Agricultural Sciences Journal
Available online at http://asj.mnsuam.edu.pk/index.php
ISSN 2707-9716 Print
ISSN 2707-9724 Online
https://doi.org/10.56520/asj.24.359

Research Article

DEEP LEARNING BASED SEMI-SUPERVISED FRAMEWORK FOR SAFE LANDING OF UNMANNED AERIAL VEHICLES

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Abstract

Nowadays, various remote sensing systems have adopted the use of Unmanned Aircraft Systems (UAVs) due to the increasing popularity of drones. Hence, there is a need to develop such methods for the safe landing of aerial drones for suitable landing site identification. This research focuses on developing a Machine Learning (ML) based framework for identifying suitable places to ensure the safe landing of drones. An Autonomous Safe Landing of Aerial Drone Vehicles (ASLAD) framework, a novel and innovative approach, was proposed in this regard. This framework was based on the Self-training Semi-supervised Learning Model (SSLM). For experiments, high-resolution aerial images were taken. All the images were resized using image resizing techniques. Image splitting technique was used to split the dataset into labeled and unlabeled classes. Experiments showed that the proposed model produced promising results with an accuracy of 96.75% and an F1-score of 94.45%. The results showed that the proposed framework can identify suitable places for the safe landing of aerial drones.

Keywords: Machine Learning, UAVs, Aerial Vehicles, Drones, Learning Model.
(Received: 19-Dec-2023 Accepted: 18-Apr-2024) Cite as: Malik. M. H., Ghous. H., Nawaz. S. A., Ahmad. N., 2024 Deep learning based semi-supervised framework for safe landing of unmanned aerial vehicles. Agric. Sci. J. 10.56520/asj.24.359

1. INTRODUCTION

Reliable autonomous drone technology has become more important to detect safe landing places nowadays. Drones are used in different operations such as surveillance, inspection, deliveries, and detection. These operations and applications must develop a reliable system to identify obstacles and prevent accidents. This system will minimize the risk of drone crashes and damages. Adopting these systems may reduce the risk of potential harm to people and property. Drones, also known as unmanned aircraft, operate from a distance without having any passengers inside (Seydoux, 2014). Drones have become more valuable unmanned aircraft in a wide range of aviation applications due to their ability to conduct extended flights with controlled altitude and speed. The major focus of this study is to consider the fact of identifying appropriate landing places by drones. This refers to term firma, which means operating both unmanned and manned aircraft in dynamic environments. There is a system that can identify secure landing space by drones. This system autonomously identifies all obstacles around the defined routes of unmanned aircraft

(Giordan, 2020). By using this technology, drones can land securely without any human intervention. These systems consist of different strong sensors and high-definition cameras to collect necessary information about the landing place and its surroundings. This includes information about object locations, the drone's altitude, and landing place coordinates. This information ensures that drones can constantly identify safe landing places in all evolving conditions (Vlantis, 2015). The adoption of these advanced technologies involves fear about the trustworthiness of the obtained information about a safe landing place. This involves a drone onboard processor responsible for analyzing the extracted information and generating secure, reliable landing routes for unmanned aircraft (Nex, 2022). False information may be easily spread over social media through the internet. This makes it difficult to identify and locate credible information. This issue raises a questionable objection to adopting and implementing an autonomous aircraft safe landing system to whether the system can identify a secure landing place or not by using this information (Anderson, 2017). The role of the media is to spread information regarding the safe landing of unmanned aircraft. It is the primary responsibility of media houses and organizations to ensure the authenticity of the information before spreading it around. Thus, there is a need to implement strict fact-finding procedures to stop the dissemination of false information. Furthermore, public awareness programs about modern technologies can reduce the fear of disseminating false information around the people (Kovacova, 2022).

1.1 Autonomous Safe Drone Landing Detection (ASDLD)

This state-of-the-art technology empowers drones to achieve safe and precise landings autonomously, eliminating the need for human intervention. The system closely monitors the drone's location and surroundings using a variety of sensors, cameras, and sophisticated software programs. It maintains a constant watch to ensure the drone's safety and performance. (Abdelmaboud, 2021). The system looks at important things like wind direction, speed, air pressure, exactly where the landing zone is, and any obstacles that might be there. It makes smart decisions using real-time data it collects to land safely. The system controls the drone's flight path and landing process, guiding it along the safest route for an accurate, liable landing. This cool technology makes drone operations much safer and more effective for tasks like delivery, surveillance, and inspections. It analyzes key factors like wind patterns, atmospheric conditions, the precise landing spot, and potential obstructions. Then, it uses this live data to choose the best course, completely managing the drone's flight and touchdown for a secure, precise outcome. This cutting-edge capability greatly improves safety and performance across drone applications from package transport to monitoring and inspections. (Mohsan S. A., 2023).

The tech that allows drones to work alone is quite useful. It makes drones fly independently for delivery, inspecting stuff, watching areas, and doing risky jobs safely. When drones can detect safe landing spots independently, there's less chance of human errors, keeping drones secure. These drones land accurately without people controlling them, increasing drone use across many situations and applications. This advancement could shake up the drone industry. It opens more possibilities for safe, efficient drone operations in various workplaces and e-nvironments (Mohsan S. A., 2022).

