

Mitigating Transportation Risks: Addressing Safety Challenges in Inclement Weather Conditions

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Abstract— Frequent accidents resulting from adverse weather conditions worldwide have prompted the need for improved safety measures. Tragic events like automobile disasters, train derailments, airline crashes, and ship collisions have been featured in recent headlines. This paper presents deep convolutional neural networks (CNNs), namely Sequential, VGG, and ResNet50 models, for weather condition recognition by utilizing the progress made in deep learning. The dataset used in this study encompasses real-life data collected from Kaggle. The dataset comprises images representing five distinct weather classes, such as Shine, Rainy, cloudy, foggy, and sunrise, emphasizing the practical challenges that any weather classification system must address. With approximately 1500 labelled images, including validation data, the dataset reflects the variability in image dimensions and sizes. Based on the specified class, each photograph is arranged into distinct folders and corresponds to a specific weather category. The analysis of numerous experiments shows that the suggested ResNet50 outperforms Sequential and VGG algorithms in terms of recognition accuracy. This research on deep learning-based weather condition recognition using CNNs addresses the urgent need for enhanced safety measures in transportation, aiming to mitigate frequent accidents caused by adverse weather conditions worldwide, thereby contributing to societal well-being and safety. Moreover, the societal impact extends beyond transportation safety, influencing various sectors dependent on weather-sensitive activities such as agriculture, emergency response, and urban planning.

Index Terms— Accidents, Computer Vision, Image Classification, Transportation safety, Weather detection.

I. INTRODUCTION

Incidents stemming from adverse weather conditions, including car accidents, collision of ship, plane crashes, and train derailments, persistently make headlines worldwide, underscoring the critical issue of safety in adverse weather scenarios. Weather and extreme weather events impact transportation, with evidence showing that heatwaves, storms, heavy rain, floods, and wildfires increasingly affect transport infrastructure, operations, and travel behaviour [1].

From the literature review, we come to know that existing weather detection systems often rely on expensive sensor arrays or human intervention, prompting researchers to explore computer vision techniques for weather classification using single images. While humans find weather assessment from images intuitive, the task poses challenges for autonomous systems, necessitating the development of effective weather classifiers.

This research leverages data collected from kaggle, with approximately 1500 labelled images, the dataset encompasses diverse image dimensions and sizes, further complicating the classification process. Three distinct algorithms, namely Sequential, VGG, and ResNet50, are employed for weather classification. On a scale of 0 to 4, each photograph is assigned a rating that corresponds to cloudy, foggy, rainy, sunny, and sunrise conditions. Advancements in smart transportation technologies have resulted in the deployment of numerous surveillance devices along roadways.[2]. In this study, we investigate and compare the classification performance of three prominent deep learning algorithms, namely VGG, Sequential, and ResNet50, utilizing a dataset comprising 1500 weather images.

The structure of this document is as follows: Following the problem definition, we first offer relevant earlier publications and our suggested approach for comparing the networks selected for the study, together with descriptions of the models and data sets. After that, we provide a thorough analysis of the outcomes gathered from various datasets.

A. Objective

- To evaluate the performance of three distinct deep learning algorithms, namely VGG, Sequential, and ResNet50, in classifying weather images using a dataset comprising 1500 images.
- To determine the classification accuracy, recall of each algorithm to assess their effectiveness in accurately identifying weather conditions.
- To compare the performance of the VGG, Sequential, and ResNet50 algorithms in terms of classification accuracy and other evaluation metrics to identify the most effective algorithm for weather image classification [3].
- Providing insights into their suitability for real-world applications in transportation safety and weather prediction.

To contribute to the advancement of research in intelligent transportation systems and weather prediction by presenting empirical evidence on the performance of state-of-the-art deep learning algorithms in weather image classification tasks.

II. LITERATURE REVIEW

Weather image classification has garnered significant attention from researchers aiming to develop robust algorithms capable of accurately categorizing various weather conditions. In this literature review, we examine the objective, algorithmic approaches, pre-processing techniques, feature selection methods utilized in the field and performance analysis. CNN, in particular, has been quite successful since it performs better in terms of prediction than other machine learning algorithms. Researchers Pin Wang et al. have used two different algorithms, SVM and CCN. In comparing the precision of two algorithms with varying image sizes, the CNN achieved a classification accuracy of 0.71, surpassing the SVM's classification accuracy of 0.62. The performance of CNN and SVM is evaluated and examined under different image dimensions.[4].

Handwritten text and image recognition problems are successfully recognized by CNN. Deep learning, an advancement of machine learning, is made up of several layers that autonomously train by making predictions on and analysing a dataset [5].

Researchers Kamal et al. have used three different algorithms VGG16, VGG19 and ResNet50, the results clearly indicate that this study met expectations and led to highly relevant findings. The VGG-16 architecture proved to be the most effective for medical image classification, demonstrating superior performance compared to the VGG-19 and ResNet50 architectures [6].

Researcher Patryk Młodzianowski et al. have evaluated the performance of various deep learning models in weather image classification tasks. Among these models, ResNet50, MobileNetV2, and InceptionV3 have demonstrated notable capabilities. In a study utilizing a dataset comprising six classes of poor quality images, these models achieved accuracies ranging from 70% to 73%. However, when tested on a higher quality dataset consisting of four classes, the accuracies increased significantly to 95% to 97%[7].

