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DEEP LEARNING DRIVEN REAL-TIME AIRSPACE MONITORING USING SATELLITE IMAGERY

ANIRUDH SINGH *, SATYAM KUMAR†, AND DEEPJYOTI CHOUDHURY ‡

Abstract. Detecting aircraft in remote sensing images poses a formidable challenge due to the diverse characteristics of aircraft, including type, size, pose, and intricate backgrounds. Traditional algorithms encounter difficulties in manually extracting features from numerous candidate regions. This paper introduces an innovative aircraft detection approach that combines corner clustering with a diverse set of Deep Learning (DL) models. The proposed method involves two main stages: region proposal and classification. In the region proposal stage, initial candidate regions are generated using a mean-shift clustering algorithm applied to corners detected on binary images. Subsequently, a comprehensive set of classifiers, encompassing CNN, DenseNet, MobileNetV2, Inception v3, Random Forest (R.F), ResNet50, ResNeXT, Support Vector Machine (SVM), VGG16, Xception, EfficientNet, and InceptionResNetv2, is employed for feature extraction and classification. The presented approach demonstrates superior accuracy and efficiency compared to conventional methods. By leveraging the autonomous learning capabilities of CNN and DL models on extensive datasets, the methodology generates a reduced yet high-quality set of candidate regions. Inspired by the detection methodology employed by image analysts, the approach adopts a coarse-to-fine strategy using CNN and DL models. The first CNN proposes coarse candidate regions, and the second identifies individual airplanes within these regions in finer detail. This framework results in a decreased number of candidate regions compared to existing literature while extracting distinctive deep features. Experimental evaluations on Google Earth images validate the efficiency of the proposed method, underscoring its potential for practical applications in both civilian and military contexts.

Key words: aircraft detection, remote sensing, corner clustering, image analysis, object recognition, aerial surveillance

1. Introduction. In a variety of domains, including military applications, environmental monitoring, and aviation safety, airplane detection in remote sensing images is essential. Traditional methods often struggle with limitations such as high false positives, manual feature engineering, and limited adaptability. This necessitates exploring new approaches with improved accuracy, speed, and adaptability. In the field of UAVs, these versatile platforms have become essential for executing missions in life-threatening environments where manned aircraft would be constrained. The escalating demand for military and civilian UAVs is driven by their operational efficiency and cost-effective pilot training. Collision avoidance with other aircraft emerges as a critical challenge in both military and civilian contexts, emphasizing the need for highly reliable technology to ensure the safety of UAV operations.

The International Civil Aviation Organization (ICAO) actively engages in discussions In the oversight and standardization of the integration of national airspace for both manned and unmanned aircraft, there is an ongoing focus. The notion of Unmanned Aerial Systems(UAS) is under consideration, envisioning a scenario where ground-based pilots operate UAVs remotely. This poses challenges due to low- quality images resulting from communication limitations. Reliable and real-time detection of these aerial vehicles is essential to ensure the safety of manned and unmanned aircraft operations, prompting the need for advanced detection techniques. In recent years, DL techniques, particularly CNNs, have demonstrated remarkable success in various computer vision tasks. CNNs possess the ability to automatically learn hierarchical features directly from raw image data, eliminating the need for manual feature engineering. This autonomous learning capability makes DL models highly effective in capturing the intricate patterns and subtle details required for accurate aerial vehicle detection.

This paper presents a DL-based framework for real-time detection of airplanes, military jets, and UAVs in remote sensing imagery. The proposed approach combines a region proposal stage leveraging corner clustering

*Department of AIML, School of CSE, Manipal University Jaipur, Rajasthan 303007 (asrofficial18@gmail.com).
†Department of AIML, School of CSE, Manipal University Jaipur, Rajasthan 303007 (satyamkumar9742@gmail.com).
‡Department of AIML, School of CSE, Manipal University Jaipur, Rajasthan 303007 (deepjyotichoudhury05@gmail.com).

with a comprehensive set of DL models for feature extraction and classification. Specifically, we employ CNNs, including DenseNet, MobileNetV2, Inception v3, ResNet50, ResNeXT, VGG16, Xception, EfficientNet, and InceptionResNetV2, along with traditional ML techniques like Random Forest and SVM.The framework adopts a coarse-to-fine strategy inspired by the detection methodology employed by image analysts. Initially, a CNN proposes coarse candidate regions, and subsequently, a second CNN identifies individual aerial vehicles within these regions in finer detail. This approach results in a reduced set of candidate regions compared to existing methods while effectively extracting distinctive deep features for accurate vehicle detection. The experiments demonstrate that the DenseNet model achieves the highest accuracy of 99.52%, outperforming other models. Detailed results and analysis of all employed models are presented in the Results and Analysis section.

The detection of aircraft from satellite imagery is a critical task that holds immense significance across various domains, including surveillance, environmental monitoring, defense intelligence, and transportation management. With the advent of commercial imagery providers like Planet, which employ constellations of small satellites to capture images of the entire Earth on a daily basis, the volume of satellite data has grown exponentially. This deluge of imagery has outpaced the ability of organizations to manually analyze each captured image, necessitating the development of advanced machine learning and computer vision algorithms to automate the analysis process. In the field of surveillance and intelligence, the ability to accurately detect and locate aircraft in satellite imagery plays a pivotal role in monitoring air traffic patterns, tracking unauthorized flights, and identifying potential threats to national security. By leveraging this technology, authorities can gain comprehensive situational awareness, enabling timely responses to potential security breaches or illicit activities. Moreover, environmental agencies can employ aircraft detection techniques to monitor air pollution levels and assess the environmental impact of aviation activities, contributing to the development of sustainable practices and policies. The significance of aircraft detection extends beyond security and environmental considerations. In the domain of transportation management, accurate detection of aircraft from satellite data can facilitate the optimization of airport operations, enabling efficient resource allocation and streamlining of air traffic control processes. This technology can also prove invaluable in search and rescue operations, expediting the location of downed aircraft and potentially saving lives. Our research contributes significantly to the advancement of aircraft detection technology in satellite imagery, offering practical implications for improving surveillance and monitoring systems. By leveraging the power of DL models, we pave the way for more robust and efficient aircraft detection solutions that can address the evolving challenges in remote sensing and aerial surveillance. Furthermore, our study delves into the interpretability of the models' decision-making processes, elucidating the factors influencing their performance and providing valuable insights into their inner workings. By unraveling the mechanisms behind the models' decision-making, we aim to enhance the transparency and trustworthiness of aircraft detection systems deployed in real-world scenarios.