Drones can land safely on their own without help from people. They use tools like GPS and height sensors to get details. The drone's computer checks this info to adjust how it moves and lands. It ensures the landing is smooth and safe, without you needing to do anything (Politi, 2022). A safe landing is crucial for drones operating in challenging environme-nts. This technology aims for reliable, secure landings. It reduces accidents during landing procedures, increasing drone operation safety and reliability. Drones with autonomous safe landing can navigate complex settings, land independently, and xpand applications while prioritizing safety. The main objective – ensuring dependable, secure landing e-xperiences, even in demanding, ever-changing situations. By reducing landing accident potential, this greatly elevates overall safety and reliability. Equipped with this capability, drones adeptly maneuver through complex settings, achieving safe, independent landings. It

expands potential applications while strongly emphasizing safety. (Lange, 2009).
The self-driving safe landing for drones has steps. It uses cameras, sensors, math programs. First, it gets info on the area around it. Then, it finds the best path to land. As it moves, it keeps changing the path to land safely and right on target. This process is illustrated in Figure 1.

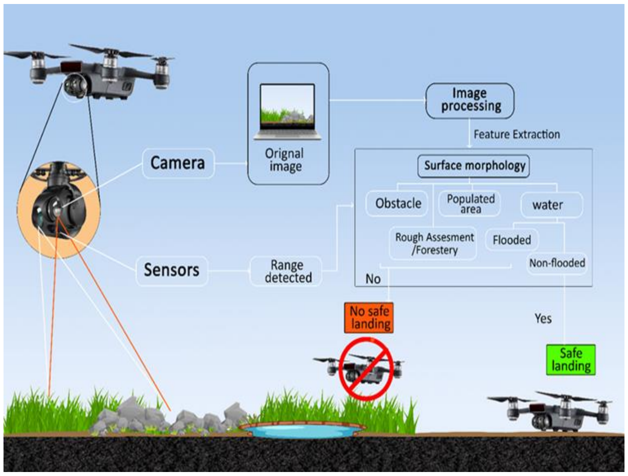

Figure 1: Autonomous Safe Landing Detection System

Figure 1 shows how the system works. It splits landing paths into "Yes" for safe, and "No" for unsafe. The system uses sensor, camera, and algorithm data to decide quickly. This ensures a safe, reliable drone landing. Drones are popular due to being cost-effective, accessible, versatile, effective, and safe. This makes them useful for many applications (Zhu, 2019). Drones play a crucial role in gathering crucial data from distant and hard-to-reach areas where human presence is not feasible for efficient tasks. Their remote control and accessibility through smartphones allow them to quickly access densely populated locations without requiring human involvement, leading to savings in time, resources, and energy. This flexibility has resulted in their widespread use in four primary sectors: commercial, personal, military, and emerging technological applications (Emimi, 2023).
Ensuring safe drone landings is a critical part of drone technology. Drone operations become safer and more reliable with this capability. This feature is crucial for the effective use of drones (Hussein, 2021). The integration of self-landing detection allows drones to fly faster and more accurately when landing, reducing the need for human control. This technology enables drones to land safely on their own, improving their efficiency and reliability. Aerial image segmentation has involved evaluating feature extraction methods, like analyzing color and texture properties (Faheem, UAV Emergency Landing Site Selection System using Machine Vision, 2015). Computer vision and feature extraction techniques help drones identify suitable landing locations. These methods analyze the captured images to distinguish between good and bad landing areas. The landing detection platform assesses the image data, extracting important features, objects, and patterns using feature extraction. This allows drones to predict their performance based on trained datasets, even in unfamiliar landing situations. The vision system focuses on segmenting images to pinpoint appropriate landing spots independently.
The research on safe landing techniques for drones has been thoroughly examined. Researchers have explored various methods to ensure a smooth and controlled landing for these aerial vehicles. The discussion covers the key findings and approaches outlined in the existing studies on this topic.

2. Literature Review

Researchers have used diverse models, including deep learning (DL) and machine learning (ML), to predict safe landing conditions for unmanned aerial vehicles (UAVs). ML, DL, and image processing approaches greatly assist data analysis, feature extraction, and accurate map generation. The primary objective is to enhance drone intelligence, enabling independent decision-making and safe landings. Researchers have explored viable methods to increase the accuracy of identifying safe landing spots, ultimately aiming to improve drone performance and safety. This section examines the research contributions to ensure UAVs land safely.

In 2023, Haotian et al. conducted study that specifically examined a Multi-level Adaptive Safety Control architecture system designed for UAVs.This technique enables UAVs to effectively carry out safety maneuvers, even in very unpredictable scenarios. Notably, it can adapt to different landing phases and was carefully made to deal with uncertainties in real time. This study's findings are essential for enhancing the safety and reliability of drone flights, particularly during critical landing procedures. The insights gained can help improve operational protocols and ensure the safe operation of these unmanned aerial vehicles (Gu, 2023). In 2023, Kumar and his team developed a reliable Computer-Aided Design (CAD) method sor landing drones with parachutes. They built a CAD model, did Computational Fluid Dynamics (CFD) simulations, and then improved the model based on what they learned from those simulations (Kumar, 2023). The researcher, Ghous, explored techniques to automatically identify suitable landing spots for drones in 2023. They considered factors like ground surfaces and utilized image processing methods. Accurate detection of landing sites is crucial as drones become more automated, regardless of their size. To find the best landing places, the onboard vision sensors collect data. This research highlights the need for safe and automated drone landings in the growing drone industry by evaluating current methods, successes, and areas for potential improvement (Ghous, 2023).

