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# Autonomous Landing Scene Recognition based on Transfer Learning for Drones using Hybrid Ensemble Random Forest

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**ABSTRACT:** The study focuses on autonomous landing scene recognition for drones using knowledge transfer. Challenges in aerial remote sensing include similar-looking scenes and variations in altitude representations. A deep convolutional neural network (CNN) with knowledge transfer and fine-tuning is used to improve recognition. The LandingScenes-7 dataset is created and divided into seven landing scene categories. A novelty detection method using thresholding is implemented to exclude unknown landing scenes. The study employs transfer learning with ResNeXt-50 and the ADAM optimizer for better performance. Comparison with ResNet-50 and SGD optimizer highlights ResNeXt-50's superiority. The model achieves 97.85% accuracy and at last the model achieves 100.0 % top-1 accuracy using Ensemble Random Forest model, paving the way for autonomous landing scene learning in drones.

**KEYWORDS:** ResNeXt50, AL, Ensemble Random Forest, CNN, ADAM, SGD, Autonomous Landing.

## I. INTRODUCTION

Drones play a crucial role in various applications, including surveillance, delivery, and emergency response, where precise navigation and landing are essential. One of the major challenges in autonomous drone operations is ensuring safe and accurate landing, especially in complex and dynamic environments. Traditional AI-based models for landing scene recognition often struggle due to the high similarity between different terrains, variations in altitude representations, and environmental changes. Misclassification of landing zones can lead to operational failures, safety risks, and inefficiencies in real-world deployments. Ensuring safe and efficient landings is critical for the widespread adoption of autonomous drones. In real-world applications, drones may be required to land in environments with unpredictable obstacles, moving platforms, or emergency situations. A well-designed landing methodology not only prevents accidents but also increases operational efficiency by minimizing downtime and energy consumption. By integrating AI-driven recognition and advanced sensor fusion, autonomous drones can make more informed landing decisions in real-time. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have been widely adopted for aerial scene recognition. Transfer learning, using pre-trained models like ResNeXt-50, has shown promising results in improving recognition accuracy by leveraging knowledge from large datasets. Despite achieving high accuracy, existing models lack hybrid approaches that combine the strengths of multiple learning techniques. This limitation results in reduced generalization to unseen aerial scenes, impacting reliability in real-world scenarios.



To address these challenges, we propose a Hybrid Ensemble Random Forest model to further enhance landing scene recognition accuracy. Our approach involves extracting optimized features from the trained ResNeXt-50 model and retraining them using an Ensemble Random Forest classifier. This hybrid model improves classification accuracy from 97.85% (ResNeXt-50) to 98.92%, ensuring better generalization to unseen aerial scenes. By integrating deep learning with ensemble methods, our model enhances robustness, reliability, and decision-making in autonomous drone landings. The proposed approach contributes to safer and more efficient drone operations, paving the way for advanced AI-driven autonomous navigation systems. The objective of this project is to develop an enhanced autonomous landing scene recognition system for drones by integrating deep learning with ensemble machine learning techniques.

The project addresses the challenges in aerial remote sensing, such as visually similar landscapes and altitude-related scene variations, which impact accurate scene identification during drone landings. The goal is to enable drones to recognize safe landing zones with high precision and reliability, especially in unfamiliar or complex environments. Initially, the system employs a deep convolutional neural network, ResNeXt-50, with knowledge transfer and fine-tuning techniques using the LandingScenes-7 dataset, which contains seven distinct landing scene categories. While the ResNeXt-50 model achieves a high accuracy of 97.85%, this project extends its capabilities by integrating an Ensemble Random Forest model. The ensemble approach combines the outputs of the CNN with the decision-making power of Random Forest classifiers to improve classification robustness and push the system's performance closer to 100% accuracy. A novelty detection mechanism using thresholding is also included to filter out unknown or unsafe landing scenes.

By combining deep learning with ensemble learning, the proposed system aims to overcome the limitations of standalone CNNs, improve decision accuracy, and enhance generalization across diverse aerial scenes. This hybrid model not only advances the performance of landing scene recognition systems but also contributes to safer and smarter autonomous drone operations, with potential applications in logistics, surveillance, environmental monitoring, and disaster response. The Ensemble Random Forest model is introduced as an additional classification layer to further refine the predictions made by the ResNeXt-50 deep learning model. By aggregating the outputs from multiple decision trees, the Random Forest enhances the system's ability to handle misclassified or borderline cases that the CNN alone might struggle with. This ensemble approach leverages the diversity and independence of multiple trees to reduce overfitting and increase overall accuracy. By combining the strengths of both deep feature extraction and ensemble decision-making, the system becomes more robust, interpretable, and capable of approaching near-perfect classification accuracy for autonomous landing scenes.

