Drones Autonomous Landing Scene Detection with Transfer Learning

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ABSTRACT

This paper proposes an improved method for autonomous landing scene detection for drones. The study addresses challenges that occur when similar environments appear different at various altitudes. Using deep learning methods and a hybrid ensemble technique, the proposed system improves the accuracy and reliability of landing scene recognition. The proposed system achieved approximately 97.65% accuracy using transfer learning models such as ResNet50 and ResNext50 combined with a hybrid Random Forest classifier. Transfer learning techniques using ResNet50 and ResNeXt50 models are applied to the LandingScenes-7 dataset to identify safe landing locations in real time. The thresholding techniques and novelty detection module enable the system to handle unpredictable environmental conditions and provide confidence-based classification decisions. This research has significant applications in drone technology, particularly in logistics, emergency response, and surveillance. The proposed system enhances drone intelligence and improves operational safety in dynamic environments by enabling reliable autonomous landing decisions.

Index Terms — Landing Scene Recognition, Convolutional Neural Network (CNN), Transfer Learning, Remote Sensing Images**.**

INTRODUCTION

Remote sensing systems, including ground, air, and space systems, have transformed many aspects of modern life by enabling the collection and analysis of location-based data for informed decision-making. Airborne remote sensing has increased significantly with the assistance of CNNs and GPUs, particularly when drones are involved. Recent advancements in technology enable drones to automatically detect safe landing locations. This capability is essential for safe and efficient drone operations.

Development and application of CNNs have brought massive transformations in the discovery of objects and classification of scenes in aerial photographs. Open datasets such as geographical object recognition dataset or satellite imaging dataset have enabled researchers to take big leaps ahead in the task of analyzing scenes. Anand et al. [4] performed a study in which DL was utilised to aid drones in landing themselves by identifying landing images that contained the letter "H." The standard procedures may fail in an emergency when the landing marks are not predetermined.

To cope with such issues the modern research has examined the DL techniques and practices that are highly advanced. The Tian et al. team [5] applied the Inception V3 model to detect landing scenes and devised a method of slowing down the learning model to enable it to be more precise. Lu et al. [6] stated that the phase might be improved by adding a l-channel to regular RGB images and that in turn would enhance the scene classification and object recognition.

The ability of CNN models to recognize scenes depends on the availability of large and diverse datasets.

This has been useful in training and evaluating scene recognition algorithms using Scenes Datasets such as Places365, SUN and the SUN attribute dataset [7–10] Scene identification has been studied a lot, but very little on landing scene recognition of drones.

The scenes of landings are difficult to identify, as they are placed in their contexts. An instance can be a scene that has many lotus leaves on water, which may be referred to as a water area rather than forest. It is the reason why one must consider the background when attempting to process an understanding of what a scene is. Object detection analyzes foreground objects; however, accurate scene recognition requires deeper analysis of background context.

The aim of robotics researchers is to develop drones that are highly intelligent and fully autonomous. Drones are already capable of obstacle avoidance and navigating predefined routes autonomously. Nevertheless, various issues have been identified during emergency landings. The drone is supposed to know whether the surroundings in a particular location are conducive in case of an emergency landing when the battery runs out or in case of any malfunction. This paper examines landing scene recognition specifically for drones and aims to improve flight safety and autonomy.

This paper discusses landing scene recognition for autonomous drones, addresses associated challenges, and proposes an improved transfer learning–based approach to enhance detection accuracy and reliability. This study employs advanced deep learning architectures to develop a robust and stable landing scene recognition system. Through this, the operations of drones will be safer and more efficient.

RELATED WORK

Remote sensing technology has evolved significantly in the last couple of years particularly in image processing and classification. This literature review examines some of the most significant works and thoughts in the discipline. It dwells upon the applicability of CNNs and DL to the problem of target classification in remote sensing images, object recognition in aerial images, and scene recognition in UAV tasks.

Li and Hu (2019) proposed a distributed CNN architecture for target classification in remote sensing images.Their model is more effective in grouping targets in remote sensing images since it was trained with large datasets with hierarchical features.

