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MobileNetV2 based deep neural network for automated rain condition detection in UAV imagery

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Abstract

Unmanned Aerial Vehicles (UAVs) are used rapidly in different fields. Few of the important areas where UAVs are necessary to use are defence, disaster management and agriculture due to the cost effective and access to remote areas. However, adverse weather conditions like rain hinder their navigation. This study is a deep learning approach using MobileNetV2 to detect rainy conditions from UAV captured images. It aims to enhance the operational safety and efficiency. The balanced dataset of 245K images across seven rain classes was used. The dataset was divided into training, testing, and validation sets in the ratio 70:15:15. This convolutional neural network model achieved a test accuracy of 95.35%. This suggests that the model is reliable and robust and can be further researched for real-time deployment.

Keywords: MobileNetV2, Unmanned Aerial Vehicle, Convolutional Neural Network, Navigation

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1. Introduction

Unmanned Aerial Vehicle (UAVs), commonly called drone, is an aircraft that is controlled remotely or is autonomous and does not have a human pilot, crew, or passengers on board[7, 5]. They have drastically changed industries such as agriculture, surveillance, infrastructure inspection, environmental monitoring, disaster response, and delivery services. What makes them unique is their ability to access remote or difficult areas where humans cannot access and provide real-time data has helped make industries do their tasks faster, safer and more efficient. In spite of these developments, ensuring the reliability of UAV perception systems in harsh weather conditions for navigation, particularly during rainfall, remains a significant challenge[1, 2].

Rain is the one of the most adverse weather conditions causing a significant challenge to UAV perception[1]. Rain becomes an obstacle for UAVs vision producing distortions and noise which degrades the sensor data creating false information in object detection, visual odometry and other sensor data[1]. In contradiction to ground based autonomous vehicles where they have a protective windshield, UAV sensors are directly exposed to the outer environment making them susceptible to the artifacts caused by

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rain and visibility loss[1, 2]. In addition to this, the rapid movement of UAVs, changing altitudes and varying altitudes increases the complication, as raindrops pile up on camera lenses and other sensors, creating inconsistent image quality and navigation errors[2].

Several researches have pointed out that specialized datasets and algorithms are required to deal with these challenges. For instance, Chang et al. (2024) developed the UAV-Rain1k dataset to provide a benchmark for raindrop removal from UAV aerial imagery, using synthetic modelling of raindrop shapes and diverse background images captured from various flight angles[2]. This dataset enables detailed analysis of deraining algorithms and supports the development of robust models trained to the unique conditions faced by UAVs[2]. Further, heavy precipitation effects the visual odometry performance that leads to significant tracking errors and compromise the safety and reliability of autonomous UAV operations[1].

In addition to visual challenges, rain can also impact other sensor modalities. LiDAR and radar which are generally more robust to weather than cameras, can still experience signal attenuation and noise in heavy precipitation[6]. However, integrating data from multiple sensors introduces new challenges, such as calibration complexity, synchronization and increased computational demands, particularly for lightweight UAV platforms with limited onboard resources[8].

Our motivation behind this work arises from the need for reliable and safe UAV operations in challenging weather which in turn becomes the objective of the work. Further, our aim is to efficiently classify different classes of rain from images for UAVs for better navigation. Finally, Adapt and fine-tune a lightweight neural network (MobileNetV2) for fast, accurate classification of rain. This work uses MobileNetV2, a lightweight and efficient convolutional neural network (CNN) architecture which offers a balance between accuracy and efficiency, employing depth wise separable convolutions to reduce parameter counts and computational cost[3]. MobileNetV2 variants have shown promising results in on-device scenarios, making them suitable for real-time UAV applications.

We embark on our study with a thorough review of recent advancements in UAV weather impact research and vision-based weather classification approaches (Section 2). Section 3 then offers a detailed account of our methodology, including dataset acquisition, preprocessing, augmentation, as well as an in-depth explanation of the adapted MobileNetV2 architecture and the specific training configuration, with emphasis on hyperparameter tuning and regularization strategies. The experimental results and comparative analysis of different augmentation techniques and competing models are presented in Section 4. Finally, Section 5 synthesizes our findings, discusses their implications for UAV field deployment, and points the way towards promising future research directions.