After a brief introduction in Section 1, Section 2 presents important related investigations performed in recent years. In Section 3, proposed approach is discussed in detailed manner. Results Analysis is elaborated in Section 4. We have compared some previous works with our proposed approach in this section. Section 5 highlights the conclusion, challenges and future work.

2. Related Work. The realm of aircraft detection has witnessed significant progress through diverse methodologies, each contributing to the advancement of this pivotal technology. For instance, Kiyak and Unal [1] focused on employing deep learning for the detection of small aircraft, offering insights that are particularly applicable to Unmanned Aerial Vehicles (UAVs). Groundbreaking efforts by Chen et al. [2] involved aircraft detection through deep convolutional neural networks, laying foundational groundwork for the integration of deep learning in this domain. Furthermore, Hassan et al. [3] introduced a DL framework for the automatic detection of airplanes in satellite images, contributing to the repertoire of available techniques. Alshaibani et al. [4] presented an innovative perspective by employing the Mask Region Convolution Neural Network (Mask RCNN) for airplane detection. This work illustrates the adaptability of deep learning to intricate tasks, extending its application to drone images for airplane type identification. Yilmaz and Karsligil [5] broadened the scope by extending deep learning applications to security camera images, demonstrating the versatility of these techniques in diverse contexts.

Li et al. [6] contributed a coarse-to-fine approach for airplane detection through convolutional neural networks, enriching the methodological landscape. Azam et al. [7] explored aircraft detection in satellite imagery, emphasizing the role of DL-based object detectors. Zeng et al. [8] proposed a hierarchical airport detection method combining spatial analysis and DL. Alshaibani et al. [9] delved into airplane identification based on RCNN and drone images, illustrating the flexibility of deep learning in addressing intricate tasks. Additionally, Bakirman and Sertel [10] contributed to the field by providing a high-resolution airplane dataset tailored for deep learning. Rahamathunnisa et al. [11] provided a comprehensive perspective on ML and DL applications for intelligent systems in aircraft scenarios.

Zhang et al. [12] investigated weakly supervised learning based on coupled CNNs for aircraft detection, offering valuable insights into learning approaches. Wang et al. [13] introduced a novel airplane detection algorithm based on CNN, showcasing continuous innovation in detection methodologies. Mutreja et al. [14] conducted a comparative assessment of various DL models for aircraft detection, offering valuable insights into model performance. Brandoli et al. [15] specifically focused on aircraft fuselage corrosion detection using A.I., demonstrating the adaptability of DL to diverse aspects of aircraft safety. Shen et al. [16] proposed a DL based framework for automatic damage detection in aircraft engine, showcasing the applicability of deep learning to damage assessment. Al Mansoori et al. [17] contributed an effective airplane detection method in satellite images using the YOLOv3. Ning et al. [18] explored the application of DL in big data analytics for detecting anoma- lies in aircraft complex systems, providing insights into anomaly detection. Zhang et al. [19] focused on aircraft detection in remote sensing images based on RCNN, introducing advancements in speed and accuracy. Hammell [20] contributed the “Planes in Satellite Imagery” dataset, offering valuable data for training and validating aircraft detection models in satellite imagery.

Inspired by recent advancements in aircraft detection, this paper aims to enhance precision and versatility. It builds upon novel contributions in deep learning and diverse techniques highlighted in the existing literature.

3. Proposed Approach. Work flow of our proposed approach is depicted in Fig. 3.1.

3.1. Data Vectorization. Data vectorization plays an important role in the success of aircraft detection models. This procedure entails converting raw image data into a format well-suited for machine learning algorithms, facilitating the extraction of meaningful features for accurate classification. Initially, images containing aircraft and non-aircraft scenes are loaded into the system. Each image is represented as a numerical matrix, capturing pixel intensity values. This matrix serves as the foundational data structure for subsequent processing. To standardize the input dimensions and ensure consistent model performance, images are reshaped into a uniform size. Additionally, normalization techniques, such as Min-Max scaling, are applied to constrain pixel values within a predefined range. This step is crucial for mitigating variations in lighting conditions and enhancing the convergence of machine learning models.

3.2. Feature Selection. The models utilized for aircraft detection excels at hierarchical pattern recognition. Through a series of data transformations, it discerns distinctive spatial features and textures present in the images. This intrinsic ability to identify salient patterns serves as an implicit form of feature selection, allowing the model to focus on elements crucial for distinguishing between aircraft and non-aircraft scenes. The selected models autonomously learns and extracts discriminative features from the raw image data during the training process. This eliminates the need for manual intervention in specifying relevant features, as the model adapts and refines its understanding of essential characteristics for accurate classification. By virtue of the model’s architecture, it maximizes the utilization of comprehensive information encoded in the input data. The learning process encompasses various levels of abstraction, enabling the model to capture nuanced details and intricate structures, further enhancing its ability to discern between different classes.