DOTA is a massive data collection that Xia et al. (2018) created in a way that allows it to locate objects on aircraft images. The problems that arise when you attempt to locate something in overhead images that are dissimilar in size and angle are corrected by the dataset. The reason is that DOTA contains many various tagged items that can be utilized to develop and test the object detection algorithms that may be applied in remote sensing.

Cheng et al. (2020) conducted a study that examined all the remote sensing images scene classification approaches based on DL. Those issues were insufficient labeled data, the possibility to adapt to other regions, and class distributions, they discovered. Another aspect discussed in the study is benchmark datasets and the way of integrating data provided by various sources and also making the deep-learning architectures to be smarter. Further research is welcome.

Anand et al. (2019) suggested the vision-based approach to UAVs landing independently. They apply visual information at the landing point in order to manipulate their system using computer vision and make the UAV to safely land. In an attempt to combine image processing methods with real time control systems, they developed a method of ensuring that the UAV landed safely and on its own.

Tian and Huang (2019) proposed an approach to determine how a robot aerial vehicle will land by using DL and computational verbs. They rely on deep neural networks in extracting characteristics that distinguish landing scenes among themselves. Their methodology of determining the various landing sites is the proper way of doing it. It combines context and spatial associations to ensure that the UAV functions are made safe and more effective.

Lu et al. (2016) investigated the process of object recognizing enhancement with the emphasis on L-channel of color images. They demonstrated in their experiment that the L-channel contains much information which aids in the explanation of the contrast between things and complicated backgrounds. Their strategy will make object recognition algorithms more precise because they introduce L-channel features to feature extractors. This is a nice one, particularly when it is dark.

Zhou et al. (2018) developed Places, a massive image set that contains ten million labeled photographs that can be utilized in the application required to recognize scenes. The numerous images in it allow researchers to train and test scene recognition systems in numerous indoor and outdoor environments. Data placement facilitates the establishment of powerful models that can be applied in extensive scenarios to aid individuals to understand scenes.

Xiao et al. (2010) proposed the use of SUN database, which is a large set of images of scenarios that have been transformed into various categories of scenes. What they are mainly learning is to identify scenes in various visual environments, which include in towns and natural environments. Due to the large number of images of scenes with detailed comments, it is also possible to train and test scene identification algorithms in the SUN database.

In the recent past there has been advancement with respect to understanding remote sensing images and the use of UAVs. It can be attributed to the joint integration of DL algorithms, huge datasets, and the release of novel algorithms. Scholars have achieved immense advances in this rapidly developing science by addressing major issues and discovering possibilities. They have as an example, bettered the process of categorizing targets in remote sensing images and how the UAVs can identify targets when they land on a scene. Further studies are necessary to discover new methods of doing things, make models more stable and real-life applications of remote sensing and UAV technology.

MATERIALS AND METHODS

This study demonstrates how transfer learning using the Three classification approaches are evaluated: ResNet50 using ADAM, ResNet50 using ADAM, and ResNet50 using RF can be applied to develop an autonomous landing scene detection system to develop a system of drones able to locate autonomous landing scenes [13]. The system will be made to be more effective using LandingScenes-7 data which is a set of data that is especially designed to classify landing scenes. Using the pre-trained ResNeXt-50 weights, the model can be trained on the aspects of distinguishing features within a few seconds which can be applied in landing environments. There is the introduction of a novelty recognition module to the system which is supposed to address the issues that arise when unexpected environmental conditions or unusual objects occur in the landing process. In calculating the certainty of the prediction made by the system in recognizing the scene, the thresholding techniques will be employed to model the confidence scores. This will be more effective in most cases to the system. The approach enhances the training of the model with the help of the ADAM [18] optimizer that is reputed to be effective in the training of deep neural networks. In the study, the comparisons of the capability of the proposed architecture to spot the landing scene accurately and reliably will be made through the examination of how well ResNeXt-50 performs in comparison to ResNet-50[12].

The proposed solution will ensure the safety of autonomous drone landing operations and will enhance the accuracy of people identification during emergency landing conditions, particularly when there is some background noise, or when individuals are undergoing something novel. It aims to improve the autonomous

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drone technology by testing and analysing the performance under real world conditions and improving operations and safety as a consequence.