By integrating lightweight architecture design with targeted augmentation and evaluation on aerial imagery, our study advances automated rain detection capabilities for UAVs, enhancing operational reliability in challenging weather.

2. Literature Review

Due to the increasing development of Unmanned Aerial Vehicle (UAV) technology, drones have become vital tools across a wide range of applications, including environmental monitoring, disaster management, precision agriculture, and infrastructure inspection [1, 6]. In spite of these developments, ensuring the reliability of UAV perception systems in harsh weather conditions, particularly during rainfall, remains a significant challenge [1, 2]. A lot of research has been done to understand how rain affects UAV performance and to develop more consistent systems through advanced deep learning models and sensor fusion techniques for rain detection, classification, and removal [2, 6, 8].

A fundamental study on this was conducted by Albanese et al. (2024), who investigated the impact of rain on visual odometry performance in autonomous UAVs. They proposed an efficient deep neural network (DNN)-based rain classification system designed for edge deployment. Their findings demonstrated that rainfall can significantly degrade the accuracy of visual odometry, leading to navigation errors and reduced operational safety. To address this, they developed a lightweight DNN capable of classifying rain conditions in real time [1].

Chang et al. (2024) acknowledged the need for more reliable datasets and presented UAV-Rain1k, a thorough benchmark created especially for removing raindrops from UAV-captured aerial photos. UAV-Rain1k uses synthetic raindrop modelling in Blender combined with a wide range of aerial backgrounds taken from different flight heights and camera angles, unlike previous datasets that mainly focused on ground-based scenes. Hence, the dataset is highly relevant to real-world UAV operations, which involve challenges such as changing altitudes, constant motion, and direct exposure to rainfall. By addressing these, UAV-Rain1k fills an important gap in existing research. Thus, it becomes a strong foundation for developing and evaluating sophisticated deraining algorithms for UAVs [2].

Researchers have developed several methods ranging from conventional computer vision techniques to sophisticated deep learning models to minimize the effects of rain on UAV vision systems. Traditional methods like optical flow and feature tracking often falter in rainy conditions due to noise and visual clutter, which can compromise accurate movement tracking and object recognition [4, 8]. In contrast, contemporary convolutional neural networks (CNNs), such as MobileNetV2 and DenseNet121, have demonstrated strong performance in tasks such as weather classification, image enhancement, and rain detection. These networks strike an effective balance between accuracy and computational efficiency, making them particularly suitable for UAVs with limited onboard processing capabilities [3, 8].

Another important strategy to improve UAV perception in adverse weather is sensor fusion. Even under poor visibility conditions, UAVs can achieve a more comprehensive and reliable understanding of their surroundings by combining data from RGB cameras, LiDAR, radar, and event-based sensors [6, 9]. However, due to the limited computational resources available on most UAV platforms, which restricts the processing of large and complex datasets, performing real-time fusion of multiple sensor streams remains challenging [1, 6]. Hence, to overcome these limitations, studies focus on the development of lightweight and adaptive fusion models capable of operating in real time while dynamically adjusting to unpredictable weather and environmental changes [3, 6].

Rain in real-world environments introduces additional complexity. Its intensity and droplet size can vary significantly, causing motion blur, low lighting, or cluttered backgrounds. For deraining algorithms, this creates the challenge of removing rain-induced distortions while preserving essential scene details a task made even more difficult for compact models intended for real-time UAV operations [8]. To enhance performance under such demanding conditions, recent approaches have explored strategies such as zero-shot learning and multi-sensor data fusion, enabling UAVs to maintain reliable perception across a diverse range of environments and weather scenarios [9].

