



Intelligent Landing Zone Identification for Drones Using Transfer Learning

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ABSTRACT

Autonomous Landing Scene Recognition Based on Transfer Learning for Drones focuses on identifying safe and suitable landing areas for unmanned aerial vehicles using deep learning techniques. In drone applications such as surveillance, disaster rescue, agriculture, delivery, and military monitoring, safe landing is one of the most important tasks. Traditional landing systems depend on manual control, GPS location, or predefined landing pads, which may fail in complex outdoor environments. To overcome these limitations, this project uses transfer learning to recognize landing scenes from aerial images and classify them as safe or unsafe for landing.

The proposed system uses pre-trained convolutional neural network models such as VGG16, ResNet50, MobileNet, or EfficientNet. These models are already trained on large image datasets and can extract important visual features such as ground texture, obstacles, roads, water bodies, buildings, trees, and open spaces. By fine-tuning the model with drone landing scene images, the system can accurately classify different landing environments. This reduces training time and improves performance even with limited datasets.

Keywords: Autonomous Drone, Landing Scene Recognition, Transfer Learning, Deep Learning, CNN, UAV, Image Classification, Safe Landing, Computer Vision, Scene Detection.



I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs), commonly known as drones, have become an essential part of modern technology due to their wide range of applications in areas such as surveillance, agriculture, disaster management, logistics, environmental monitoring, and military operations. As drone usage continues to expand, the need for fully autonomous systems has become increasingly important. Among all autonomous capabilities, safe and accurate landing is one of the most critical and challenging tasks. Improper landing can lead to damage of the drone, loss of data, or even safety hazards in populated areas.

Traditional drone landing systems rely heavily on GPS coordinates, pre-defined landing zones, or manual operator control. However, these approaches have several limitations. GPS-based landing may not be accurate in environments with signal interference, such as urban areas or dense forests. Pre-defined landing pads are not always available in real-world scenarios, especially in emergency situations like disaster relief or search and rescue missions. Manual control, on the other hand, requires skilled operators and increases the risk of human error.

To address these challenges, intelligent landing systems based on computer vision and machine learning have gained

significant attention. By using onboard cameras, drones can visually analyze the environment and make decisions about suitable landing areas. Scene recognition plays a crucial role in this process, as the system must distinguish between safe surfaces (such as open ground or flat terrain) and unsafe areas (such as water bodies, obstacles, buildings, or uneven terrain).

In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown remarkable performance in image classification and scene understanding tasks. However, training deep learning models from scratch requires large datasets and high computational resources. This is where transfer learning becomes highly effective. Transfer learning utilizes pre-trained models that have already learned rich feature representations from large datasets, and adapts them to specific tasks such as landing scene recognition. This approach reduces training time, improves accuracy, and works well even with limited domain-specific data.

II. LITERATURE REVIEW

Several research works have been carried out in the field of autonomous drone landing, scene recognition, and the



application of deep learning techniques for aerial image analysis. This section reviews important contributions related to landing site detection and transfer learning-based approaches.

Early studies focused on traditional computer vision techniques for landing zone detection. These methods used edge detection, color segmentation, and texture analysis to identify flat and obstacle-free regions. Although such approaches were computationally efficient, they were highly sensitive to lighting conditions, shadows, and environmental variations, which limited their real-world applicability.

With the advancement of machine learning, researchers began using supervised learning algorithms for scene classification. Techniques such as Support Vector Machines (SVM) and Random Forest classifiers were applied to extract handcrafted features like Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT). While these methods improved performance compared to traditional approaches, they still depended heavily on manual feature engineering and lacked robustness in complex environments.

The introduction of deep learning, particularly Convolutional Neural Networks (CNNs), significantly improved image classification and scene recognition tasks. Researchers demonstrated that CNNs can automatically

learn hierarchical features from images, making them more effective for identifying complex patterns such as terrain type, obstacles, and landing surfaces. Models like VGGNet, AlexNet, and ResNet have been widely used for aerial scene classification and object detection tasks.