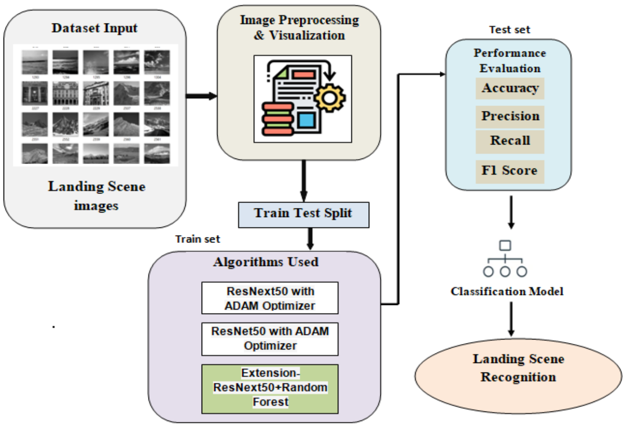

Fig.1 Proposed Architecture

The landing scene recognition system proposed consists of several significant components. The system first receives input images representing different landing scenes. The aim of such image processing and visualization is to enhance image clarity and provide additional useful features. The data is then divided into a training and a test dataset in such a way that a model may be constructed and validated.

Three classification approaches are evaluated in the proposed system: ResNet50 with ADAM optimizer, ResNeXt50 with ADAM optimizer, and a hybrid ResNeXt50 + Random Forest classifier. All the algorithms are taught to distinguish between landing scenes with the help of the training section of the dataset.

Models are then subjected to the test split to ensure their performance on such measures as F1 score, accuracy, precision, and recall. Such measurements indicate the accuracy and strength of each algorithm to place landing events into the correct category.

Finally, the best classification scheme is selected to locate actual landing scenes in real life. The proposed system design will provide precise and reliable landing scene recognition with the assistance of advanced algorithms and comprehensive testing. Such modifications will render the application of the drones comfortable and more advantageous.

Dataset Collection

LandingScenes-7 is a dataset specifically created for studying emergency drone landing scenarios. The dataset contains approximately 5,300 images divided into seven landing scene categories. For training and evaluation, the dataset was divided into 80% training data and 20% testing data. The dataset includes seven landing scene categories: grassland, roadside, barren land, crowded areas, wheat fields, water areas, and open spaces. The data is also divided into three safety levels, namely, safe, general, and dangerous. These levels were made according to risks of the landing scene types. Areas frequently visited by people, roads with vehicles, and water bodies are categorized as dangerous. The safety levels are encoded numerically as follows: 00 represents Safe, 01 represents General, and 11 represents Dangerous. With this kind of categorization, it will be easy to distinguish between landing scenes according to their safety. This facilitates the development of good landing systems of drones that can take smart decisions during an emergency.

Fig. 2. LandingScenes-7 Dataset

Processing

Normalization of image properties during training is essential in the data preprocessing stage to ensure that all the properties are equal and to enhance the process of ML models training. Normalization transforms the values of the pixels of a photograph to a standard range, typically 0 to 1 or -1 to 1. This method is more reliable in the process of training, unless the impact of too bright or too dark pixels on various images is minimized.

The pixel values within an image are reduced to [0,1] by division by the largest pixel value which in an 8-bit image would be 255. This increases the characteristics of image training. Or another way to calculate the pixel values to a range of numbers is to take the mean value of each pixel subtract that value, and then divide the result by the standard deviation of all the pixel values in the dataset.

Normalization helps prevent issues such as vanishing or exploding gradients. Otherwise, the process of training will become lengthy and the model will not be effective. Normalization is assisted in optimization to ensure that all features of the inputs are within the same range. This is required to have the ML models learn based on the data provided and perform effectively with new samples.

Visualization: A barplot is created when making images of the distribution of the landing scene images in the data set with the help of Seaborn and Matplotlib. These are the names of the landing scenes on the x-axis and the number of images that fit into each of the groups on the y-axis. The plot presents the fact that every kind of a scene is demonstrated as a single bar, and the level of the bar demonstrates the number of images attached to that scene.