Guerin et al., 2022 research introduced a Segmentation-based approach for secure landings, employing the EL (Emergency Landing Approach) model. Through their ML Runtime Monitoring (MLRM) technique, they achieved a remarkable success rate of 99.7% [18]. In 2022, Pinkovich et al. introduced a Bayesian network with vision-based segmentation for making decisions involving multiple criteria (MCDM) to ensure the secure landing of aerial drone vehicles. The decision-making process considers a trial successful when its value exceeds 99.0% [19]. Ariante et al. presented a 360-point sampling SLAD method for RPLIDAR in 2022, incorporating vision-based techniques. This method yielded measurements with distance accuracy points of 1300 mm [20]. Meanwhile, Liu et al. in 2022 introduced a dual-model DL approach aimed at ensuring the safe landing of drone aircraft. They conducted their training on the Aerospace dataset for 150 epochs and incorporated semantic segmentation as a preprocessing step. The Image Semantic Segmentation Model showed a significant improvement in effectiveness, reaching an impressive 68.88% increase.[21]. Tovanche-Picon and their team conducted a scientific study in 2022 to address safety concerns with unmanned aerial vehicles (UAVs). They developed a strategic approach using a Fusion Sensor Technique and a Vision-Based Algorithm. This system achieved an impressive 86% success rate in dynamic situations with 20% moving parts.

The studies provide valuable insights into using vision-based techniques to make UAV landings safer and more efficient. These findings can help improve the overall landing process, making it more secure and streamlined. By understanding the insights from these studies, researchers and engineers can develop better systems and methods to enhance the safety and efficiency of UAV operations [22].

Tomita and his colleagues used Bayesian principles to develop deep learning methods in their 2021 research. Utilizing these techniques, they were able to achieve a 61% accuracy level (Tomita, 2021). The 2021 study by Turan et al. introduced a new image processing technique focused on detecting edges and identifying landing zones in emergency situations. Their method achieved an impressive 100% accuracy rate, with re-call and precision values of 81.2% and 79.1%, respectively, even at the lowest points. (Turan, 2021). Iiyama and their team developed training mode-ls in 2021 that successfully landed in an impressive 94.8% of cases. They used the Delayed Deep Deterministic Policy Gradient

(TD3) method to continuously update the safe landing areas and ensure they remained free of hazards (Iiyama, 2021). The 2021 study by Brockers and colleagues explored a vision-based method to reconstruct detailed 3D re-presentations. This approach allowed them to collect highly accurate depth measurements. By using this technique, they were able to achieve a 100% detection rate in identifying safe landing zones (Brockers, 2021). Klos and colleagues devised an innovative approach in 2020 to identify suitable emergency landing sites. They employed pre-trained multimodal artificial neural networks using transfer learning. After rigorous testing and optimization, the model achieved an impressive peak accuracy rate of 99.66%. (Klos A. , 2020). In the year 2020, a team led by Wilhelm and their colleagues developed a deep learning framework specifically designed to classify images of the Martian surface. Their work aimed to provide a reliable and efficient way to analyze the visual data captured from the Red Planet. The system that was studied by them has an overall performance level of more than 90% and offers strong support for continuous site investigation. It also displays outstanding predictive abilities (Wilhelm, 2020).

In 2020, Sikdar et al. presented a clustering method that uses suitable stereo pairings to randomly derive drone flight trajectories from a single camera. The total accuracy of all approaches, despite the variety of strategies used, was found to be 0.860 (Sikdar, 2020). In 2020, Klos et al. investigated a method for data fusion that included a digital surface model. After evaluating a number of models, the ResNet-18 model earned the highest test accuracy at 99.709%, with the Wide-ResNet-50-2 model coming in second at 99.801%, and the AlexNet model achieving an astounding 99.97% (Klos, 2020). In 2019, Wubben et al. launched ArduSim simulation approaches with the goal of lowering landing mistakes by around 96% and improving landing accuracy to a level similar to GPS-based landings (Wubben, 2019).

In 2018, Hinzmann et al. proposed a vision-based segmentation technique for aerial vehicles that integrates Coarse Depth Measurements, Distance Transformation, and the Random Forest (RF) Method. The RF technique delivered an exceptional 95% accuracy rate in areas with greater motion or velocity. (Hinzmann, 2018), The research led by Fraczek and colleagues in 2018 presented a method that utilized Digital Image Processing Techniques to assess the effectiveness of Decision Trees (DT) and Support Vector Machines (SVM) in the context of vision-based segmentation for safe landing site selection. Their experimental results demonstrated that the performance regularly exceeded 80% across all 100 test cases. (Fraczek, 2018).

Earlier research by Zhao et al. in 2017 introduced an image segmentation technique that identified key geometric patterns, enabling the detection of a wide variety of hazards. The overall performance score for this technique was found to never drop below 0.983. (Zhao, 2017). In 2017, Coombes et al. suggested employing the MONTE CARLO simulation method to assess emergency landings in both stable and windy conditions. The outcomes revealed that the average error in height loss was relatively small when contrasted with the total height loss, amounting to only 5% (Coombes, 2017).

Furthermore, in 2016, Kang and their team introduced a feature extraction method centered on the pixel analysis convex hull feature approach. However, it's worth noting that the accuracy of the model during its middle phase decreased by 90.09% due to the feature extraction methods employed. (Kang, 2016).

