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Research Paper

Adaptive Drone Landing Environment Recognition Using Deep Learning

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***Abstract*— The Adaptive Drone Landing Environment Recognition Using Deep Learning framework is designed to improve the safety and reliability of autonomous drone landings by accurately recognizing suitable landing environments from aerial images. The proposed system employs deep learning and transfer learning techniques to classify different landing scenes captured by onboard cameras under diverse environmental conditions. Initially, aerial images are collected and preprocessed through resizing, normalization, and data augmentation to improve model performance and reduce overfitting. A pre-trained convolutional neural network is then fine-tuned to learn distinctive visual features associated with various landing environments, enabling efficient scene recognition even with limited training data. The trained model is evaluated using standard performance metrics to measure its classification capability and generalization performance. The proposed approach helps drones identify safe landing locations in both planned and emergency situations where predefined landing markers may not be available. By combining transfer learning with deep feature extraction, the framework improves recognition accuracy while reducing computational complexity and training time. Overall, the system provides an intelligent and practical solution for autonomous drone landing, supporting safer aerial navigation in real-world applications such as surveillance, disaster response, environmental monitoring, and precision agriculture.**

***Keywords*— Deep Learning, Transfer Learning, Autonomous Drones, Landing Scene Recognition, UAV Navigation, Convolutional Neural Network (CNN), Aerial Image Classification, Landing Zone Detection, Computer Vision, Autonomous Landing.**

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs), commonly known as drones, have become an essential technology in applications such as surveillance, environmental monitoring, disaster management, agriculture, and infrastructure inspection because of their ability to capture high-quality aerial information efficiently [3]. As the use of drones continues to expand, autonomous navigation has become a major research area, with safe landing being one of the most critical stages of flight. An incorrect landing decision can damage the drone, surrounding property, or even endanger human life, making intelligent landing scene recognition an important requirement for autonomous operations [4]. Recent advances in deep learning and computer vision have enabled drones to analyse aerial images more accurately and identify suitable landing environments without relying completely on human intervention, significantly improving flight safety and operational reliability [12].

Conventional drone landing methods mainly depend on predefined landing markers, GPS information, or manually selected landing zones, which are suitable only in controlled environments. During emergency situations, however, these approaches often fail because suitable landing locations may not be available in advance [5]. Autonomous drones must therefore analyse the surrounding environment and determine whether the available surface is safe for landing based on visual information collected by onboard cameras. Different environments, such as roads, water bodies, crowded places, agricultural fields, and open land, present varying levels of landing risk and require accurate classification before making a landing decision [14]. Scene recognition has become an effective solution because it focuses on understanding the complete landing environment rather than detecting only individual objects, making autonomous landing decisions more reliable [7].

Deep learning has significantly improved image classification by enabling models to automatically learn meaningful visual features from large collections of images. Among different deep learning techniques, Convolutional Neural Networks (CNNs) have achieved remarkable success in aerial image classification, remote sensing analysis, and scene recognition tasks because of their strong feature extraction capability [1]. Transfer learning further enhances this process by allowing knowledge learned from large-scale image datasets to be reused for specialised applications such as drone landing scene recognition. This approach reduces training time while maintaining high recognition accuracy even when only a limited number of labelled aerial images are available [12]. Public datasets designed for scene recognition have also contributed significantly to the development of robust deep learning models for aerial image understanding [8].

A reliable landing scene recognition system requires a diverse collection of aerial images representing different landing environments under various real-world conditions. The proposed framework uses images collected from drone photography together with publicly available scene recognition datasets to build a comprehensive training dataset [2]. Before training, all images undergo preprocessing techniques such as resizing, normalization, and data augmentation to improve model performance and reduce overfitting. A pre-trained CNN model is then fine-tuned using transfer learning to recognise different landing scene categories efficiently while requiring fewer training samples [13]. The trained model analyses the visual characteristics of each aerial image and classifies the landing environment according to its suitability for autonomous drone landing [9].