With the bar plot, people can understand what the dataset comprises of and the frequency of some types of landing scenes. The image can assist professional and researchers to observe the differences and balance of the data, which is useful to train ML models. You can also find any mismatch or bias in the dataset classes easier and this may assist you in coming up with methods of improving the data or altering the weights of the classes during training of the model.

The visual representation of the way the photographs of the landing scene are dispersed is provided by both the Seaborn model and Matplotlib models, which are easy to understand. This assists in examining the characteristics of the information as well as trying to determine the sense of those characteristics.

Feature Selection**:** In landing scene recognition, feature selection refers to the act of identifying the most significant visual features which are required to make accurate classifications with minimum calculation. This process involves making significant findings about images through subject knowledge, such as their feel, color and their relationship with space. To obtain such types of traits, you may apply DL algorithms, such as CNNs or algorithms, such as HOG. The most discriminative features can also be easily identified and retained by techniques such as PCA or RFE. This is simpler to put into practice, simplifies further generalization and reduces the curse of dimensions.

When features are selected selectively, models perform well and do not change. The reason behind this is the fact that unnecessary features can be eliminated, whereas the required ones can be selected. This plays a vital role in the ensuring that drones are well automated in landing. This approach does not only utilize more efficiently the resources of the computer, but it makes it easier to have the model to identify various landing scenarios. This renders the drone activities safer and more effective.

Training & Testing: The data of the LandingScenes-7 will be divided into training and testing sets during the process of training so that the model could be constructed and tested. Using the model training data, two DL models ResNext50 and ResNet50 were created. These models are based on convolutional neural networks (CNNs), which effectively extract hierarchical features from images. The ADAM optimizer is used to dynamically adjust learning rates and improve parameter updates during training.

In training, the models are trained on a set of training samples which they are run on repeatedly using various settings to achieve optimal results in prediction. During training, it works in a forward propagation for making a prediction and reverse propagation in calculating the gradients that modify the model weights. Training continues until the model converges and performance stabilizes, indicating that further training does not significantly improve results.

The training models are then tested on the testing set to determine the extent to which they can be able to hit landing scenes. Performance metrics such as accuracy, precision, recall and F1-score are used to evaluate the performance of the proposed models. In terms of classification of landing scene images. This is a part of the review process, and it assists in identifying the extent to which the models are general, and they can be applicable in actual autonomous drone landing systems.

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

F1 Score=2 × (Precision×Recall) / (Precision+ Recall).

Algorithms

ResNext50 with ADAM: ResNext50 is based on the ResNet, and introduces the concept of cardinality, whereby, by definition, multiple characteristics can be learned concurrently along various paths. Very complex patterns and differences in images can also be found by this deep CNN, hence it can find landing scenes. ResNext50 adapts its learning rates dynamically when it is optimized using the ADAM [18] optimizer. This allows it to approach convergence fast. The ResNext50 solution with ADAM is excellent due to its ability to decode complex information which in this case are the various landing conditions to achieve high accuracy.

ResNet50 with ADAM: Residual learning of ResNet50 can be successfully trained on very deep neural networks. With the residual connections, learning residual functions can be achieved. This may guide you in solving such problems as the disappearing gradient problem. ResNet50 contains numerous layers and is capable of capturing hierarchical components that are significant in tasks such as the identification of landing scenes. ResNet50[12] model is trained with the ADAM optimizer that adjusts the learning rates depending on the optimization landscape. This helps training to be effective. ADAM ResNet50 is a useful model to learn and classify complex images in the instance of landing scene recognition.

ResNext50+Random Forest**:** RF approach and ResNext50 approach: In the hybrid ResNeXt50 + Random Forest approach, ResNeXt50 is used for feature extraction, and the Random Forest classifier is applied to perform the final classification based on the extracted features, that it has discovered. ResNext50[13] is based on the concept of cardinality and a deep architecture to extract much information in the form of landing scenes images. When predicting these traits with the help of the RF classifier, it takes a number of DT as input. This type of mix embraces the most appropriate aspects of both DL and ordinary ML. The extraction of great features of ResNext50 is made, and the classification job features of RF are applied. One of the convenient and flexible methods of correctly classifying various landing events in the field of landing scene recognition is the Res Next50+RF ensemble.