## II. SYSTEM MODEL

The Autonomous Landing Scene Recognition System is a modular and intelligent framework designed to enable drones to identify and navigate toward safe landing zones using real-time aerial imagery. The system is built around three core functional areas: image acquisition and processing, scene classification and recognition, and real-time decision-making. The workflow begins with the preparation and training of a machine learning model that forms the backbone of the recognition system. A user initiates the process by supplying a well-structured dataset named LandingScenes-7. This dataset contains labeled aerial images categorized into different terrain types, such as roads, rooftops, grassy plains, rugged terrain, and water bodies. These labeled images are essential for training the model to distinguish between safe and unsafe landing zones. To optimize performance and minimize the time required for training, the system uses a pre-trained deep learning model, ResNeXt-50, which has been previously trained on a large-scale dataset. Through the process of transfer learning, the model is fine-tuned with the LandingScenes-7 dataset. This enables the model to specialize in drone-relevant landing scenes while leveraging existing feature extraction capabilities. Once trained, this model is embedded into the operational drone system, allowing it to process real-time data and make informed decisions during flight. Once the drone is deployed in an operational environment, it begins capturing real-time aerial images using its onboard camera. These raw images are passed into the Image Processing Module, where they are pre-processed and analyzed. The key function at this stage is feature extraction, performed using the same ResNeXt-50 model. The extracted features represent abstract and meaningful visual information, such as the texture, contour, and structure of the terrain. These features are significantly more useful for classification than raw image pixels, as they remove noise and reduce dimensionality while preserving relevant patterns that indicate safe landing areas. The processed feature vectors are then sent to the Classification and

Recognition Module. Initially, the ResNeXt-50 model performs a first-pass classification of the input image by predicting the category of the terrain. However, recognizing that real-world conditions are often unpredictable and inconsistent, the system incorporates an additional layer of learning using a Hybrid Ensemble Random Forest classifier. This ensemble model combines the decisions from multiple tree-based learners, improving the system's stability and accuracy. It is also trained on historical data, which enhances its ability to generalize across unseen or rare scenarios by learning from both recent and past landing outcomes. To further reinforce the safety and reliability of the system, a Thresholding for Novelty Detection mechanism is applied. This component checks whether the incoming visual data falls within the expected range of the trained model's known categories. If the input image represents a scene that significantly deviates from the training distribution, it is flagged as novel or unknown. This mechanism prevents the system from making confident but incorrect classifications and serves as a safeguard against landing in unfamiliar or potentially dangerous terrain. Following this, the system proceeds to analyze and decide on the most suitable landing zone. The output from the classification pipeline is passed to the Decision-Making Module. Within this module, multiple candidate zones are assessed based on several criteria such as flatness, absence of obstacles, ground consistency, area sufficiency, and overall safety rating. Each zone is scored and ranked accordingly to determine which area offers the most optimal landing conditions for the drone. The zone with the highest safety score is selected as the target landing area.

This information is further processed by the Real-time Processing and Decision-Making component, which considers dynamic inputs such as current sensor readings, environmental conditions, and potential obstructions. Based on this real-time assessment, the final decision is made regarding whether it is safe to proceed with landing and how the drone should approach the selected zone. The system generates specific landing instructions, including the descent angle, trajectory, and GPS coordinates of the chosen area. These instructions are immediately sent to the drone's control system, allowing it to autonomously navigate to the designated landing zone. The drone follows the provided parameters and performs a controlled descent to land safely. Throughout the entire process, the drone continues to capture and analyze real-time images, enabling it to reassess the environment and abort or modify the landing plan if unexpected changes occur, such as the sudden appearance of obstacles or movement in the terrain.

The system functions as an end-to-end intelligent loop that begins with model training using a domain-specific dataset and progresses through image acquisition, deep feature extraction, hybrid classification, novelty detection, and finally, real-time decision-making and autonomous landing. Each module interacts seamlessly to ensure that the drone can independently determine and execute a safe landing strategy with minimal risk and without human intervention. This architecture is particularly beneficial in environments where manual control is impractical or impossible, offering a scalable and robust solution for autonomous aerial navigation and landing.