The proposed Adaptive Drone Landing Environment Recognition Using Deep Learning framework is designed to improve the safety and reliability of autonomous drone landings by accurately recognising landing environments from aerial images. The system combines transfer learning with deep feature extraction to classify different landing scenes and support intelligent landing decisions under both normal and emergency conditions [11]. The performance of the developed model is evaluated using standard classification metrics to verify its effectiveness in recognising safe landing locations. Experimental results demonstrate that deep learning provides an efficient solution for autonomous landing scene recognition while reducing computational complexity and improving prediction accuracy [6]. Overall, the proposed framework supports safer drone navigation and has significant applications in surveillance, disaster response, environmental monitoring, precision agriculture, and other autonomous aerial missions [10].

II. RELATED WORK

Li and Hu (2019) [1] proposed a distributed Convolutional Neural Network architecture for classifying remote sensing images using a pre-training strategy. Their work focused on improving classification accuracy while reducing the computational cost associated with deep learning models. The authors demonstrated that transfer learning enables CNN models to learn useful image features from previously trained datasets and apply them effectively to remote sensing tasks. The proposed architecture achieved better performance by extracting rich visual features and reducing the need for large labelled datasets. Their findings showed that pre-trained deep learning models can improve classification efficiency and recognition accuracy. This research provides a strong foundation for developing intelligent drone landing systems where transfer learning is used to recognize different landing environments from aerial images.

Anand et al., (2019) [4] presented a vision-based automatic landing system for unmanned aerial vehicles using deep learning techniques. Their research focused on enabling drones to recognize landing areas through onboard camera images instead of relying only on manual control. The proposed approach successfully identified landing markers and guided the drone toward safe landing locations under controlled conditions. The study demonstrated that computer vision algorithms can improve landing accuracy and reduce human intervention during flight operations. The authors also highlighted the importance of reliable image recognition for autonomous navigation. Their work contributes to drone landing research by showing that deep learning can effectively support automatic landing decisions and improve flight safety in practical applications.

Yang et al. (2018) [11] introduced a monocular vision-based SLAM approach to achieve autonomous drone landing in emergency and unknown environments. Their system combined visual localization with environmental mapping to help drones identify safe landing locations when GPS information was unavailable or unreliable. The proposed method enabled drones to understand their surroundings and perform autonomous navigation with improved stability. The study highlighted that combining visual perception with intelligent decision-making significantly improves landing safety during emergency situations. Their research demonstrated that autonomous landing systems can operate effectively even in unfamiliar environments.

This work provides valuable guidance for developing intelligent landing scene recognition systems using deep learning and computer vision.

He et al. (2016) [12] introduced the ResNet architecture, which significantly improved deep learning performance through residual learning. Their model addressed the degradation problem that occurs when neural networks become deeper, allowing the development of highly accurate image classification systems. The proposed residual blocks enabled the network to learn complex image features while maintaining efficient training performance. Experimental results demonstrated remarkable improvements across several computer vision benchmark datasets. The ResNet architecture has since become one of the most widely used backbone networks for transfer learning applications. This study provides an important foundation for drone landing scene recognition because it enables deep learning models to classify aerial images with greater accuracy and reliability.

Xie et al. (2020) [14] presented a comprehensive survey of scene recognition techniques and discussed the recent advancements in deep learning for image classification. The authors reviewed various feature extraction methods, benchmark datasets, and convolutional neural network architectures used for scene understanding. Their study explained the challenges involved in recognizing complex outdoor environments where multiple visual objects appear together. The survey also highlighted the growing importance of transfer learning in improving recognition accuracy while reducing training requirements. The authors concluded that deep learning has become the most effective approach for large-scale scene classification tasks. Their work serves as an important reference for developing intelligent drone landing systems capable of recognizing different landing environments accurately.