3.3. Dataset Description. This meticulously compiled dataset is tailored for the exploration of aircraft detection using machine learning and deep learning techniques, featuring 32,000 high-resolution 20x20 RGB images sourced from Planet satellite imagery over diverse California airports. The dataset employs a binary classification system, distinguishing between “plane” and “no-plane” classes. The “plane” class, encompassing 8000 images, is characterized by a comprehensive focus on entire airplanes, including wings, tail, and nose. In contrast, the “no-plane” class, comprising 24,000 images, introduces intricacy by incorporating various land cover features, partial planes, and instances previously mislabeled. Each PNG-formatted image is represented as a list of 1200 integers, encapsulating the red, green, and blue channel values arranged in a row-major order. Additional details, such as labels, scene IDs, and location coordinates, are encapsulated in a JSON-formatted

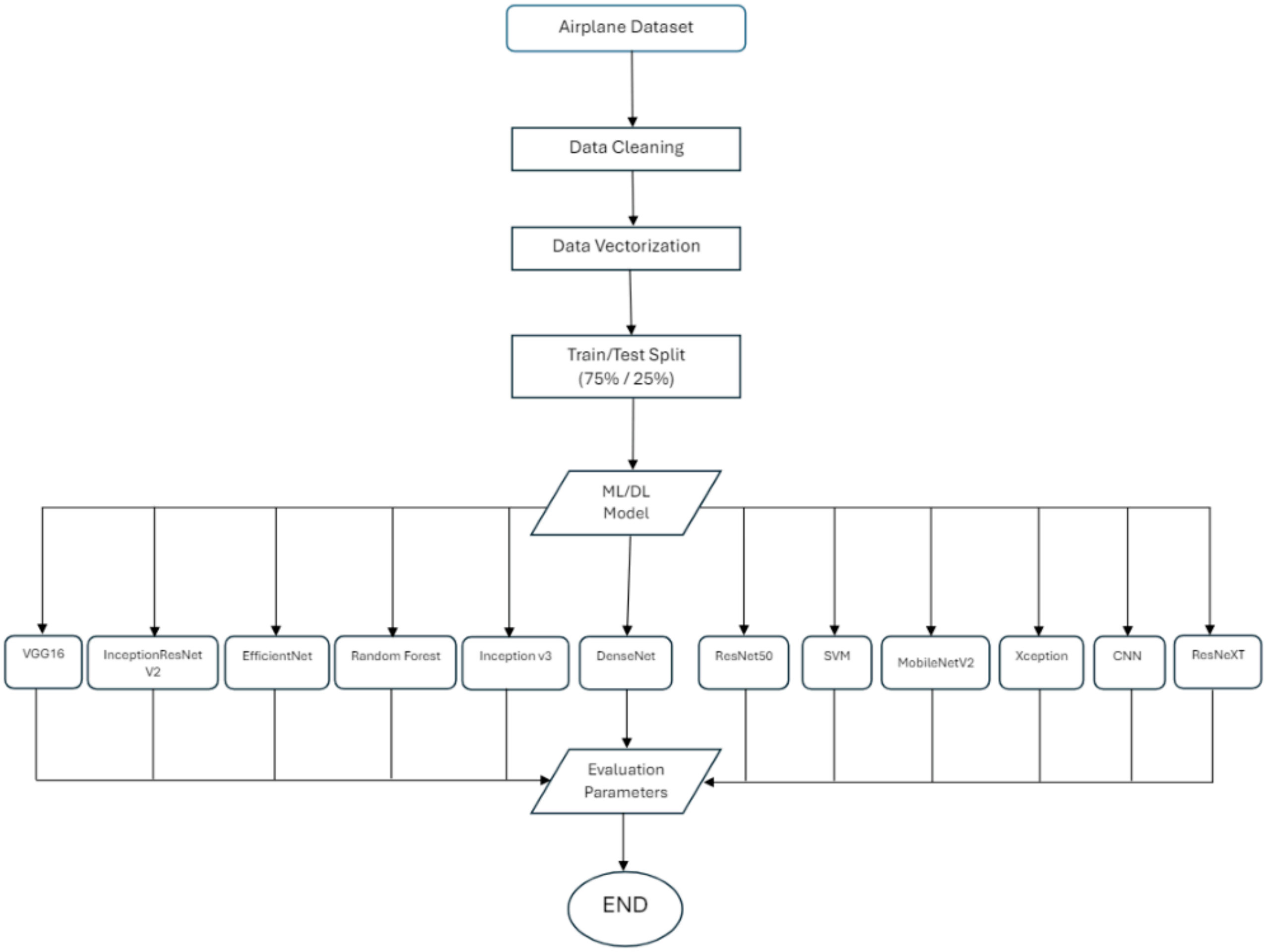

Fig. 3.1: Working Flow of Proposed Approach

text file. This dataset addresses the pressing need for automated analysis, considering the overwhelming volume of satellite data. Its applications extend to airport monitoring, traffic pattern analysis, and defense intelligence.

3.4. Deep Learning & Machine Learning Models. Different DL & ML have been used in our implemented work. These are discussed with respect to our work as follows:

- Convolutional Neural Network (CNN): CNN is a DL architecture designed for image processing tasks, utilizing convolutional layers for feature extraction. CNN is ideal for plane detection in satellite images as it excels in capturing hierarchical features, making it effective for recognizing complex patterns and structures in visual data.
- DenseNet: DenseNet is a neural network architecture characterized by dense connections between layers, promoting feature reuse and information flow. DenseNet is beneficial for plane detection as its dense connectivity enhances feature propagation, facilitating the extraction of intricate spatial dependencies crucial for identifying aircraft in satellite imagery.
- MobileNetV2: MobileNetV2 is a lightweight neural network architecture optimized for mobile and edge devices, striking a balance between efficiency and accuracy.MobileNetV2 is valuable for plane detection in resource-constrained environments, providing a computationally efficient solution without compromising performance.
- Inception v3: Inception v3 is a deep neural network architecture with inception modules designed for

Fig. 3.2: Sample Image from Dataset

Fig. 3.3: Sample Image from Dataset

efficient feature extraction. Inception v3 is advantageous for plane detection, leveraging its diverse receptive fields to capture both local and global features, enabling comprehensive analysis of satellite imagery.

- Random Forest(RF): Random Forest is an ensemble learning method consisting of multiple decision trees, combining their outputs for improved accuracy and robustness. Random Forest is useful for plane detection due to its ensemble nature.