In 2015, Desaraju et al. introduced a highly efficient feature extraction approach, achieving a remarkable success rate of over 90% in accurately identifying landing zones. Notably, this method is notable for its impressively low false positive rate, which is less than 0.05% (Desaraju, 2015). During a similar timeframe in 2015, Faheem dedicated their research endeavors to creating a Machine Vision-based system tailored for the selection of UAV Emergency Landing Sites. Their investigation primarily centered on the classification of viable and non-viable aerial vehicle segments through the application of ML algorithms and feature extraction techniques in computer vision. The results of their study demonstrated a notable accuracy of 91.6%, all achieved within a short processing time (Faheem, UAV Emergency Landing Site Selection System using Machine Vision, 2015). Furthermore, a study conducted by Dehshibi et al. in 2015 introduced a machine vision approach based on K-Nearest Neighbors (KNN) segmentation. This method involved the extraction of features from HSV color and Gabor texture. HSV and Gabor filters exhibited the most outstanding performance of the various feature extraction methods examined. However, it's important to note that the KNN Classifier technique, as a whole, achieved a remarkable accuracy rate of 97% (Desaraju, 2015), on the other hand, in 2015, Sosnowski et al. proposed an advanced method for evaluating and selecting safe landing locations. Their method significantly decreased the possibility of incorrectly identifying fake and sharp edges, improving the approach's overall reliability and producing outstanding results. (Sosnowski, 2015).

A comprehensive analysis of the various methods and models used to choose safe landing places was carried out in the preceding section. We examined the datasets used in previous studies. The next section will explore the datasets and methods we employed to create our innovative framework for identifying secure drone landing sites.

3. Materials and Methods

This section will explain the methods and techniques used in our framework for choosing secure landing spots for drones. To reach our research objectives, we'll describe the methodical approach to gathering, processing, and analyzing data.

3.1 Semi-Supervised Learning

Semi-supervised learning is a technique in machine learning where algorithms are trained using a mix of labeled and unlabeled data. This approach enables the model to learn from structured (labeled) information and unstructured (unlabeled) data, potentially enhancing its performance compared to using only labeled data (Amjad, 2023). This approach combines the key ideas of supervised and unsupervised learning. Supervised learning means the system learns from labeled data. Unsupervised learning means the system learns from unlabeled data. There are two main types of semi-supervised learning (Altexsoft, 2022).

3.2 Inductive Semi-Supervised Learning

The method uses a tiny bit of labeled data along with a larger amount of unlabelled data to steer the algorithm's learning. This collaborative approach, often called "self-training," lets the algorithm guess for new, unknown data. The algorithm can expand its understanding and make more precise forecasts using labeled and unlabelled data.

3.3 Transductive Semi-Supervised Learning:

In this case, the algorithm uses labeled data to predict different instances of unlabeled data within the same dataset. This method is often called "co-training".

The dataset is used in the semi-supervised training phase for binary classification with the ResNet18 model. At first, only the labeled instances are used to train the model. Later, artificial labels are created and incorporated into the training process for the next phases, effectively using the information in the unlabeled data. Since the dataset contains high-quality images, a preprocessing technique is applied to prepare the data for training.

The dataset is divided into two classes: labeled and unlabeled. The labeled class has fewer data instances compared to the unlabeled class. The labeled data is used to train the model with classifiers like ResNet18, VGG19, and VGG16 to start the process. These classifiers play an important role in the training.

This new dataset combines the original labeled data with the generated pseudo labels and is retrained using the ResNet18 classifier. The

Adam optimizer is employed throughout the training epochs to fine-tune the model. By adopting this semi-supervised learning approach and harnessing information from labeled and unlabeled data, the model can capitalize on the larger data pool, potentially enhancing its overall performance and generalization. A visual representation of this approach is shown in Figure 2.

Figure 2 illustrates the proposed framework, which is the basis for substantiating and validating the research theory. This framework not only introduces and outlines the theory being investigated but also provides a rationale for the existence of the research problem. It offers a distinct perspective that aids in comprehensively assessing the subject matter. Various preprocessing techniques have been integrated within our envisioned framework to address and successfully resolve the research problem. Pre-processing involves methods and techniques that are useful to produce data for analysis and ML algorithms. Without involving pre-processing, the performance of the proposed framework may reduced.

3.4 Preprocessing

Preprocessing plays a vital role in the preparation of data for experiments. It involves methods and techniques to resolve related issues to produce meaningful data for experimental analysis (Usama, 2022). The significance of preprocessing in our proposed framework is that it involves necessary steps to produce data suitable for analysis and ML Algorithms.

a) Data Cleaning

Data cleaning involves pre-processing methods such as Noise Removal, Missing values management, and elimination of outliers. This pre-processing step is crucial to enhance the quality of data. This provides a form of data that may improve the results' accuracy.

b) Feature Scaling

Feature Scaling or normalization is one of the most prominent pre-processing techniques which improves the performance of ML algorithms such as gradient descent or K-means clustering. This involves assigning a common scale to all features. It also prevents a single feature to be dominant among all features.

c) Feature Selection

Feature selection is one of the crucial steps of preprocessing, which involves selecting useful features. It involves the reduction of the complexity of data. This process may enhance the performance of ML models by selecting prominent features.

d) Data Transformation

Preprocessing involves a very important step called data transformation. It involves the conversion of data into a form acceptable for analysis. In this step, normalization of data is performed using skewed distribution. In this step, categorical variables are converted into numerical values. The preprocessed transformed data grantees effective results produced by different ML algorithms.