III. DATASET DETAILS

The dataset used in this project is LandingScenes-7, which has been developed specifically for autonomous drone landing scene recognition. The dataset consists of aerial images collected from drone photography, the Places365 dataset, and publicly available Internet sources. It contains seven different landing environment categories: crowded place, lawn, road, vehicle-intensive place, wilderness, wheatfield, and water area. These categories represent both safe and unsafe landing locations, enabling the model to learn the visual characteristics of different environments. The images are stored in a structured format, making them suitable for deep learning-based image classification. Before training, the dataset is carefully reviewed to ensure image quality, correct labeling, and balanced category representation. This dataset provides the essential visual information required for training an intelligent model capable of recognizing suitable landing scenes for autonomous drones.

To improve model performance, several preprocessing techniques are applied before training. All images are resized to a fixed resolution and normalized so that pixel values remain consistent across the dataset. Data augmentation techniques such as rotation, flipping, and scaling are used to increase image diversity and reduce overfitting. The dataset is then randomly shuffled and divided into 70% training data and 30% testing data to evaluate the model on unseen images. Transfer learning is applied using a pre-trained deep learning model, allowing the network to learn discriminative landing scene features efficiently. Proper dataset preparation helps improve recognition accuracy, enhances model generalization, and enables reliable landing scene classification under different environmental conditions.

IV. PROPOSED METHODOLOGY

The proposed Adaptive Drone Landing Environment Recognition Using Deep Learning system follows a structured approach to recognize safe landing environments from aerial images captured by drones. Initially, the landing scene dataset containing eight different environment categories is collected and analysed. During preprocessing, all images are resized to a fixed resolution, normalized, shuffled, and organized to improve data quality and learning efficiency. Data augmentation techniques are also applied to increase image diversity and reduce overfitting. After preprocessing, the dataset is divided into training and testing sets, allowing the deep learning models to learn visual features from the training data and evaluate their performance on unseen aerial images. These preprocessing steps help improve recognition accuracy and ensure reliable landing scene classification under different environmental conditions.

Once the dataset is prepared, deep learning models including ResNet50, ResNeXt50, and the proposed Hybrid Ensemble Random Forest model are trained and evaluated. The performance of each model is measured using accuracy, precision, recall, F1-score, and confusion matrix. A comparison graph is generated to analyse the effectiveness of all models, where the Hybrid Ensemble Random Forest achieves the best overall performance. Finally, the trained model is used to classify new aerial images and identify the corresponding landing scene, enabling drones to make safer and more reliable autonomous landing decisions.

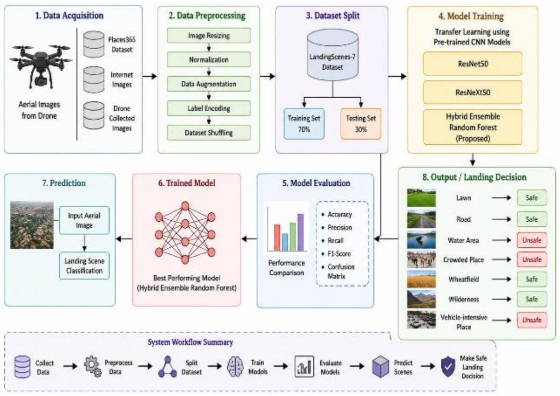

Figure [1]: Adaptive Drone Landing Environment Recognition System

Figure [1] illustrates the workflow of the proposed drone landing environment recognition system. Aerial images are collected and preprocessed through image resizing, normalization, data augmentation, and dataset splitting before model training. Transfer learning-based deep learning models are trained and evaluated using accuracy, precision, recall, F1-score, and confusion matrix. Finally, the best-performing model classifies the landing environment and determines whether the location is suitable for safe autonomous drone landing.