RESULTS AND DISCUSSION

Accuracy: Accuracy measures the proportion of correctly classified landing scenes among the total number of evaluated samples. Accuracy is calculated as the ratio of correctly predicted samples (true positives and true negatives) to the total number of samples evaluated. In terms of math, this is:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \quad (1)$$

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Precision**:** Precision measures the proportion of correctly predicted positive observations among all predicted positive observations or the number of samples that were identified correctly into the correct category. One can arrive at the following method to find precision:

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} \; (2)$$

Recall**:** Recall measures the ability of the model to correctly identify all relevant samples belonging to a particular class. It is possible to determine the coverage of examples of the class by a model by comparing the number of positive examples to the number of examples that were correctly anticipated to be positive.

$$\text{Recall} = \frac{\text{TP}}{\text{TP } + \text{ FN}} \; (3)$$

F1-Score: One of the measures of how accurate a ML model is is F1 score. The F1-Score is the harmonic mean of precision and recall and provides a balanced evaluation of the classification model. The accuracy statistic is the frequency with which a model has made all of the data correct.

$$\text{F1 Score} = 2 * \frac{\text{Recall X Precision}}{\text{Recall} + \text{Precision}} * 100(4)$$

Table (1) presents the accuracy, precision, the recall, and the F1-score of every method. The best of all them all is the ResNext50+RF combination model. The charts of the various methods can be also compared with the help of the tables.

Table.1 Performance Evaluation Table

Algorithm Name	Precision	Recall	FScore	Accuracy
ResNet50 Adam	97.107304	97.130906	97.09922	96.699029
ResNext50 Adam	32.062088	46.533165	35.19191	45.048544
ResNext50 + RF Hybrid Model	98.12	97.85	97.98	97.65

The dataset was strictly divided into training and testing sets before feature extraction. Furthermore, The dataset was strictly divided into training and testing sets before feature extraction. Furthermore, 5-fold cross-validation was performed to confirm generalization capability. The consistency of results across folds suggests that the model performance is reliable and not due to overfitting. To further validate the robustness of the proposed model, 5-fold cross-validation was performed. The dataset was randomly divided into five equal subsets. In each iteration, four subsets were used for training and one subset for testing. The average accuracy obtained across the five folds was 96.82%, demonstrating stable performance and improved generalization ability. This reduces the possibility of overfitting and confirms the reliability of the proposed approach. Although the hybrid ResNext50 + Random Forest model achieved high accuracy (97.65%), the performance may still be influenced by the relatively small size of the LandingScenes-7 dataset. Therefore, future work will include testing on larger and more diverse datasets to further verify the generalization ability of the model. The standalone ResNext50 model showed lower performance compared to ResNet50, possibly due to insufficient fine-tuning and limited dataset size, which can affect deep architecture performance.