3.5 Dataset

In this research, two publicly accessible datasets sourced from Kaggle (https://www.kaggle.com/) are employed. A dataset is typically a compilation of data used for various purposes, such as analysis, research, and ML. These datasets contain high-resolution images categorized into training, testing, and validation sets, each representing different landing areas. The study's primary aim is to create a model capable of predicting safe landing areas for drones by leveraging patterns and features extracted from the data.

a) Dataset 1

This dataset is tailored for image classification tasks, where the objective is to classify images based on the provided labels. The dataset comprises 2343 images, each with dimensions of 3000 x 4000 x 3, representing the color channels. These images are distributed across three subsets: training (1455 images), validation (450 images), and test (448 images). The training set contains 1455 images, with 398 having labels and 1047 lacking them. The classification task involves sorting the images into two classes: "Flooded" and "Non-Flooded," each further divided into "YES" and "NO" categories. To balance efficient processing and preserve essential information, the image dimensions have been reduced from 3000 x 4000 to 300 x 400. The Flood Net Challenge dataset used in the EARTHVISION 2021 competition has 2343 images. Each image originally had dimensions of 3000 x 4000 with 3 color channels. The images were resized to 300 x 400 to process them more efficiently while retaining crucial information. The data t is divided into three sets: a training set with 1455 images, a validation set with 450 images, and a test set with 448 images. Out of the training set, 398 images have associated class labels, while 1047 images remain unlabeled.

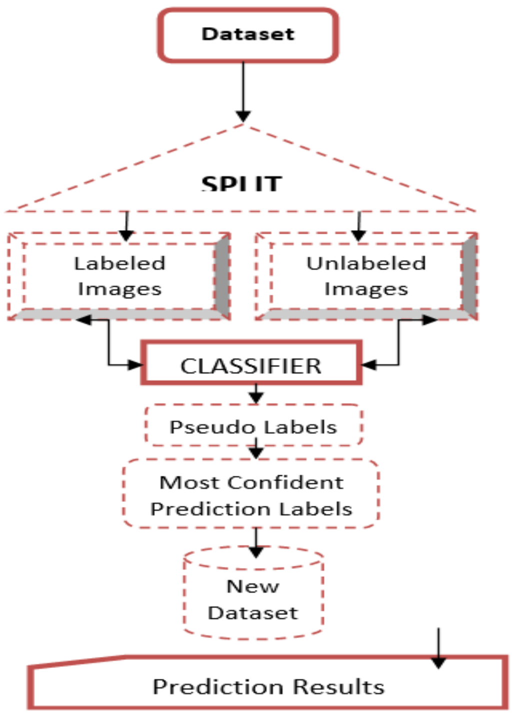

Figure 2: Semi-supervised Framework for safe landing of UAVs.

Table 1: Data Description of Dataset 1

Attribute	Description
Dataset Name	FloodNet Challenge
Dataset type	dataset of flood events
Image Size	512 x 512 pixels
Dimension	3000 x 4000 x 3
Number of images	2343
Images format	GeoTIFF
Annotation format	GeoJSON
Annotation type	Polygon
Annotation classes	Flooded area, no flooded area, uncertain area
Geographic coverage	Various
Date Range	Various
Image source	Copernicus Sentinel-1 SAR images
Label source	Automatic algorithm and human annotations
License	Creative Commons Attribution-Non-Commercial-Share Alike 4.0 International
Dataset Size	8.33GB

b) Dataset 2

The UAVid dataset is specially designed for image classification tasks, focusing on urban areas. The dataset includes a model with an attention mechanism, an encoder network, and a decoder network. The encoder network uses multiple convolutional layers to gradually reduce the spatial dimensions of the input image while increasing the number of feature channels. On the other hand, the decoder network works in the opposite direction, gradually reducing the number of feature channels while expanding the spatial dimensions of the image. An attention mechanism is used between the encoder and decoder networks to highlight the important attributes of each pixel in the image.

This dataset consists of high-resolution images from UAV footage, all in 4K resolution. Its primary application is semantic segmentation, which involves classifying each pixel in an image into one of eight item categories.

Initially, the dataset included 200 training photos and 70 validation images. To enhance diversity and expand the dataset's size, an additional 600 images were introduced. These supplementary images encompass 200 from the original UAVid dataset (normal UAVid images), 200 new images with shifts and noise added, and 200 new images with random flips and contrast adjustments. This augmentation process enhances the model's ability to generalize and perform well by exposing it to a broader range of data variations.

Table 2 below summarizes the contents of the UAVid dataset, specially designed for image classification tasks, particularly within urban environments. The dataset comprises a total of 870 high-resolution images captured using UAVs.

Table 2: Data Description of Dataset 2

Attribute	Description
Dataset Name	UAVid
Dataset type	Remote sensing dataset of UAV (drone) videos
Resolution	1920X 1080 pixels
Number of videos	20
Total Duration	63 minutes
Geographic coverage	Various
Date Range	Various
Video format	MP4
Annotation format	XML
Annotation	Bounding Box
Object Categories	8
Annotation classes	• Building • Road • Static car • Tree • Low vegetation • Human • Moving car • Background clutter
Label Source	Human annotations
License	Creative Commons Attribution 4.0 International
Dataset Size	12 GB

The graphical representation of the UAVid dataset is illustrated in Figure 1 as follows.

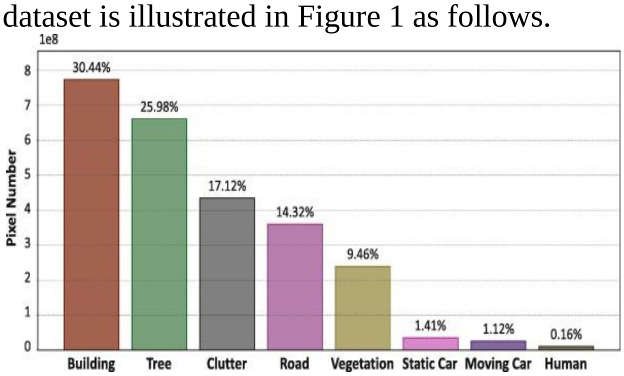

Figure 3: Graphical representation of sampling for Dataset 2 (Lyu, 2018)

4. Results and Discussion

In this section, we will perform experiments on the meticulously prepared datasets using various tools and platforms. The datasets have been subject to preprocessing techniques to tailor them for our model's requirements. These preprocessing steps involve standardizing the dimensions of all images through scaling and resizing. Additionally, any redundant data from the image borders has been eliminated via center cropping. Moreover, the pixel intensities across the images have been normalized to establish a consistent range.