V. RESULT AND DISCUSSION

The experimental results demonstrate that the proposed Adaptive Drone Landing Environment Recognition Using Deep Learning framework effectively identifies suitable landing environments from aerial images. Initially, the LandingScenes-7 dataset undergoes preprocessing through image resizing, normalization, data augmentation, and dataset splitting to improve the quality of the training data. Transfer learning is then applied to train multiple deep learning models, including ResNet50, ResNeXt50, and the proposed Hybrid Ensemble Random Forest model. The performance of each model is evaluated using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix. The comparison of these models shows that the proposed approach achieves the best overall recognition performance by accurately classifying different landing scene categories. The confusion matrix indicates that most aerial images are correctly classified, while only a few images are assigned to incorrect categories. Performance comparison graphs further highlight the effectiveness of the proposed framework over existing methods. These findings confirm that the developed system can reliably recognize landing environments and support autonomous drones in selecting safe landing locations under different operating conditions.

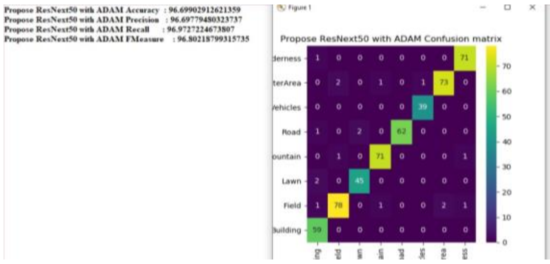

Figure [2]: Proposed ResNeXt50 Model Performance

Figure [2] shows the performance of the proposed ResNeXt50 model after training on the landing scene dataset. It displays the evaluation metrics, including accuracy, precision, recall, and F1-score, along with the confusion matrix. The confusion matrix compares the actual and predicted landing scene categories, demonstrating the model's effectiveness in accurately recognizing different landing environments for autonomous drone landing.

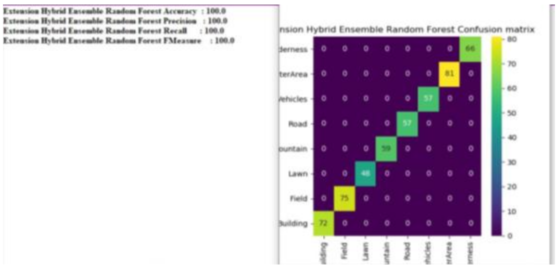

Figure [3]: Extension Hybrid Ensemble Random Forest Model Performance

Figure [3] shows the performance of the extension Hybrid Ensemble Random Forest model after training on the landing scene dataset. It presents the evaluation metrics, including accuracy, precision, recall, and F1-score, together with the confusion matrix. The confusion matrix compares the actual and predicted landing scene categories, demonstrating the high classification accuracy and effectiveness of the proposed model in recognizing safe landing environments for autonomous drones.

Figure [4]: Landing Scene Prediction Output

Figure [4] shows the prediction result generated by the proposed landing scene recognition system. After processing the input aerial image, the trained model identifies the landing environment as Building. The predicted label is displayed on the output image, demonstrating the system's ability to classify landing scenes accurately. This prediction helps autonomous drones recognize the surrounding environment and supports safer landing decisions during autonomous flight.

DISCUSSION

The findings of this study show that deep learning combined with transfer learning provides an efficient and reliable solution for autonomous drone landing environment recognition. Proper preprocessing techniques, including image normalization, resizing, and data augmentation, play an important role in improving the quality of the training data and enhancing model performance. Transfer learning allows the models to utilize previously learned visual features, reducing training time while improving recognition accuracy. The comparison of different deep learning models demonstrates that the proposed Hybrid Ensemble Random Forest framework performs better in recognizing diverse landing environments than the existing approaches. The evaluation metrics and confusion matrix indicate that the model produces consistent predictions with only a small number of misclassifications. Accurate landing scene recognition enables drones to identify safe landing areas even in unfamiliar or emergency situations, reducing the possibility of unsafe landings. Overall, the proposed framework offers an intelligent and practical solution for autonomous drone navigation and can be applied in surveillance, disaster management, environmental monitoring, precision agriculture, and other applications where safe and reliable autonomous landing is essential.