Recent studies have explored the use of transfer learning to overcome the limitations of training deep neural networks from scratch. By leveraging pre-trained models on large datasets like ImageNet, researchers fine-tuned these models for drone-specific tasks such as landing site detection. Transfer learning not only reduces training time but also enhances accuracy, especially when the available dataset is limited. Models such as MobileNet and EfficientNet have been preferred for drone applications due to their lightweight architecture and suitability for real-time processing on embedded systems.

III. EXISTING SYSTEM

The existing systems for drone landing primarily rely on traditional techniques such as manual control, GPS-based navigation, and basic sensor-based approaches. These systems have been widely used in earlier drone technologies but suffer from several limitations when operating in dynamic and complex environments.



One of the most common approaches is **manual landing control**, where a human operator remotely controls the drone and selects a suitable landing spot. While this method provides flexibility, it heavily depends on the operator's skill and experience. In critical situations such as disaster zones or low-visibility environments, manual control becomes difficult and increases the risk of crashes.

Another widely used method is **GPS-based landing systems**. In this approach, drones use pre-defined coordinates to land at specific locations. Although GPS provides a simple solution, it lacks precision in urban environments with signal interference, tall buildings, or dense forests. GPS alone cannot identify whether the landing surface is safe, flat, or free from obstacles.

Some systems utilize **sensor-based landing mechanisms**, such as ultrasonic sensors, LiDAR, or infrared sensors, to measure distance from the ground and detect obstacles. These systems help in altitude control and collision avoidance but have limited capability in understanding the surrounding environment. They cannot effectively classify different types of landing surfaces like grass, water, sand, or concrete.

Earlier research also explored **traditional image processing techniques** for landing site detection. These methods include edge

detection, color segmentation, and texture analysis to identify flat regions. However, these approaches are highly sensitive to lighting conditions, shadows, and environmental variations, making them unreliable in real-world scenarios.

Additionally, some machine learning-based systems use **handcrafted features** with classifiers like Support Vector Machines (SVM) or Decision Trees. While these methods provide moderate accuracy, they require manual feature extraction and are not robust enough to handle complex aerial scenes.

IV. PROPOSED SYSTEM

The proposed system introduces an intelligent and fully autonomous landing scene recognition framework for drones using transfer learning and deep learning techniques. Unlike traditional systems, this approach enables the drone to visually analyze its surroundings and make real-time decisions about safe landing zones without human intervention.

The system is designed to process aerial images captured by the drone's onboard camera and classify the scene into categories such as safe landing area (e.g., open ground, flat terrain) or unsafe area (e.g., water bodies, buildings, trees, obstacles). This is achieved using pre-trained Convolutional Neural



Network (CNN) models that are fine-tuned for the specific task of landing scene recognition.

In this approach, transfer learning plays a key role. Instead of training a deep neural network from scratch, models such as VGG16, ResNet50, MobileNet, and EfficientNet are used as base architectures. These models are pre-trained on large datasets and are capable of extracting high-level features like texture, edges, shapes, and spatial patterns. By fine-tuning these models with drone-specific datasets, the system achieves high accuracy even with limited training data.

V. METHODOLOGY

The methodology of the proposed autonomous landing scene recognition system is designed to enable drones to identify safe landing areas using transfer learning and deep learning techniques. The process begins with dataset collection, where aerial images representing various landing conditions such as open fields, roads, grasslands, water bodies, and obstacle-filled areas are gathered from publicly available datasets and drone-captured images. These images are then labeled into categories like safe and unsafe landing zones.