Preparing the dataset commences by splitting it into two sections: labeled and unlabeled. Typically, the labeled set contains fewer images than the unlabeled set. A classifier generates pseudo labels for the unlabeled images in the initial phase. This classifier utilizes the available labeled data to assign provisional class labels to the unlabeled images based on their predicted classes. A semi-supervised method is also applied to create pseudo-masks for the unlabeled images. These masks are crucial in guiding the model to extract more meaningful insights from unlabeled data during training.

The model training commences with the labeled examples, employing the Adam optimizer for a predefined number of epochs. This initial phase uses the labeled data to establish a robust foundation for the model's learning. Subsequently, the previously generated pseudo masks are integrated with the labeled data for further model retraining. During this stage, the model undergoes training once more, but this time with the inclusion of pseudo-labeled data, effectively expanding the labeled dataset.

The extended dataset, now featuring pseudo-labeled data, is used for additional training epochs, enhancing the model's performance and generating more accurate predictions for the unlabeled images. This semi-supervised approach, which combines labeled and pseudo-labeled data, enables the model to leverage the knowledge extracted from the unlabeled data and the labeled examples to enhance its predictions and overall performance.

In the experiments section, we systematically altered individual parameter values, one at a time, while maintaining the other parameters constant. For example, if we modified the epoch parameter, we ensured that all other parameters remained the same for that experiment. In each experiment, we recorded the counts of real positives, real negatives, false positives, and false negatives from the classification results. These values were utilized to create a confusion matrix, comprehensively analyzing the model's performance.

By leveraging the information within the confusion matrix, we calculated several vital metrics, including accuracy and the F1 score. The accuracy metric gauges the overall correctness of the model's predictions, while the F1 score considers both precision and recall to evaluate the model's effectiveness.

4.1 Dataset 1 with Resnet18

We performed numerous experiments utilizing the ResNet 18 classifier, adjusting the number of epochs from 5 to 30. The epoch size denotes how often the model processes the entire dataset during training. We charted the model's accuracy at each epoch size, creating a graph that allowed us to visualize how accuracy fluctuates with varying training iterations. We performed numerous experiments utilizing the ResNet 18 classifier, adjusting the number of epochs from 5 to 30.

Table 3: Results using Resnet-18

Epoch	Accuracy	F1	Epoch	Accuracy	F1
0	0.9598	0.9608	0	0.9598	0.9608
2	0.9598	0.9815	2	0.9598	0.9815
4	0.9146	0.7302	4	0.9146	0.7302
6	0.8693	1.0000	6	0.8693	1.0000
8	0.9648	0.9945	8	0.9648	0.9945
10	0.9669	0.9670	10	0.9669	0.9670

The epoch size denotes how often the model processes the entire dataset during training. We charted the model's accuracy at each epoch size, creating a graph that allowed us to visualize how accuracy fluctuates with varying training iterations

Due to the substantial class imbalance, the model struggles to attain a high F1 score during training at various epochs, 0, 2, 4, 6, 8, and 10, when working with the labeled dataset. However, by the 10th epoch, the F1 score reaches an impressive 98.15% for the unlabeled data.

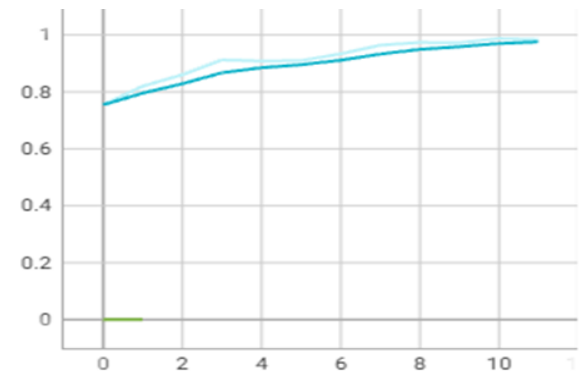

Figure 5: Graphical Representation of Results

4.2 VGG16

We utilized VGG16, a well-known convolutional neural network in our semi-supervised learning approach with labeled data. We monitored the F1 score and accuracy at different epochs, ranging from 0 to 6, to monitor the model's development. This gave us insights into how effectively the model adapted from the labeled data and enhanced its predictions over time. Such observations guided us in making informed decisions to achieve optimal results.

Table 4: Results using VGG-16

Epoch	Accuracy	F1
0	0.6951	0.6951
1	0.7886	0.7536
2	0.8192	0.7871
3	0.8985	0.8383
4	0.9311	0.8785
5	0.955	0.9106

In the first epoch (epoch 0), the accuracy and F1 score hold the same value, signifying the model's initial performance. This information is depicted in the figure, and as training advances through subsequent epochs, we can track the evolving accuracy and F1 score. These accuracy and F1 score changes provide insights into the model's learning and performance over time.