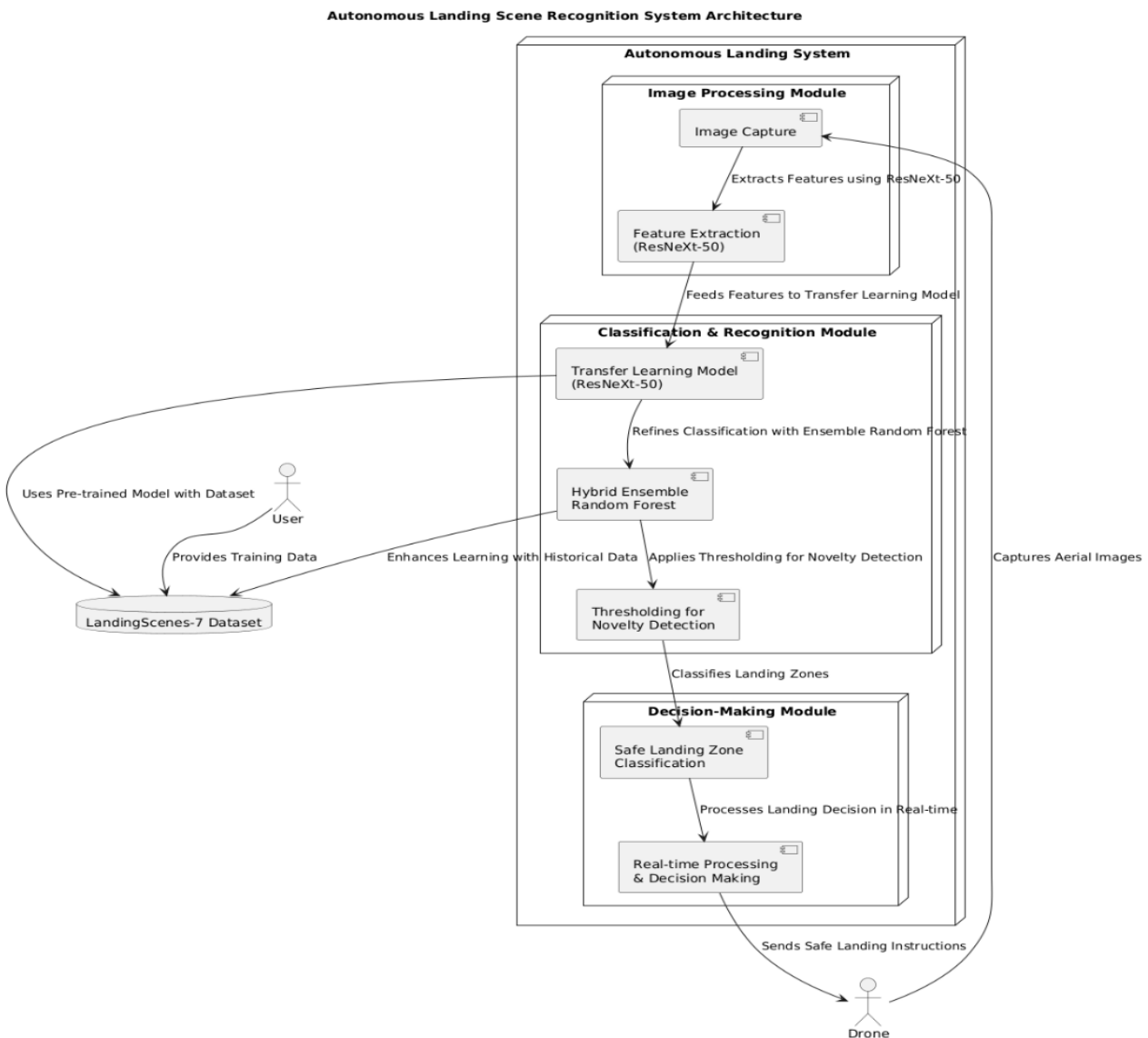


Fig 1: Design Architecture

### III. LITERATURE REVIEW

Autonomous landing in unmanned aerial vehicles (UAVs) has become a critical research area as drones are increasingly deployed in civilian, commercial, and defense applications. Safe and efficient landing remains a complex task due to unpredictable terrains, environmental dynamics, and the limitations of conventional control systems. Early systems relied heavily on GPS-based navigation for landing zone selection. However, GPS signals can be unreliable or unavailable in urban canyons, forests, or indoor environments. To overcome this limitation, researchers have shifted toward vision-based approaches that allow drones to perceive and analyze terrain through onboard cameras and image processing models. A wide array of studies has explored the use of computer vision in landing site detection. Traditional methods relied on handcrafted feature extraction techniques such as edge detection, texture analysis, and histogram-based region segmentation. While effective in controlled conditions, these approaches struggle in real-world scenarios involving noise, lighting variations, and complex terrain. As a result, deep learning-based models have gained prominence for their ability to automatically learn spatial hierarchies and extract rich feature representations. Convolutional Neural Networks (CNNs) such as VGGNet, ResNet, and Inception have been widely