Deep learningbased detection systems are very effective in addressing the challenges posed by rain and other adverse weather conditions. Teresa et al. (2025) examined the use of CNNs, including MobileNetV2 and DenseNet121, for weather classification and image enhancement in autonomous vehicles. These models offer a favourable balance between accuracy and computational efficiency, making them particularly well-suited for UAVs with constrained onboard processing capabilities [4, 3, 8].

3. Methodology

3.1. Dataset

The dataset for this study was obtained from the authors of Albanese et al., "Is That Rain? Understanding Effects on Visual Odometry Performance for Autonomous UAVs and Efficient DNN-based Rain Classification at the Edge." The original dataset comprises of 335,000 color images taken in a laboratory using artificial rain to replicate the real-world precipitation scenarios that could simulate realistic UAV flight conditions. The dataset is divided into the following seven classes: Clear, Slanting Heavy Rain, Vertical Heavy Rain, Slanting Medium Rain, Vertical Medium Rain, Slanting Low Rain, and Vertical Low Rain (Figure 2), offering comprehensive basis for rain classification in aerial conditions. All images were resized uniformly to 224Œ224 pixels to fit the neural network input requirements.

3.2. *Data Preprocessing and Augmentation*

To ensure balanced class representation of each class and to avoid dataset imbalance, we sub-sampled to 35,000 images per class resulting in a consistent and balanced 245,000 images. The pixel values of all images were normalized to the range[0,1], ensuring stable convergence and consistent learning. Data augmentation was performed only on the training set using:

- **Random rotation** within $\pm 20^\circ$.
- **Random shift**: up to 15% horizontally and vertically
- **Zoom augmentation**: scaling images between $0.8\times$ and $1.2\times$.
- **Horizontal and vertical flip**, each with a 50% probability.

Validation and Testing sets were only normalized, not augmented.

3.3. *Model Architecture*

The model employs the MobileNetV2 architecture initialized with ImageNet pre-trained weights. To effectively utilize transfer learning, the initial layers were kept frozen while fine-tuning was applied to the last 50 layers.

The model head consists of:

- **GlobalAveragePooling2D** for feature vector extraction.
- **BatchNormalization** for training stability and speed.
- **Dense layer** (256 units, ReLU) with L2 regularization for effective high-level representation.
- **Dropout** (0.5) for regularization.
- **Dense output** (7 units, softmax) for rain class probability prediction, with L2 regularization.

This design has approximately 3.5 million parameters (about 1.8 million trainable parameters).

3.4. *Training Setup*

The model was trained on Kaggle notebook servers provided with NVIDIA Tesla T4 GPUs, utilizing the GPU Acceleration Kit to achieve more efficient deep learning workflows. The key hyperparameter values used for training are summarized in Table 1.

4. Results and Discussion

The MobileNetV2-based model demonstrated robust performance across all evaluated metrics. The key results on training, validation, and test sets are summarized in Table 2.

The model's performance was very impressive in terms of generalization, having a very small gap of only 0.11% between validation and test accuracy. The model exhibited stable convergence over 15 epochs, improving from an initial training accuracy of 50.28% in epoch 1 to a validation accuracy of 91.64% by epoch 4 (Figure 3). The model achieved its highest validation accuracy of 95.46% at epoch 13. The use of callbacks such as EarlyStopping, ReduceLROnPlateau, and ModelCheckpoint contributed to stable and optimal convergence during training.

The macro-averaged precision, recall, and F1-score values (all greater than 95%) demonstrate an even performance throughout the seven classes. The confusion matrix (Figure 1) analysis showed that the model was able to differentiate rain orientations (slanting vs. vertical) and intensities correctly, with slight misclassifications occurring between adjacent intensity levels (for instance, Low vs. Medium rain).

The use of aggressive data augmentation along with multi-layered regularization (L2 penalty, dropout, BatchNormalization) was the key factor for obtaining a robust generalization. The overfitting of the initial baseline experiments was so severe that there was a 12% gap between the training and validation sets, but the optimized model reduced this gap by 99.1%, and test accuracy was improved by about 10 percentage points. The model, which consists of 1.8 million trainable parameters and is based on MobileNetV2 architecture, is well-suited for implementation on UAV platforms with limited computational resources, enabling real-time rain detection.