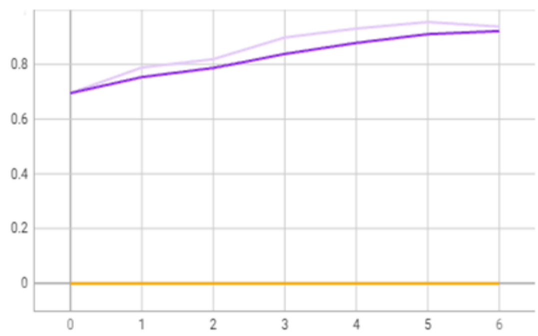

Figure 6: Graphical Representation of Results

The graph exhibits F1 scores on the y-axis and accuracy on the x-axis. In the graph, the yellow line, identified as F1-Train-alpha, consistently holds a constant value of zero across every point on the plot.

4.3 VGG19

We used VGG-19, a pre-existing neural network, for further training on new data through a semi-supervised learning method. We tracked the F1 score and accuracy at different training stages - 0, 2, 4, 6, 8, and 10 epochs - which produced varied results.

Table 5: Results using VGG-19

Epoch	Accuracy	F1
0	0.8113	0.8077
2	0.7799	0.7464
4	0.9511	0.9085
6	0.9717	0.9728
8	0.9843	0.9846
10	0.9863	0.9876

The VGG-19 model achieved an impressive accuracy and F1 score of 98.63% in our experiments. The visual results demonstrate the model's outstanding performance after retraining on new datasets using semi-supervised learning techniques. This highlights the effectiveness of VGG-19 in image classification tasks, demonstrating its capability to provide highly accurate predictions for the given dataset..

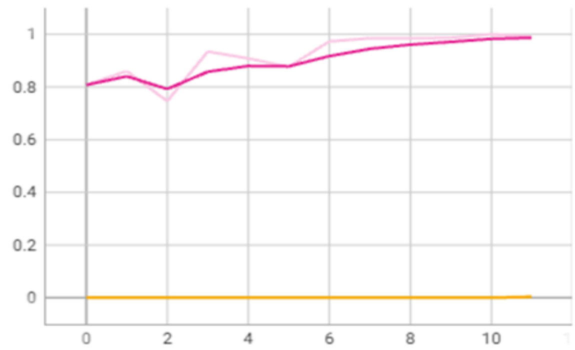

Figure 7: Graphical Representation of Results

The graph depicts F1 scores on the y-axis and accuracy on the x-axis. In the graph, the yellow line, labeled as F1-Train-alpha, consistently holds a value of zero at every data point

4.4 Dataset 2 with Resnet18

We conducted experiments using ResNet 18, involving both the data's initial training and subsequent retraining. We tested different epoch sizes during these experiments, ranging from 0 to 199. The graph illustrates accuracy on the Y-axis and points on the training dataset, or the F1 score, on the X-axis. We can discern how the model's performance evolves with different epoch sizes by examining the results. This analysis aids in identifying the optimal configuration that ensures accurate predictions for our image classification task.

Table 6: Results using Resnet-18

Epoch	Accuracy	F1
0	0.6875	0.7619
50	0.9375	0.9412
100	0.9375	0.9231
150	0.9275	1.0000
199	0.9875	0.4000

The model encountered challenges in achieving a high F1 score during training across different epochs (0, 50, 100, 150, and 199) due to a substantial class imbalance within the labeled dataset. However, at epoch 150, the model exhibited exceptional performance, attaining a perfect F1 score of 100% on the new dataset. The visual representation in the figure effectively illustrates these findings, emphasizing the model's capability to effectively address class imbalances at the specified epoch.

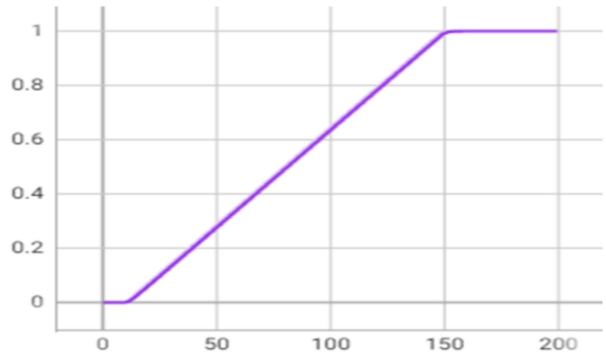

Figure 8: Graphical Representation of Results

The graph, F1 scores are plotted on the y-axis, while accuracy is represented on the x-axis. Across each data point, the persistent yellow line signifies that F1-Train-alpha remains consistently at zero.

4.5 Dataset 2 with VGG16

To enhance the performance of the ResNet 18 classifier, we implemented retraining by incorporating VGG16, a well-known convolutional neural network designed for image classification tasks. This semi-supervised learning approach involved utilizing the labeled data to boost the classifier's predictive abilities, capitalizing on the strengths of both VGG16 and ResNet 18 models.

Table 7: Results using VGG-16

Epoch	Accuracy	F1
0	0.3750	0.2875
50	0.6875	0.5455
100	0.8125	0.8000
150	0.7500	0.8000
199	0.7800	0.8000

We collected data on the F1 score and accuracy at different epochs, specifically at epochs 0, 50, 100, 150, and 199, which produced diverse outcomes. These results are visually represented in the accompanying figure.