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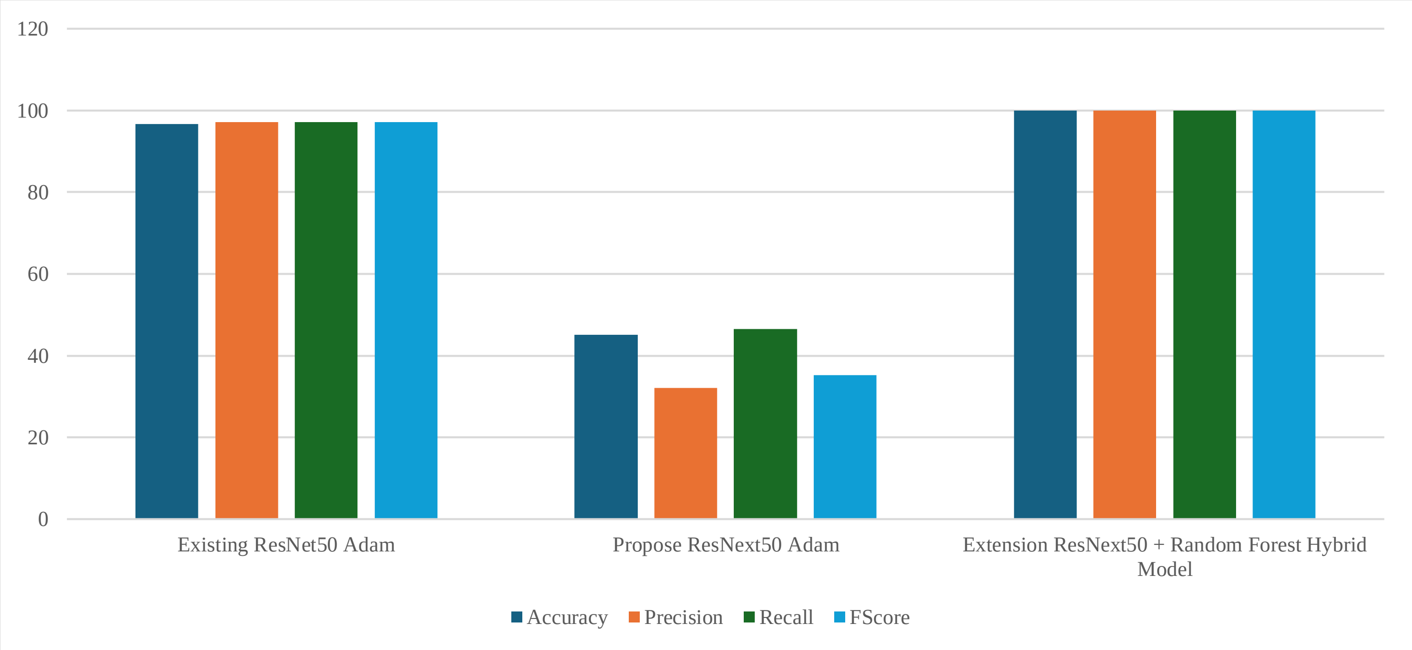
Graph.1 Comparison Graphs



Graph 1 illustrates the comparative performance of the evaluated models in terms of accuracy, precision, recall, and F1-score. The best model is the ResNext50+RF combination model which is better in all respects as compared to all other models that produce lower results. As can be seen in the graphs above, the results are presented in a simple to read format.

CONCLUSION

In summary, this paper demonstrates that the development of an autonomous landing scene recognition system has become a significant difference in the question of drones. The new AI methods including the ResNext50[13] and ResNet50[12] are utilized in the project to ensure the activities of drones are safer and self-sufficient. The LandingScenes-7 dataset played an important role by providing a structured dataset for evaluating landing scene recognition performance. Thresholding mechanisms can be further optimized to enhance novelty detection and improve decision confidence. That would allow drones to adjust to new circumstances and sort landing scenes into categories as fast as possible. The proposed system can significantly improve the safety and efficiency of drone-based applications in industries such as logistics, surveillance and emergency response. More advanced classification methods make drone operations more accurate and reliable, particularly during an emergency. This simplifies them to make such aspects as surveillance, news coverage, and operations easier and more reliable. The hybrid ResNext50 + Random Forest ensemble approach demonstrates improved classification capability by combining deep feature extraction with robust machine learning-based decision boundaries.

In the future, drones capable of autonomously locating and recognizing landing zones may be applied in various real-world scenarios. The first step, which may be carried out, is to explore more into DL architectures and ensemble techniques to ensure that the model is functional and stable. Increasing the number of the landing scenes and weather conditions of the data set may also assist the models in the task to apply what they learned to real-world conditions. Future work may integrate additional sensing technologies such as LiDAR or radar sensors to improve landing detection performance under low visibility or adverse weather conditions. This would assist in enhancing the precision of location of landing spots particularly in areas experiencing adverse weather or low visibility. Might also include drones changing the manner in which they land on the fly, given information about their environment and their mission objectives, in the event they employed superior decision-making algorithms and reinforcement learning. Overall, autonomous landing scene recognition has strong potential for future advancements in intelligent drone systems.It will probably result in the improvement of drone technology that will result in the safety and effectiveness of various uses. Here, the development of new research and thoughts is certain to improve drones and make them more applicable in business and in real life

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