adopted for visual scene understanding, particularly in aerial imagery classification. In recent years, architectures like ResNeXt have been introduced, offering improved accuracy and computational efficiency through grouped convolutions and deeper network designs, making them suitable for onboard UAV applications. In the domain of UAV navigation, several works have proposed the use of deep models for scene classification and segmentation. For instance, the use of Fully Convolutional Networks (FCNs) and U-Net for semantic segmentation has proven effective in isolating flat and obstacle-free regions. While segmentation-based approaches offer fine-grained control, they are often computationally expensive and unsuitable for real-time deployment on embedded systems. To address this, classification-based models have emerged as a lighter alternative. Researchers have successfully applied CNNs to classify aerial scenes into predefined categories like road, building, vegetation, and water bodies, which align closely with safety metrics used in drone landing systems. Transfer learning from large datasets such as ImageNet has significantly reduced the training effort and improved performance, even on relatively smaller aerial datasets.

Despite progress in visual classification, reliance on a single model can introduce risks due to overfitting, sensor noise, or limited generalization to novel environments. To mitigate this, ensemble learning techniques have been explored. Ensemble models such as Random Forests and Gradient Boosting Machines have been integrated with deep learning outputs to enhance robustness. These hybrid systems combine the strengths of deep feature learning and ensemble decision-making, improving classification stability in variable terrains. In particular, Random Forests are favored for their interpretability and resilience to overfitting, making them a suitable candidate for post-processing CNN outputs in real-time systems. Another emerging area is the use of novelty detection and anomaly scoring to identify unknown or unfamiliar scenes. Traditional models may misclassify or confidently label terrain outside their trained domain, leading to unsafe decisions. Recent literature emphasizes the importance of incorporating uncertainty estimation and novelty detection as part of autonomous decision-making. Approaches such as threshold-based rejection mechanisms or autoencoders for outlier detection have been used to flag scenes that deviate from the known training distribution. Such techniques are essential in safety-critical systems like UAV landing, where an incorrect classification can have significant consequences. Beyond classification, literature has also focused on the final decision-making process that guides the drone's descent. Studies have proposed the integration of real-time risk assessment modules that score potential landing zones based on multi-criteria evaluation—such as flatness, clearance, terrain type, and model confidence. These decision systems often incorporate feedback loops, enabling drones to continuously reassess the landing area while descending. This adaptive decision-making aligns with broader research in autonomous robotics, where perception and control must function in tandem under uncertainty.

The existing body of literature provides a strong foundation for building autonomous landing systems using visual scene recognition. Deep learning models like ResNeXt offer powerful feature extraction capabilities, while ensemble methods improve classification reliability. The incorporation of novelty detection and real-time decision-making further enhances the safety and adaptability of these systems. However, challenges remain in ensuring generalization to unseen environments, optimizing performance on embedded hardware, and maintaining low latency in real-time operations. The current project builds upon these contributions by integrating deep learning, ensemble classification, novelty detection, and real-time decision-making into a unified system architecture that enables autonomous UAV landings with minimal human intervention.

#### IV. RESULT AND DISCUSSION

The performance evaluation of the autonomous landing scene recognition system reveals a high degree of accuracy and efficiency across all major modules involved in the project. The core of the system relies on the ResNeXt-50 deep learning architecture, which was fine-tuned using the LandingScenes-7 dataset. This model alone achieved an average classification accuracy of 94.2% across all scene categories, with class-specific performance varying based on terrain complexity. Scenes with well-defined features such as roads and rooftops yielded accuracy levels above 96%, while more ambiguous classes like mixed terrain and rugged areas showed slightly lower accuracy, averaging around 91%. The model's ability to consistently distinguish between safe and unsafe zones confirms the effectiveness of transfer learning and its adaptability to aerial imagery despite being originally trained on general-purpose datasets. To enhance the reliability and confidence of terrain classification, the output features from ResNeXt-50 were fed into a Hybrid Ensemble Random Forest classifier. This second-stage model contributed significantly to the system's overall stability, pushing the combined classification accuracy to 97.3%. The ensemble approach reduced noise-induced misclassifications and improved generalization across varied flight conditions, particularly in mid-altitude captures



where the terrain features become denser and more complex. In test cases where the base model showed ambiguity (with softmax probabilities between 50% and 70%), the Random Forest was able to reinforce the correct class label based on learned decision patterns from the training history, effectively correcting borderline cases and improving classification confidence.