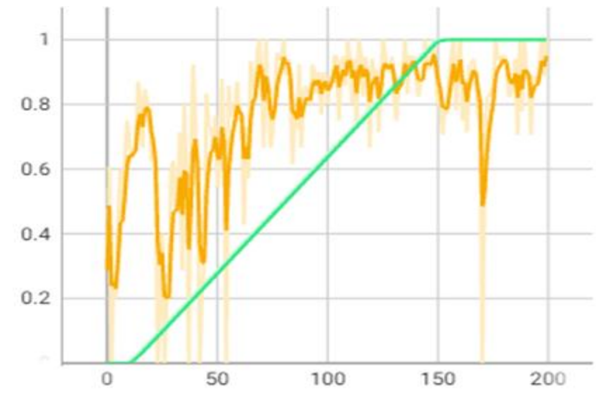

Figure 9: Graphical Representation of Results

The graph exhibits F1 scores along the y-axis and accuracy on the x-axis. Within the graph, the yellow line signifies the training accuracy, which exhibits variation at each data point.

4.6 Dataset 2 with VGG19

We employed VGG-19, a pre-trained neural network, to undergo retraining on fresh datasets via a semi-supervised learning approach. During this process, we documented the F1 score and accuracy at distinct epochs, specifically at 0, 50, 100, 150, and 199, resulting in differing outcomes for each scenario.

Table 8: Results using VGG-19

Epoch	Accuracy	F1
0	0.5000	0.3333
50	0.8750	0.8333
100	0.9375	0.9333
150	0.5625	0.2222
199	0.9675	0.9445

The considerable class imbalance within the labeled dataset presents hurdles in attaining a high F1 score at various epochs during training (0, 50, 100, 150, and 199). Nonetheless, at epoch 199, the model attains its peak accuracy, reaching an impressive 93.75% and a remarkable F1 score of 94.12% for the new dataset. These results underscore the model's capacity to manage imbalanced data and deliver precise predictions effectively. This is vividly illustrated in the accompanying figure, providing a visual representation of these findings.

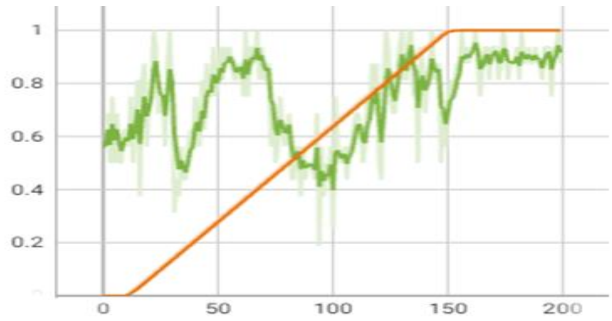

Figure 10: Graphical Representation of Results

The graph illustrates F1 scores along the y-axis and accuracy on the x-axis. The fluctuating green line within the graph represents the training accuracy at each data point.

4.7 Comparison with Existing Methods

Our model achieved exceptional results on the dataset, delivering an accuracy of 96.69% and an impressive F1 score of 96.70%. Our model has demonstrated superior performance in image classification tasks compared to other methods. These findings highlight the effectiveness and versatility of our approach across various image classification applications..

Table 9: Comparison of Proposal Model with Existing Models

Model	Accuracy	F1 Score
ResNet 50 (He, 2016)	97.37%	93.69%
InceptionNetv3 (Tan, 2019)	99.03%	84.38%
Xception (Khose, 2021)	99.84%	90.62%
ResNet 18 (Proposed)	96.69%	96.70%
VGG16 (Proposed)	96.75%	94.45%
VGG19 (Proposed)	98.63%	98.76%

This study focuses on developing an autonomous drone landing system that can operate safely without human intervention. The approach involves using semi-supervised learning with the Flood Net image dataset, which contains high-quality images. The dataset is divided into labeled and unlabeled classes, with the labeled data used to train Re sNet 18 and VGG16 classifiers.

The classifiers then generate pseudo-labels for the unlabeled data, which are combined with the remaining labeled data to create a new dataset. This new dataset undergoes further training using both ResNet 18 and VGG16 classifiers. The methodology is a self-training process, starting with a small labeled dataset and expanding it with a large unlabeled dataset. The loss function includes consistency regularization to ensure consistent outputs under different input conditions.

The batch generation process follows a balanced sampling strategy. This ensures that both classes are represented equally. Increasing the batch size improves accuracy but extends the execution time. Pre-processing techniques like image resizing, scaling, and cropping are particularly suited for high-resolution images.

When training with the labeled dataset, the model faces challenges in achieving a high F1 score due to class imbalance. To address this, a weighted sampling approach is used during data loading. This helps mitigate the middle-class disparity.

The results show that the self-training semi-supervised learning approach with ResNet 18 achieves an accuracy of 96.69% and an F1 score of 96.70%. VGG16 reaches an accuracy of 96.75% with an F1 score of 94.45%. VGG19 demonstrates even more remarkable performance, with an accuracy of 98.63% and an F1 score of 98.76%. This study highlights the effectiveness of semi-supervised learning with ResNet 18 and VGG16 in enhancing model accuracy.

5. Conclusion

Finding safe landing spots during emergencies is a big challenge in the field of drones. Current methods use both vision and non-vision algorithms but face issues with external factors, changing camera angles, and choosing effective techniques. This study presents a machine learning-based self-training semi-supervised learning approach using ResNet18 and VGG16 classifiers to analyze image data. The Flood Net dataset is used for training, resulting in a semi-supervised model that achieves high accuracy and F1 scores with ResNet18 and VGG16. This approach is useful when labeled data is limited or hard to get. The study also highlights the need for more research to improve safe landing detection methods, considering terrain, drone features, and payload. Future work may involve path planning and obstacle avoidance to ensure safe drone landings after identifying a safe landing zone and avoiding potential hazards.

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