- ResNet50: ResNet50 is a deep neural network with a residual learning framework, mitigating the vanishing gradient problem in deep networks.ResNet50 is effective for plane detection as its residual connections facilitate the training of deeper networks, enabling the capture of intricate patterns and details in satellite images.
- ResNeXT: ResNeXT is an extension of ResNet, incorporating cardinality to enhance model capacity and performance. ResNeXT is beneficial for plane detection, offering improved representational power and adaptability to varied features present in satellite imagery.
- Support Vector Machine (SVM): SVM is a supervised learning algorithm used for classification tasks, mapping input data into a high-dimensional space for effective separation. SVM complements plane detection by providing a robust classification framework, particularly useful when dealing with diverse patterns and characteristics in satellite images.
- Visual Geometry Group (VGG16): VGG16 is a deep neural network architecture with a focus on simplicity and depth, featuring small convolutional filters. VGG16 is valuable for plane detection as its deep and uniform architecture facilitates the extraction of intricate features and patterns from satellite imagery.
- Xception: Xception is an extension of Inception with depthwise separable convolutions, enhancing efficiency in feature extraction. Xception is advantageous for plane detection, offering a good trade-off between model complexity and accuracy, making it suitable for resource-constrained applications.
- EfficientNet: EfficientNet is a scalable neural network architecture designed to balance model efficiency and performance by optimizing model depth, width, and resolution. EfficientNet is useful for plane detection as it provides a well-balanced architecture, ensuring optimal resource utilization for effective feature extraction from satellite images.
- InceptionResNetV2: InceptionResNetV2 combines the inception module with residual connections, integrating the strengths of both architectures. InceptionResNetV2 is beneficial for plane detection, offering a hybrid approach that captures both intricate features and facilitates the training of deeper networks for improved performance in satellite image analysis.

3.5. ROC Curve & Accuracy Curve.

- ROC Curve: The ROC Curve serves as a visual representation, delineating the performance of a classifier across varying discrimination thresholds. It illustrates the interplay between Sensitivity (True Positive Rate) and Specificity (False Positive Rate). The area under the ROC Curve serves as a quantitative measure of the model's overall discriminatory power. A curve closer to the top-left corner indicates superior performance.
- Accuracy Curve: The Accuracy Curve illustrates how the overall accuracy of the classifier varies with changing discrimination thresholds. A steeper curve suggests that the model maintains high accuracy across diverse threshold values, showcasing its adaptability in different scenarios. These visualization tools go beyond numerical metrics, offering a detailed and nuanced understanding of the classifier's performance, enabling us to make informed decisions about its suitability for real-world aircraft detection applications.

3.6. Evaluation Parameters.

- Accuracy: Accuracy assesses the correctness of predictions.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{3.1}$$

- Precision: Precision gauges the precision of positive predictions.

$$Precision = \frac{TP}{(TP + FP)} \tag{3.2}$$

Table 4.1: Results of Different Evaluation Parameters on Aircraft Dataset

Classifier	**Accuracy(%)**	**Precision(%)**	**Recall(%)**	**F1-Score(%)**
CNN	98.85	97.41	97.99	97.70
DenseNet	99.52	98.90	99.20	99.05
MobileNetV2	98.45	96.89	96.89	96.89
Inception v3	99.38	98	99	98.75
Random Forest	95.13	92.83	87.15	89.90
ResNet50	99.26	98.30	98.74	98.52
ResNeXT	98.41	96.32	97.34	96.83
S.V.M	95.60	92.01	90.16	91.08
VGG16	99.06	97.81	98.44	98.12
Xception	99.40	98.84	98.74	98.79
EfficientNet	99.18	97.53	99.20	98.36
InceptionResNetV2	99.30	98.59	98.59	98.59

- Recall: Recall measures the ability to capture positive instances.

$$Recall = \frac{TP}{(TP + FN)} \tag{3.3}$$

- F1-Score: The F1-score offers a balanced assessment.

$$F1 - Score = \frac{2 * (Precision * Recall)}{Precision + Recall} \tag{3.4}$$

These evaluation parameters play a pivotal role in quantifying the accuracy, precision, recall and F1-score of our aircraft detection models.

4. Results Analysis. In this section, we present the results of our experiments on aircraft detection using ML & DL. Our meticulous evaluation of aircraft detection models across various classifiers, as depicted in Table 4.1.

CNN showcases exceptional performance with a robust balance between precision and recall, rendering it a dependable option for accurate aircraft detection. Its high accuracy of 98.85% underscores its effectiveness in real-world scenarios.The ROC Curve and Accuracy Curve is shown in Fig. 4.1 & 4.2. DenseNet excels in achieving remarkable accuracy, precision, and recall, making it a top-performing model. With an accuracy of 99.52%, it demonstrates superior capabilities in minimizing false positives and negatives.The ROC Curve and Accuracy Curve is shown in Fig. 4.3 & 4.4. While MobileNetV2 offers commendable accuracy, its precision and recall slightly lag behind compared to other models. However, its efficiency in processing images makes it a viable option for applications with computational constraints.The ROC Curve and Accuracy Curve is shown in Fig. 4.5 & 4.6. InceptionV3 showcases balanced performance with high accuracy and a favorable trade-off between precision and recall. Its accuracy of 99.38% positions it as a reliable choice for accurate and reliable aircraft detection. The ROC Curve and Accuracy Curve is shown in Fig. 4.7 & 4.8. Random Forest exhibits lower recall, indicating a higher rate of false negatives. However, its overall performance, especially in accuracy, makes it a viable option for scenarios where precision is crucial. The ROC Curve is shown in Fig. 4.9. ResNet50 achieves high accuracy and balanced precision and recall, making it a robust choice for airplane detection. Its effectiveness in handling complex features in images contributes to its strong overall performance. The ROC Curve and Accuracy Curve is shown in Fig. 4.10 & 4.11. ResNeXT demonstrates consistent performance, with accuracy and recall balancing well against precision. Its reliability in detecting aircraft in diverse scenarios makes it a dependable choice for our detection system. The ROC Curve and Accuracy curve is shown in Fig. 4.12 & 4.13. SVM provides balanced accuracy and precision, but with a slightly lower recall. It is suitable for applications where a balance between precision and recall is crucial, and further optimization can enhance its performance. The ROC curve is shown in Fig. 4.14. VGG16 delivers strong all-around performance with