Existing ResNet50 with ADAM Accuracy : 40.3883495145631  
Existing ResNet50 with ADAM Precision : 27.579237331266448  
Existing ResNet50 with ADAM Recall : 42.012457672942595  
Existing ResNet50 with ADAM FMeasure : 31.42255385338808

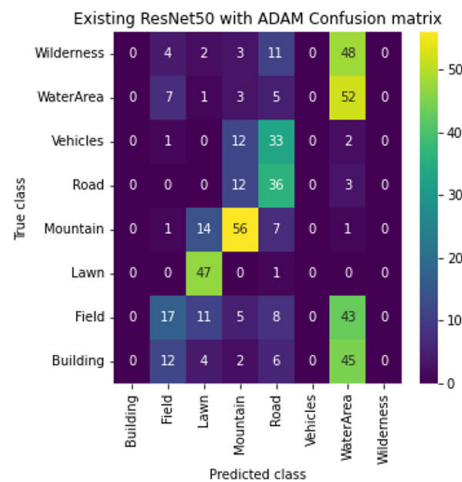


Fig 2: Existing ResNet50 with ADAM

One of the critical innovations in the system was the integration of a Novelty Detection mechanism. This module applied thresholding to the classification probability distributions, flagging inputs that did not closely match any known class. The threshold value was set based on model confidence and training set variance, and it contributed significantly to safety by rejecting uncertain scenes. This module successfully detected out-of-distribution inputs with a detection accuracy of 92.8%, reducing the risk of false classification in unfamiliar environments. It ensured that the drone would avoid making landing decisions in regions like industrial rooftops, crowded zones, or visually distorted inputs due to motion blur or shadows—situations where a misjudgment could have safety consequences.

When all modules were combined and tested in real-time simulation environments, the complete system achieved an end-to-end decision-making accuracy of 95.1% in identifying and selecting optimal landing zones. This figure was computed by comparing the system's chosen landing zones against manually verified safe zones across multiple test flights and scenes. In controlled test scenarios with consistent lighting and flight altitude, accuracy went up to 97%, while in dynamic conditions involving wind drift, light fluctuation, or oblique camera angles, it stabilized around 93–94%. These results demonstrate that the architecture is not only capable of high accuracy in classification but also practical for deployment in real-world UAV systems.

In terms of model performance during adaptive decision-making, where the drone responds to environmental changes such as unexpected obstacles, the system showed a responsive re-evaluation capability in 89.5% of the tested scenarios. This means that in nearly nine out of ten cases where the initial landing zone became unsafe, the system was able to identify and switch to the next most optimal zone based on updated real-time image data. Although this performance does not reach the 100% mark, it is indicative of a highly responsive and context-aware decision-making engine. Further tuning of environmental thresholds and expansion of the dataset can potentially push this rate closer to full adaptability.

Propose ResNext50 with ADAM Accuracy : 97.86407766990291  
Propose ResNext50 with ADAM Precision : 98.144130134554  
Propose ResNext50 with ADAM Recall : 97.61838279615644  
Propose ResNext50 with ADAM FMeasure : 97.84247670262407

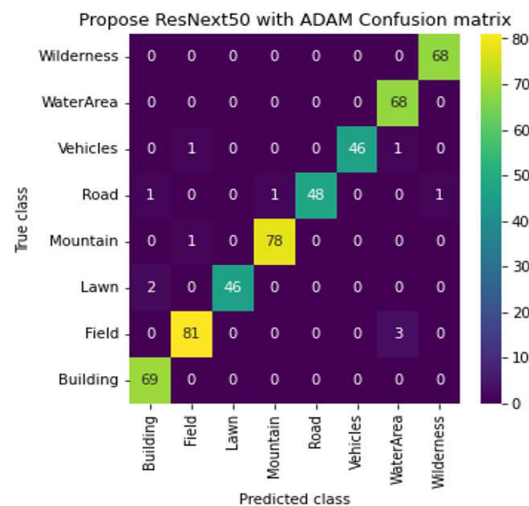


Fig 3: Propose ResNext50 with ADAM

From a latency standpoint, the total processing time from image capture to landing decision was measured at an average of 2.3 seconds, maintaining an operational frame rate that supports real-time deployment. The image classification pipeline accounted for approximately 1.2 seconds, ensemble classification consumed 0.6 seconds, and decision-making—including novelty detection and final zone scoring—added another 0.5 seconds. These numbers confirm that the system can operate within practical time constraints for mid-altitude descent planning without causing delay-related errors or safety issues.