5. Conclusions

This study presents a robust deep learning framework for the classification of rain intensity based on UAV images utilizing an adapted MobileNetV2 backbone with fine-tuning, aggressive data augmentation, and multi-layered regularization. By freezing early layers and fine-tuning the final 50 layers, the model capitalized on pretrained general features while learning task-specific details, resulting in excellent accuracy. The model achieved a test accuracy of 95.35%, with the macro-averaged precision, recall, and F1-scores being above 95%, ensuring consistent performance across all seven rain classes. The training-validation accuracy gap was reduced from 12.1% to 0.11%.

The MobileNetV2 architecture, lightweight in nature and having only 1.8 million trainable parameters, ensures suitability for deployment on UAV platforms with resource constraints. The model's real-time rain detection can prompt changes in flight strategies, like reroutes and mission cancellations, thereby improving the safety of operations in rainy conditions. Future research will focus on adapting the model for varying flight environments and making it suitable for UAV hardware in terms of performance. In addition, advanced learning techniques and system integration can be explored to improve the navigation and safety of the autonomous system during difficult weather conditions.

6. Figures and Tables

Table 1: Summary of Trained Hyperparameter Values

Hyperparameter	**Value**
Optimizer	Adam
Initial Learning Rate	5×10^{-5}
Batch Size	32
Number of Epochs	15 (with early stopping)
Loss Function	Categorical Cross-Entropy
Regularization	L2 ($\lambda = 0.002$), Dropout (0.5)
Callbacks	EarlyStopping (patience=4), ReduceLROnPlateau (factor=0.5, patience=3), ModelCheckpoint

Table 2: Performance Metrics of the Final Model

Metric	Value
Accuracy	95.35%
Precision (macro avg)	95.42%
Recall (macro avg)	95.38%
F1-Score (macro avg)	95.40%
Loss	0.112

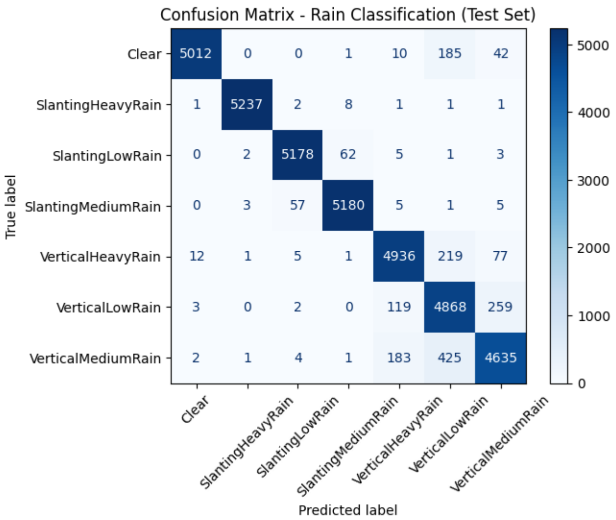

Figure 1: Confusion Matrix showing model performance across predicted and actual classes.