Next, data preprocessing is performed to improve the quality and consistency of the input data. This includes resizing images to a fixed dimension, normalization, noise

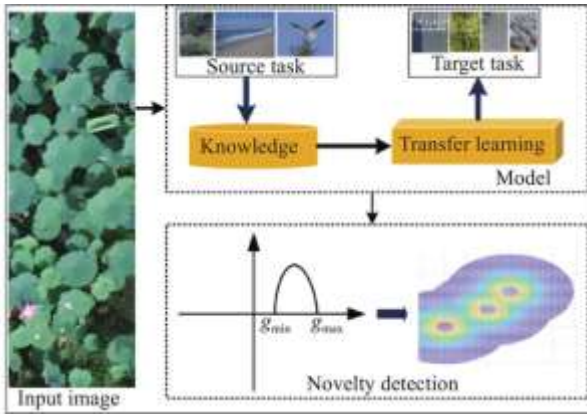
removal, and data augmentation techniques such as rotation, flipping, and scaling to increase dataset diversity and prevent overfitting. After preprocessing, the system employs a pre-trained Convolutional Neural Network (CNN) model through transfer learning. Models such as MobileNet or ResNet50 are fine-tuned by replacing the final classification layers and retraining them on the landing scene dataset.

During the training phase, the model learns to extract important visual features like terrain texture, object presence, and surface patterns. The trained model is then evaluated using performance metrics such as accuracy, precision, recall, and F1-score to ensure reliability. In the deployment phase, the drone captures real-time images through its onboard camera, which are passed through the trained model for prediction. The system classifies the scene and determines whether the area is safe for landing.

Finally, a **decision-making module** uses the classification output to guide the drone's landing action. If a safe zone is detected, the drone initiates landing; otherwise, it continues scanning the environment. This structured methodology ensures efficient, accurate, and real-time autonomous landing capabilities in dynamic environments.

VI. SYSTEM MODEL

System Architecture

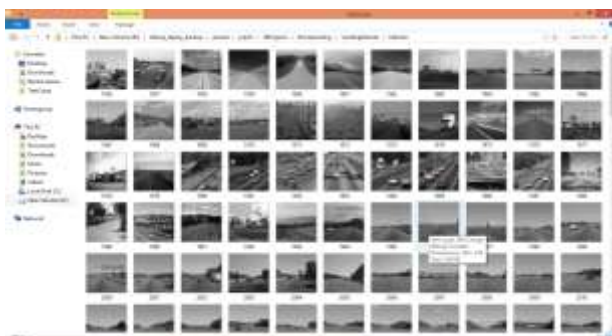


VII. RESULTS AND DISCUSSIONS

To train above algorithms author of this paper has used self constructed LandingScenes7 dataset but this dataset not available on internet so we have created own landing dataset with 8 different scenes for landing and below are the dataset images

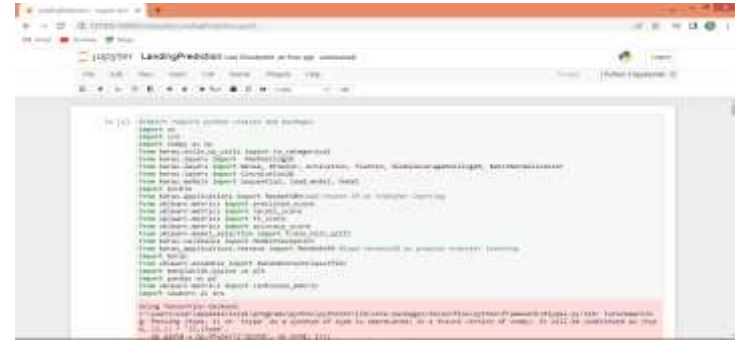


In above dataset screen we can see 8 different folders and just go inside any folder to view dataset images



In above screen we can see some images from Road class and by using above scenes location dataset we trained models and then inform to drone about landing place name.

We have coded this project using JUPYTER notebook and below are the code and output screens with blue colour comments



In above screen we are importing require python packages and classes



In above screen finding and displaying different landing scenes from dataset and then defining function to get class label from scenes names



In above screen looping and loading all images from dataset folder and then in blue colour text displaying total loaded images



In above graph x-axis represents landing scenes names and y-axis represents count of that scene images available in dataset



In above screen displaying sample vehicles images from dataset



In above screen dataset pre-processing such as normalization, shuffling and splitting dataset into train and test



In above screen defining function to calculate accuracy and other metrics



In above screen training ResNext50 algorithm with CNN layer and ADAM optimizer as transfer learning and after executing above block will get below output