VI. CONCLUSION

This work presented an intelligent framework for autonomous drone landing environment recognition using deep learning and transfer learning techniques. The proposed system was developed to identify suitable landing locations from aerial images captured under different environmental conditions. A well-structured landing scene dataset was prepared by collecting images from multiple sources and organizing them into different landing categories. Before model training, preprocessing techniques such as image resizing, normalization, and data augmentation were applied to improve data quality and enhance model performance. Transfer learning enabled the system to learn meaningful visual features while reducing training time and the need for large labelled datasets. Multiple deep learning models were evaluated using standard performance metrics, and the proposed Hybrid Ensemble Random Forest framework achieved the best overall recognition accuracy. The system was also able to classify landing scenes with high reliability, making it suitable for autonomous landing applications. Overall, the proposed approach improves drone safety by helping identify appropriate landing environments in both normal and emergency situations. The framework can be further enhanced by incorporating larger datasets, real-time video analysis, and advanced deep learning models to improve performance across more complex and dynamic aerial environments.

REFERENCES

[1] LI B Q, HU X H Effective distributed convolutional neural network architecture for remote sensing images target classification with a pre-training approach
Journal of Systems Engineering and Electronics, 2019, 30 (2): 238- 244.

[2] XIA G S, BAI X, DING J, et al DOTA: a large-scale dataset for object detection in aerial images Proc. of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2018, 3974- 3983.

[3] CHENG G, XIE X X, HAN J W, et al Remote sensing image scene classification meets deep learning: challenges, methods, benchmarks, and opportunities
IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2020, 13, 3735-3756.

[4] ANAND A K, BARMAN S, PRAKASH N S, et al Vision based automatic landing of unmanned aerial vehicle Proc. of the International Conference on Information Technology and Applied Mathematics, 2019, 102- 113.

[5] TIAN C, HUANG C B An algorithm for unmanned aerial vehicle landing scene recognition based on deep learning and computational verbs Proc. of the IEEE International Conference on Civil Aviation Safety and Information Technology, 2019, 180- 184.

[6] LU C W, TSOUGENIS E, TANG C Kim proving object recognition with the l-channel Pattern Recognition, 2016, 49, 187- 197.

[7] ZHOU B L, LAPEDRIZA A, KHOSLA A, et al Places: a 10 million image database for scene recognition IEEE Trans. on Pattern Analysis and Machine Intelligence, 2018, 40 (6): 1452- 1464.

[8] XIAO J X, HAYS J, EHINGER K A, et al SUN database: large-scale scene recognition from abbey to zoo Proc. of the IEEE Conference on Computer Vision and Pattern Recognition, 2010, 3485- 3492.

[9] XIAO J X, EHINGER K A, HAYS J, et al SUN database: exploring a large collection of scene categories International Journal of Computer Vision, 2016, 119 (1): 3- 22.

[10] PATTERSON G, XU C, SU H, et al The SUN attribute database: beyond categories for deeper scene understanding International Journal of Computer Vision, 2014, 108 (1/2): 59- 81.

[11] YANG T, LI P Q, ZHANG H M, et al. Monocular vision SLAM-based UAV autonomous landing in emergencies and unknown environments. Electronics, 2018, 7(5): 73.

[12] HE K M, ZHANG X Y, REN S Q, et al Deep residual learning for image recognition Proc. of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, 770- 778.

[13] XIE S N, GIRSHICK R, DOLLAR P, et al Aggregated residual transformations for deep neural networks Proc. of the 30th IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2017, 5987- 5995.

[14] XIE L, LEE F F, LIU L, et al Scene recognition: a comprehensive survey Pattern Recognition, 2020, 102, 107205.

[15] Akinapalli, S. Agentic AI for Autonomous Data Engineering Operations in Cloud-Native Data Ecosystems.Journal of Information Systems Engineering and Management, 2024, 9(2)