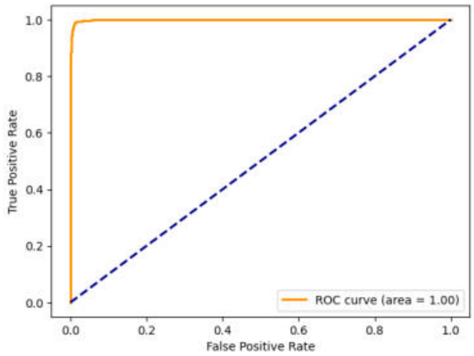

Fig. 4.1: ROC Curve generated using CNN

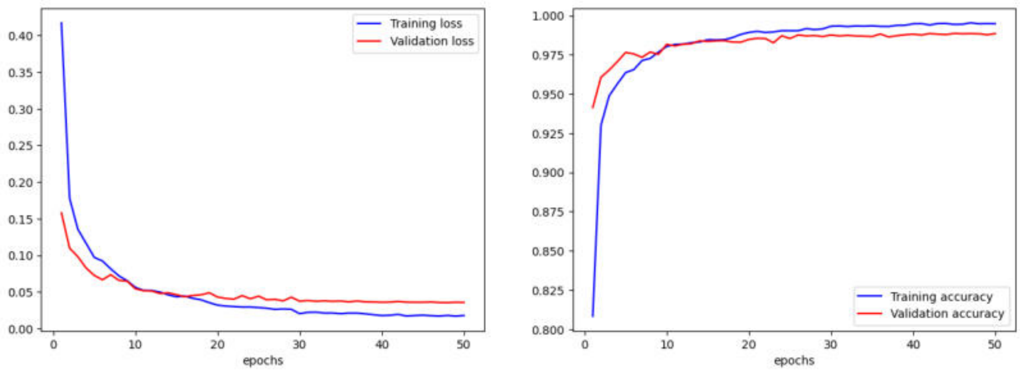

Fig. 4.2: Accuracy Curve generated using CNN

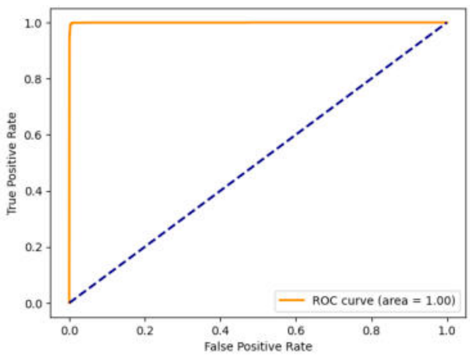

Fig. 4.3: ROC Curve generated using DenseNet

high accuracy, precision, and recall. Its robustness in handling diverse image features positions it as a reliable choice for aircraft detection in various scenarios.The ROC curve and accuracy curve is shown in Fig. 4.15 & 4.16. Xception exhibits excellent precision and recall, making it a top performer in accurate airplane detection. Its superior performance, especially in precision, makes it well-suited for applications where minimizing false positives is critical. The ROC curve and Accuracy curve is shown in Fig. 4.17 & 4.18. EfficientNet demonstrates high accuracy and an effective balance between precision and recall. Its suitability for real-time detection

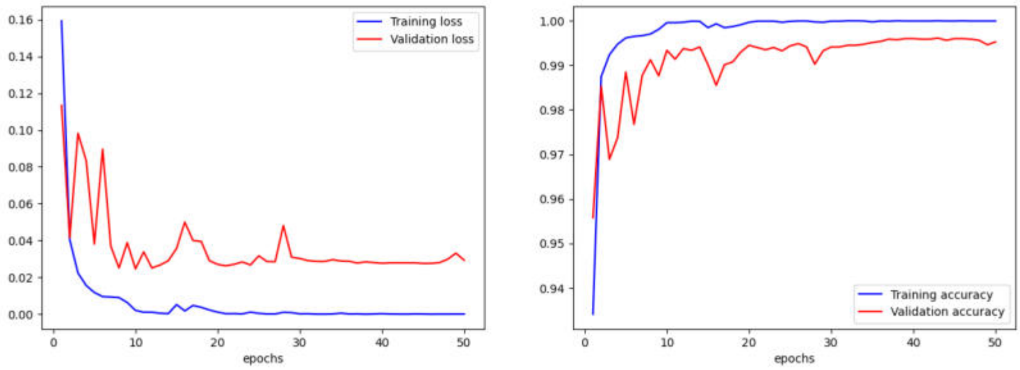

Fig. 4.4: Accuracy Curve generated using DenseNet

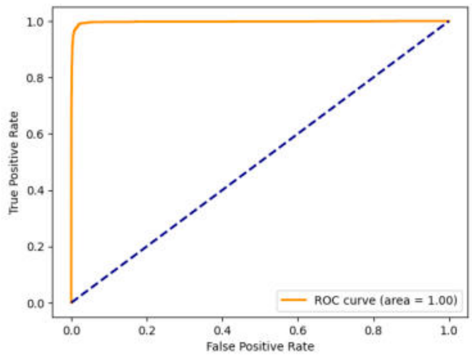

Fig. 4.5: ROC Curve generated using MobileNetV2

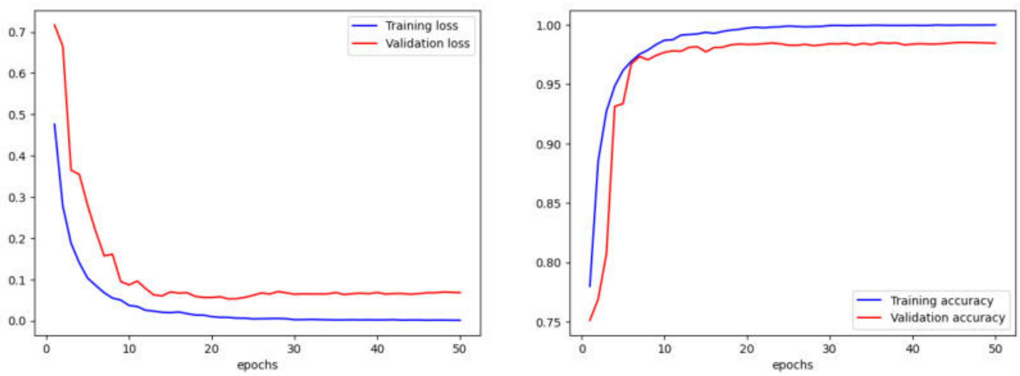

Fig. 4.6: Accuracy Curve generated using MobileNetV2

scenarios makes it a valuable model for applications with computational constraints. The ROC curve and accuracy curve is shown in Fig. 4.19 & 4.20. InceptionResNetv2 showcases robust performance, excelling in accuracy, precision, and recall. Its overall effectiveness positions it as a reliable and powerful choice for airplane detection in diverse scenarios. The ROC curve and accuracy curve is shown in Fig. 4.21 & 4.22.