In above screen propose ResNext50 got 97% accuracy and displaying other metrics also and in confusion matrix graph x-axis represents Predicted Labels and y-axis represents True Labels and all different colour boxes in diagonl represents correct prediction count and remaining blue colour boxes represents incorrect prediction count which are very few



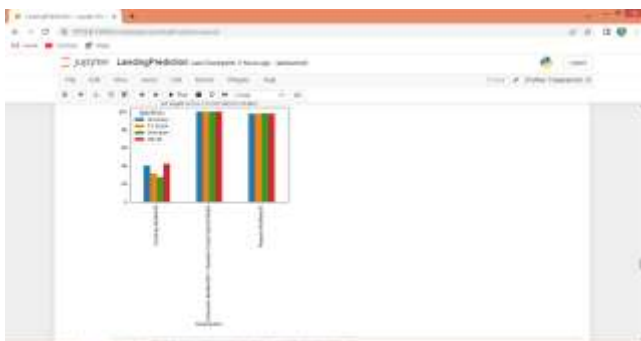
In above screen training existing ResNet50 algorithm and after executing above block will get below output



In above screen Resnet50 got 40% accuracy with ADAM optimizer and below is the extension algorithm



In above screen extension Hybrid Ensemble Random Forest got 100% accuracy which is higher than other algorithms



In above comparison graph x-axis represents algorithm names and y-axis represents accuracy and other metrics in different colour bars and in all algorithms extension got high accuracy



In above screen displaying all algorithm performance in tabular format



Above is ResNext50 training graph where x-axis represents training epoch and y-axis represents accuracy and loss values where green line represents accuracy and blue line represents loss and with each increasing epoch accuracy got increase and reached closer to 1 and loss got decrease



In above graph defining predict function and this function will take input image path and then using extension ensemble object it will classify given image scenes and in above image scene classify as building



In above image for each scene we got correct classification result

VIII. CONCLUSION

The Autonomous Landing Scene Recognition Based on Transfer Learning for Drones system provides an effective and intelligent solution for safe and reliable drone landing in real-world environments. By leveraging advanced deep learning techniques and transfer learning, the proposed system overcomes the limitations of traditional landing approaches such as manual control, GPS dependency, and basic sensor-based methods.

The integration of pre-trained models like ResNet50 and MobileNet enables efficient feature extraction and accurate classification of landing scenes, even with limited training data. The system is capable of analyzing real-time aerial images and distinguishing between safe and unsafe landing areas, thereby enhancing the autonomy and decision-making ability of drones.

Overall, the proposed approach improves landing accuracy, reduces human intervention, and ensures operational safety in complex and dynamic environments. This makes it highly suitable for applications such as disaster management, surveillance, agriculture, and delivery systems. The adoption of such intelligent landing systems represents a significant step toward fully autonomous drone operations in the future.

IX. FUTURE WORK: Future work for this

The proposed autonomous landing scene recognition system can be further enhanced in several ways to improve its performance, robustness, and real-world applicability. Although the current system achieves accurate classification using transfer learning, there is still scope for advancement with emerging technologies.



In the future, the system can be extended by incorporating **multi-modal sensor fusion**, combining camera input with sensors such as LiDAR, ultrasonic sensors, and GPS for more precise landing decisions. This will help the drone better understand depth, terrain elevation, and obstacle distance, especially in complex environments.

Another improvement involves using advanced deep learning architectures like EfficientNet and Vision Transformer (ViT) to achieve higher accuracy and better generalization. Additionally, implementing **real-time semantic segmentation** instead of simple classification can allow the system to identify exact landing zones at the pixel level, improving precision.

The system can also benefit from **reinforcement learning**, where drones learn optimal landing strategies through interaction with different environments. This would make the drone more adaptive and capable of handling unseen scenarios.

Further work can focus on **edge computing optimization**, enabling models to run efficiently on low-power onboard devices without compromising speed or accuracy. Model compression techniques such as pruning and quantization can be applied for faster inference.

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