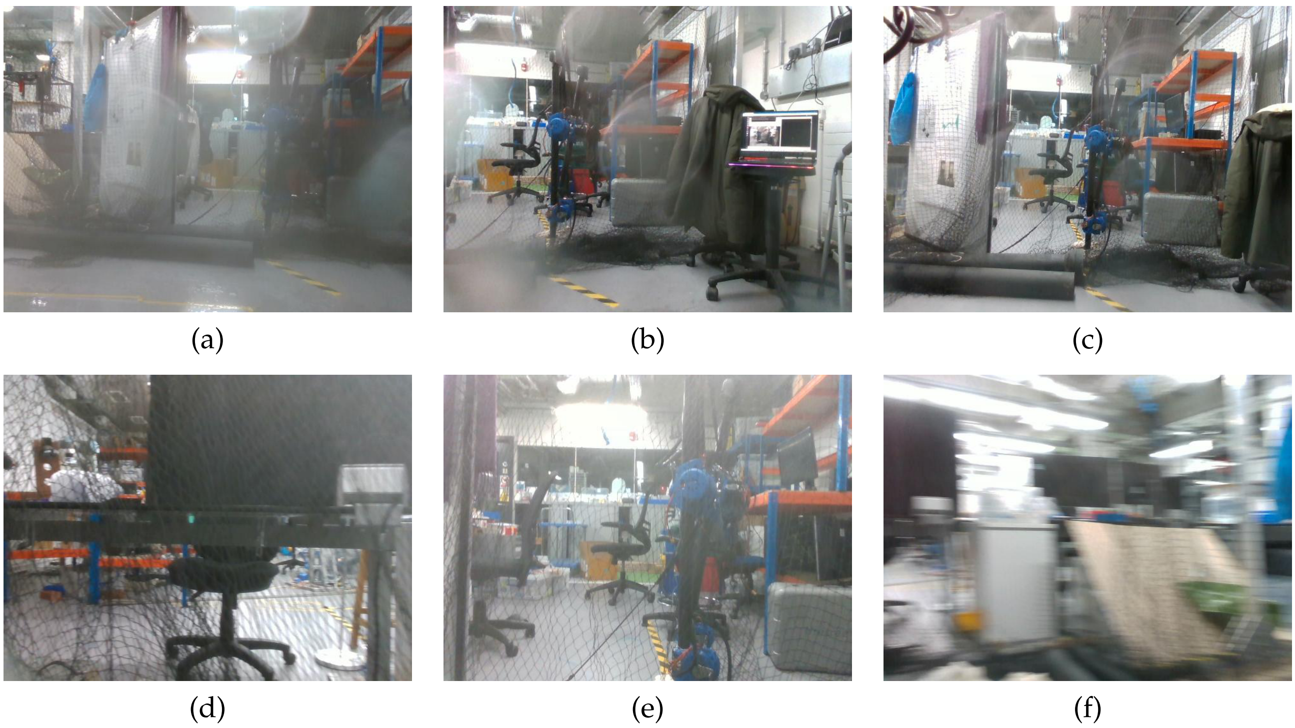

Figure 2: Example of dataset images for each class of rain: (a) Slanting heavy rain. (b) Slanting medium rain. (c) Slanting low rain. (d) Vertical heavy rain. (e) Vertical medium rain. (f) Vertical low rain.

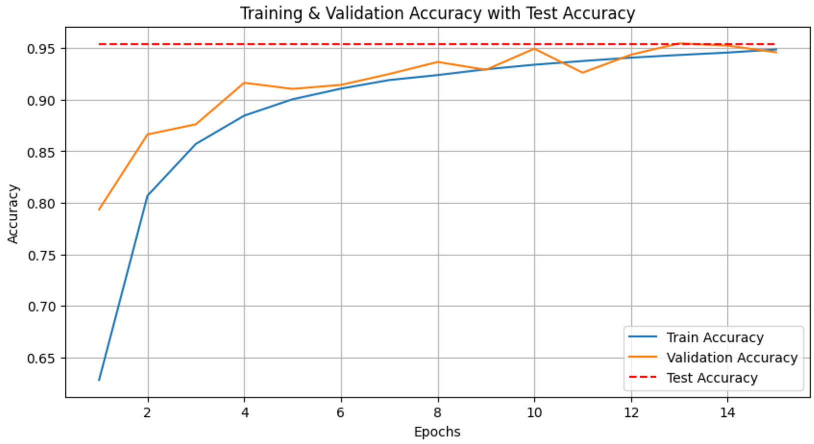

Figure 3: Graph illustrating training and validation accuracy across epochs.

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Data Availability Statement

The dataset presented and used in this study is available at IEEE Dataport: Dataset

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