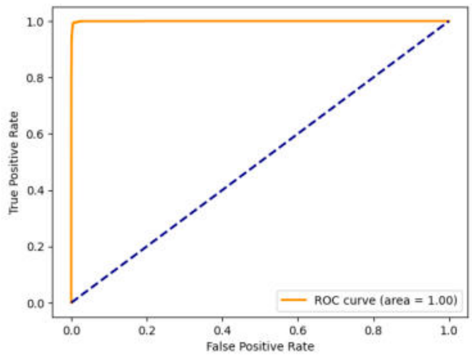

Fig. 4.7: ROC Curve generated using InceptionV3

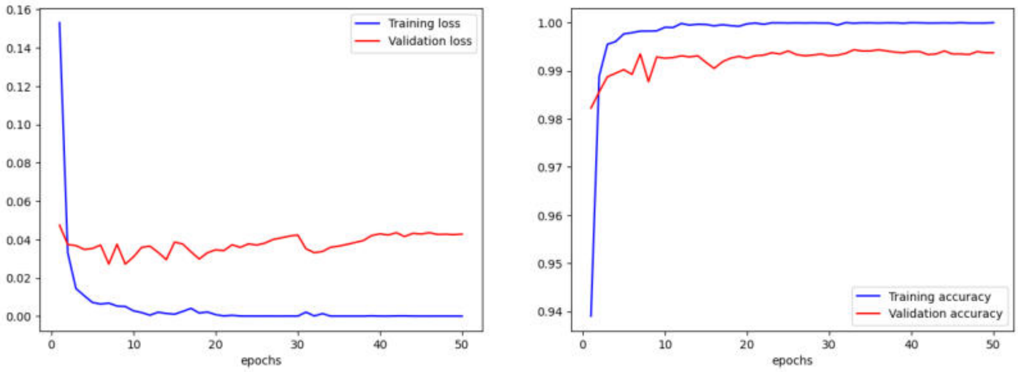

Fig. 4.8: Accuracy Curve generated using InceptionV3

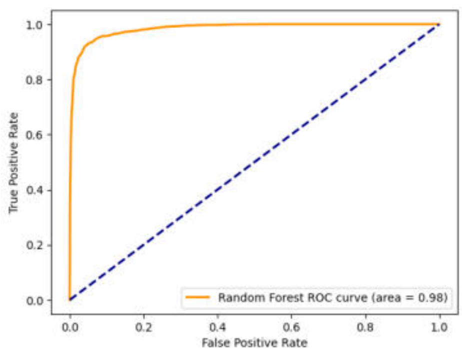

Fig. 4.9: ROC Curve generated using Random Forest

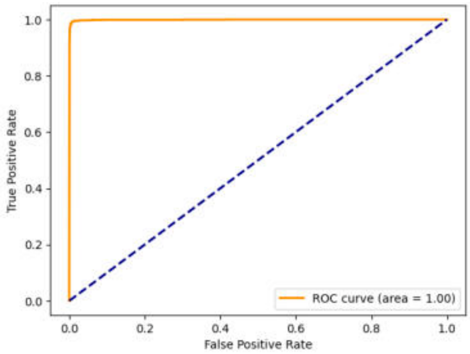

Fig. 4.10: ROC Curve generated using ResNet50

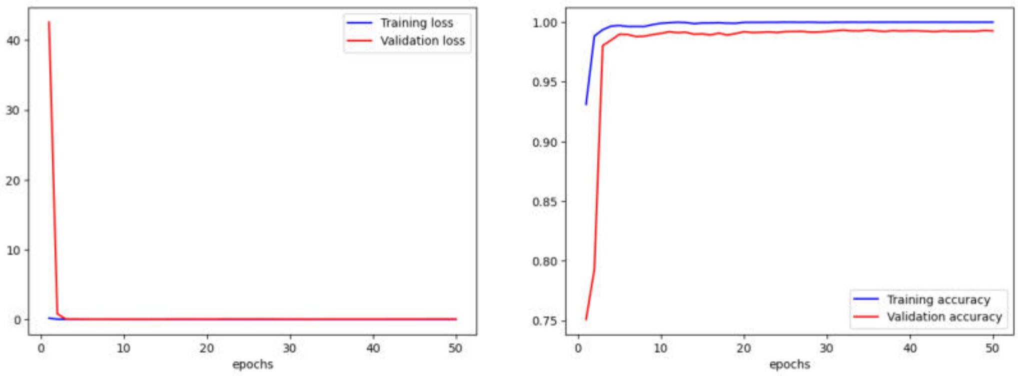

Fig. 4.11: Accuracy Curve generated using ResNet50

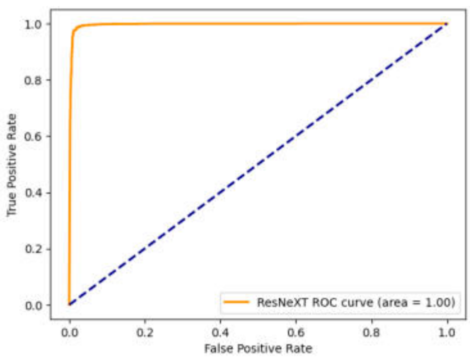

Fig. 4.12: ROC Curve generated using ResNeXT

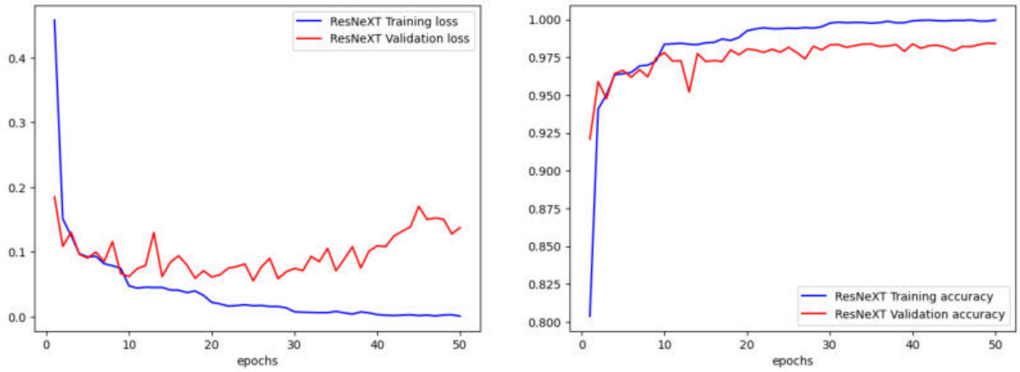

Fig. 4.13: Accuracy Curve generated using ResNeXT

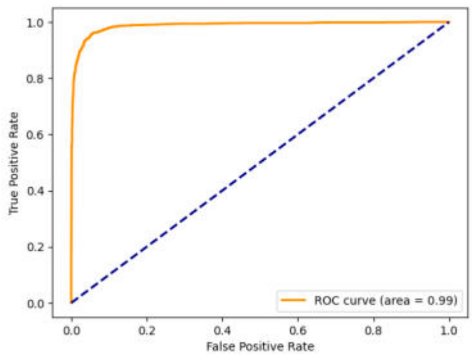

Fig. 4.14: ROC Curve generated using SVM

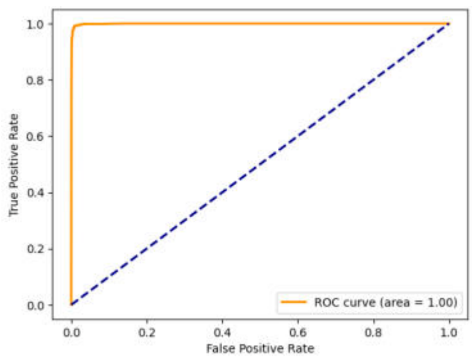

Fig. 4.15: ROC Curve generated using VGG16

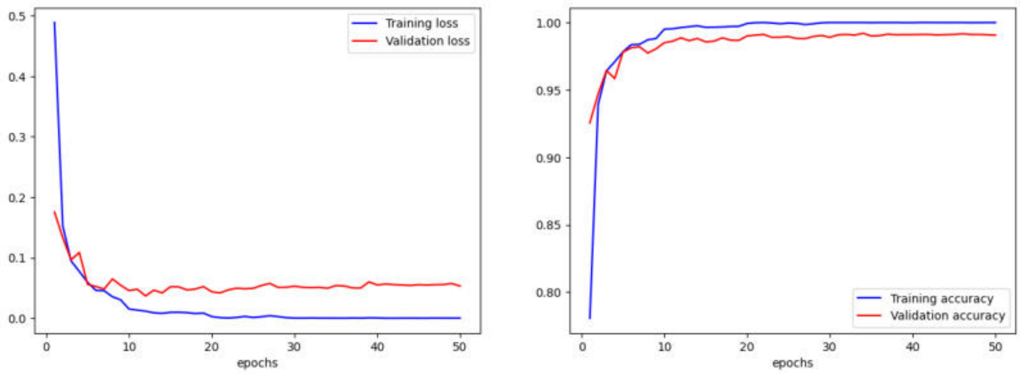

Fig. 4.16: Accuracy Curve generated using VGG16

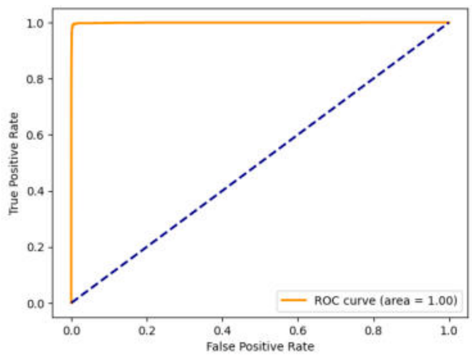

Fig. 4.17: ROC Curve generated using Xception

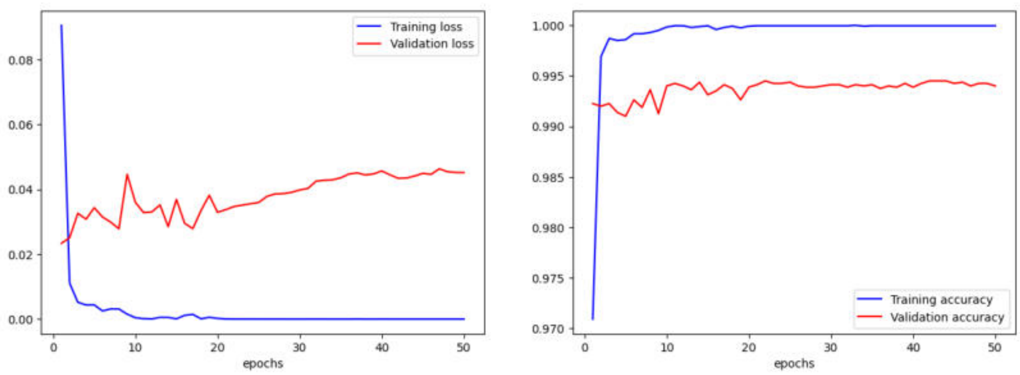

Fig. 4.18: Accuracy Curve generated using Xception

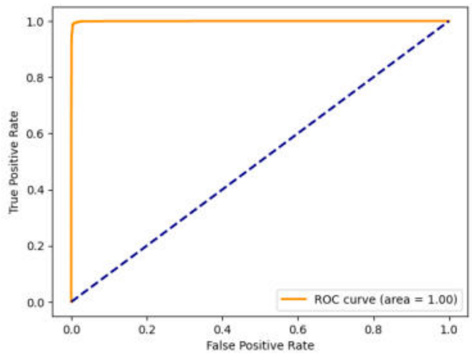

Fig. 4.19: ROC Curve generated using EfficientNet

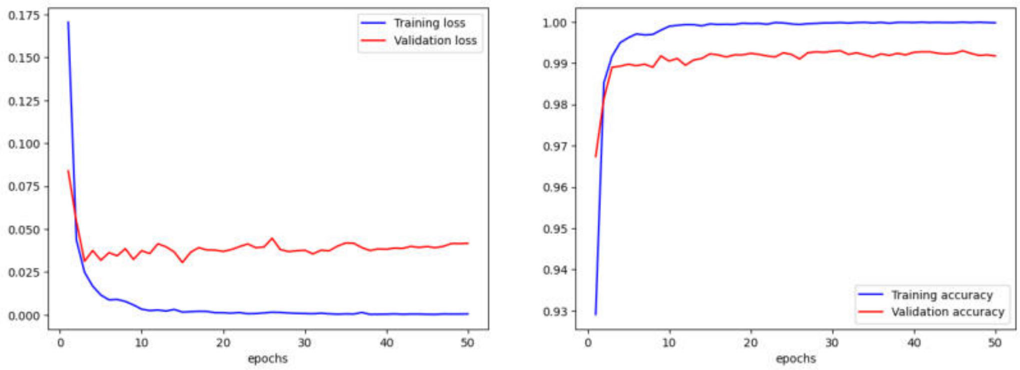

Fig. 4.20: Accuracy Curve generated using EfficientNet

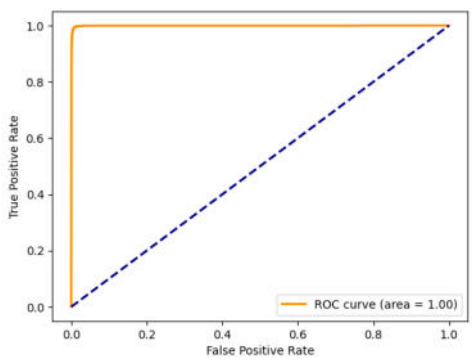

Fig. 4.21: ROC Curve generated using InceptionResNetv2

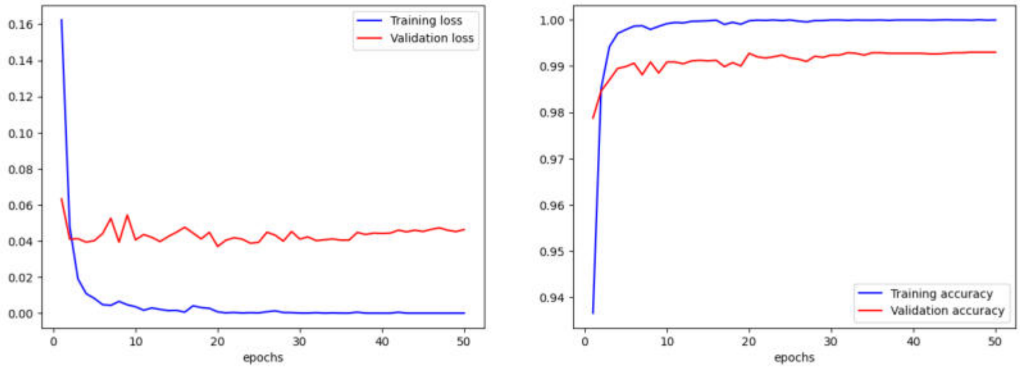

Fig. 4.22: Accuracy Curve generated using InceptionResNetv2

