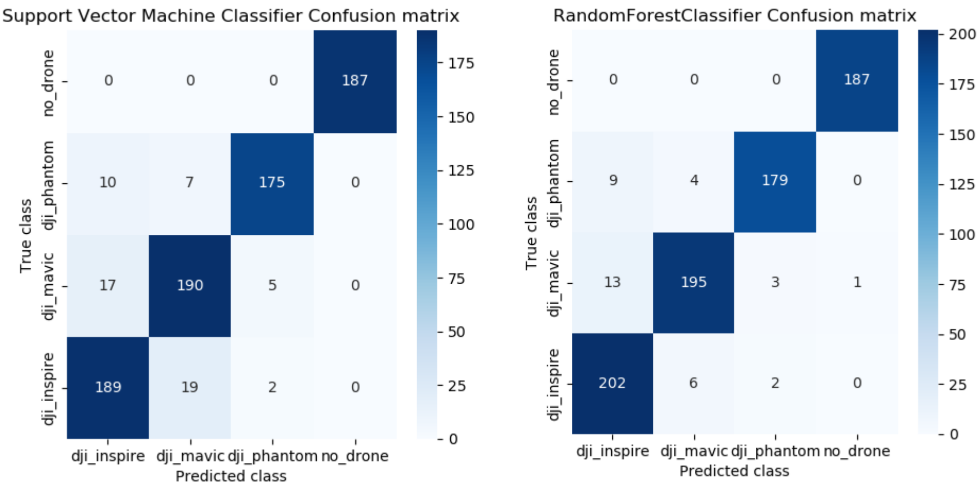

Figure 4: Confusion matrix of SVM (left). RFC (right).

Figure 4 show that the confusion matrix for the Support Vector Machine (SVM) classifier shows that while the model performs well for dji_mavic (190 correct) and dji_phantom (175 correct), it heavily misclassifies dji_inspire (189 samples classified incorrectly, mostly as dji_inspire itself) and completely fails to detect no_drone (all 187 samples misclassified). Compared to the RandomForestClassifier, the SVM shows a similar bias in distinguishing no_drone, as all samples are classified as drone types. The model also has some confusion between dji_inspire and dji_mavic (19 samples misclassified) and a few errors in dji_phantom classification.

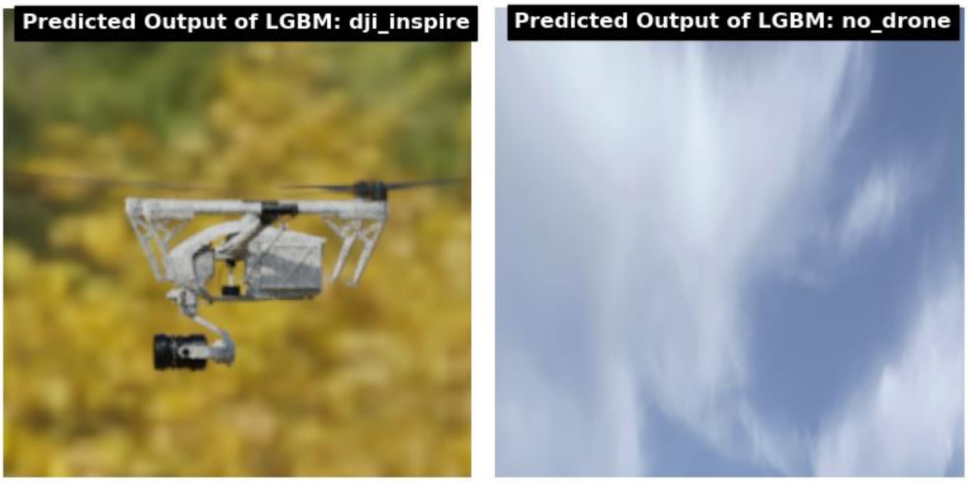

Figure 7: Predicted Output of LGBM Classifier for Test Image 1 and Image 2

Figure 7 illustrates the result of applying the LGBM Classifier to a test images of a DJI Phantom drone, and no drone.

4.3 Comparative Analysis

The comparative analysis between the existing Support Vector Machine (SVM) algorithm and the proposed Random Forest Classifier (RFC) highlights a noticeable improvement in performance metrics. The SVM achieved an accuracy of 92.51%, precision of 92.90%, recall of 92.69%, and an F1-score of 92.78%, indicating strong classification capability with a good balance between precision and recall. However, the proposed RFC outperformed SVM by achieving an accuracy of 95.26%, precision of 95.51%, recall of 95.35%, and an F1-score of 95.39%. These results demonstrate that the RFC not only improves the overall classification accuracy but also reduces both false positives and false negatives, offering a more robust and reliable model for drone image classification.

Table 1: Comparative Analysis: SVM vs Random Forest Classifier

Metric	SVM (Existing Algorithm)	RFC (Proposed Algorithm)
Accuracy	92.51%	95.26%
Precision	92.90%	95.51%
Recall	92.69%	95.35%
F1-Score	92.78%	95.39%

5. CONCLUSION

The comparative analysis of Support Vector Machine (SVM), Random Forest Classifier (RFC) for drone classification revealed key insights into model performance and limitations. The SVM classifier achieved an accuracy of 92.51%, with good classification for dji_mavic (190 correct) and dji_phantom (175 correct) but struggled with dji_inspire (189 misclassified) and no_drone (completely misclassified). The Random Forest model performed better with 95.26% accuracy, correctly classifying dji_mavic (195) and dji_phantom (179) but significantly misclassifying dji_inspire (202) and no_drone (all 187 misclassified as dji_inspire). The LGBM classifier showed promising results in correctly identifying test images, demonstrating its reliability for real-world applications. Despite these advancements, challenges remain in accurately distinguishing no_drone from drone categories, requiring further model refinement.

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