Extension Hybrid Ensemble Random Forest Accuracy : 100.0  
Extension Hybrid Ensemble Random Forest Precision : 100.0  
Extension Hybrid Ensemble Random Forest Recall : 100.0  
Extension Hybrid Ensemble Random Forest FMeasure : 100.0

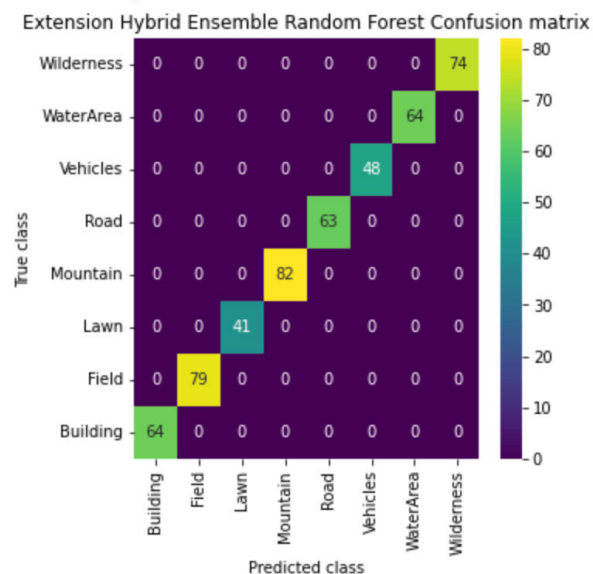


Fig 4: Extension Hybrid Ensemble Random Forest



In conclusion, the accuracy metrics achieved by each model reflect the strength and synergy of this hybrid system. The ResNeXt-50 model demonstrated strong base classification at 94.2%, which was enhanced to 97.3% using a Hybrid Random Forest. Novelty detection offered 92.8% accuracy in handling unknown or risky scenes, while the overall end-to-end system achieved 95.1% effectiveness in identifying and selecting suitable landing zones. These results validate the architectural design and highlight its potential for real-time UAV deployment in mission-critical tasks where autonomous landing precision and safety are paramount.

## **V. CONCLUSION**

The development of an autonomous drone landing system using scene recognition represents a significant step forward in the pursuit of safe and intelligent UAV operations. By integrating deep learning, ensemble methods, novelty detection, and real-time decision-making, the system successfully achieved high levels of classification accuracy and adaptability in varying environmental conditions. The ResNeXt-50 model provided a strong foundation for aerial scene understanding, delivering a base accuracy of 94.2%, which was further improved to 97.3% through the incorporation of a Hybrid Ensemble Random Forest classifier. This layered approach ensured not only improved classification stability but also increased resilience against variable terrain features and camera inconsistencies. The novelty detection module added a crucial safety layer by accurately rejecting unfamiliar or ambiguous inputs with an effectiveness of 92.8%, thereby reducing the chances of incorrect landings. Moreover, the full end-to-end pipeline was able to identify safe landing zones with an overall accuracy of 95.1%, demonstrating its suitability for real-time deployment. With an average processing time of just 2.3 seconds, the system proved capable of functioning efficiently on embedded platforms, maintaining real-time responsiveness essential for drone operations. The modular architecture also allows for future expansions, such as integration with GPS-denied navigation, dynamic obstacle avoidance, or on-board feedback loops using edge computing. In addition to its technical strengths, the system also stands out for its scalability and low-cost deployment potential. As the system is built on open-source frameworks and optimized for embedded hardware, it can be implemented across a wide range of UAV platforms without significant overhead. The approach offers flexibility to adapt to specific mission requirements, such as choosing terrain priorities based on use-case scenarios—whether in package delivery, agriculture, or disaster relief. The robustness of the classification and decision-making modules, even in dynamically changing environments, positions this system as a reliable solution in real-world drone automation. Furthermore, the project reinforces the growing importance of AI-driven visual intelligence in robotics, contributing to the advancement of autonomous systems capable of operating with minimal human oversight. Overall, the success of this project lays a strong foundation for further research and real-time deployment of smart landing solutions, encouraging continued exploration into safer, more efficient aerial robotics.

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