5. Conclusion and Future Work. In this research, we presented a comprehensive study on aircraft detection in satellite imagery, employing a diverse set of ML models, including (CNN), DenseNet, MobileNetV2, Inception v3, Random Forest (RF), ResNet50, ResNeXT, Support Vector Machine (SVM), Visual Geometry Group (VGG16), Xception, EfficientNet, and InceptionResNetV2. The primary focus was to propose an efficient a vision-based aircraft detection model designed for small Unmanned Aerial Systems (UAS) using a single camera, with a particular emphasis on real-time detection on resource-constrained embedded boards. Our proposed model, inspired by existing architectures but optimized for real-time detection, demonstrated superior performance compared to traditional methods. The evaluation across various classifiers showcased the efficacy of the models, with each exhibiting high performance metrics. Notably, the CNN and DenseNet models achieved remarkable accuracy rates of 98.85% and 99.52%, respectively. Through rigorous testing, our system exhibited robustness to diverse backgrounds, viewpoints, and relative speeds of aircraft, highlighting its adaptability to real-world scenarios. The models consistently outperformed conventional image processing methods, offering faster and more reliable aircraft detection, particularly for distant targets.

Despite the promising results, our research opens avenues for future enhancements and exploration:The current detection range, while showcasing good performance, may require further optimization for collision avoidance purposes. Future work should focus on extending the detection range to enhance the system's utility in real-world applications. Integrating our vision-based detection model with existing cooperative Systems dedicated to collision avoidance systems, such as the Traffic Collision Avoidance System (TCAS) could provide a comprehensive solution. This integration may offer enhanced safety measures, especially for larger UAVs. Further research should investigate the adaptability of the proposed model to different environmental conditions, lighting variations, and atmospheric challenges. Enhancements in these aspects will contribute to the robustness and reliability of the detection system.Conducting extensive real-world deployment tests, including scenarios with varying weather conditions and complex terrains, will validate the system's performance under diverse challenges. This step is crucial for ensuring the practical applicability and reliability of the proposed model. Continued efforts should be directed towards optimizing the proposed model for edge devices, ensuring compatibility with small embedded computers commonly used in UAVs. This optimization will enhance the feasibility of deploying the system on resource-constrained platforms. In conclusion, while our research presents a substantial step forward in vision-based aircraft detection, ongoing efforts and future work will contribute to refining and extending the capabilities of the proposed model, making it a valuable tool for ensuring the safety and integration of Unmanned Aerial Systems into civilian airspace.

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