Previous comparative studies have evaluated the performance of different deep learning architectures, including VGG, Sequential, and ResNet50, in various image classification tasks. These studies have analysed the strengths and weaknesses of each architecture in terms of classification accuracy, computational efficiency, and generalization capabilities [8]. Research exploring the application of image classification techniques in transportation safety has gained prominence in recent years. Studies have investigated the potential use of deep learning algorithms for detecting hazardous weather conditions, road obstacles, and traffic congestion, aiming to enhance safety measures and mitigate risks in transportation systems [9].

Despite significant advancements in deep learning-based image classification, challenges such as dataset variability, model interpretability, and scalability remain areas of ongoing research. Furthermore, Lack of appropriately annotated large-scale data sets [10]. Future studies may focus on addressing these challenges through the development of innovative algorithms, improved dataset curation techniques, and enhanced evaluation methodologies [11].

III. DATASET

In deep learning algorithms, data is crucial, and this is also true for the weather recognition problem in this paper. The size of the datasets has a significant impact on the deep neural network's recognition performance. Dataset link <https://www.kaggle.com/datasets/vijaygiitk/multiclass-weather-dataset/data?select=dataset>.

TABLE I. DETAILS OF WEATHER DATASET

Class	Shine	Rainy	Cloudy	Foggy	Sunrise
Number of Images	250	300	300	300	350

As show in table 1 displays this dataset's details. There are total 1500 weather photos in all in this dataset, which are broken down into five categories: shine, cloudy, rainy, shine, and sunrise as show in Figure 1(a), (b), (c), (d) and (e). The majority of these photos are gathered from the Internet and chosen in accordance with the given specifications. Aerial photography, camera, news, traffic accidents, and vehicle data recorder are among the image modes. Since the purpose of this dataset collection is to recognize the weather, the majority of the photographs include intricate scenes including open spaces, farms, freeways, cities, and jungles.. Figure 1 shows four samples of weather images from the dataset. This dataset offers some generalization and universality because it includes a big number of weather photos from each category and a range of complicated settings shot from numerous viewpoints. Large-scale datasets are typically required for deep learning methods in order to prevent overfitting during the network learning process.



Figure 1(a). Shine



Figure 1(b). Rainy



Figure 1(c). Cloudy



Figure 1 (d). Foggy



Figure 1(e). Sunrise

Fig 1. Samples for different weather condition

IV. METHOD

Employed three distinct algorithms for image classification: Sequential, VGG16, and ResNet50. Each algorithm was implemented and evaluated to determine its effectiveness in classifying weather images accurately. We chose the Sequential, ResNet50, and VGG algorithms for weather image classification based on several factors: Architectural Complexity and Performance: Generally acknowledged deep learning architectures ResNet50, VGG, and Sequential are well-known for their efficiency in image classification applications. Because ResNet50 and VGG are deeper networks than Sequential, they can possibly achieve higher classification accuracy by capturing more detailed characteristics from photos.

Previous Research and Benchmarking: These algorithms have been extensively studied and benchmarked in various image classification tasks, including weather classification. Research literature often reports their high performance and accuracy in classifying images across different domains, making them natural choices for weather image classification.

Overall, the selection of Sequential, ResNet50, and VGG algorithms for weather image classification was driven by their proven performance and architectural flexibility.

A. Sequential Algorithm

The Sequential algorithm serves as a fundamental deep learning model for image classification. It consists of a linear stack of layers, enabling straightforward architecture design. In our implementation, the Sequential model comprised convolutional layers, activation functions, pooling layers, and fully connected layers. We configured the model's architecture to suit our weather image classification task, aiming to capture relevant features from input images [12].

B. VGG16 Algorithm

VGG16 is a convolutional neural network (CNN) model that won the 2014 ILSVRC (ImageNet) competition. Its most notable characteristic is its emphasis on using 3x3 convolution layers with a stride of 1, along with consistent padding and a max-pooling layer with a 2x2 stride and 2 filters, instead of relying on a large number of hyperparameters [13].

C. ResNet50 Algorithm

Gradient problem in deep networks can be solved by ResNet50, which is a deep residual neural network architecture. It features skip connections that facilitate the training of very deep networks. In our implementation, we employed a pre-trained ResNet50 model and fine-tuned it for weather image classification. The ResNet50 architecture enabled effective feature extraction and classification, contributing to improved classification accuracy.

For each algorithm, we conducted extensive experimentation, including hyperparameter tuning and model optimization, to maximise classification performance. The models were trained using labelled weather image data and validated using separate validation sets to assess their generalization capabilities. The evaluation metrics included accuracy, F1-score, precision, and recall providing comprehensive insights into the performance of each algorithm in classifying weather images accurately and efficiently [14].

V. EXPERIMENTAL RESULTS

In order to verify the validity of the method in this paper. Conducted experiments to evaluate the performance of three distinct algorithms, namely VGG, Sequential, and ResNet50, in classifying weather images using a dataset comprising 1500 images. We divided the dataset into training and validation sets using a standard 80-20 split, ensuring that both sets contained a representative distribution of weather images.

Each algorithm was trained using the training set and evaluated using the validation set to assess its classification accuracy and performance. We employed standard evaluation metrics including accuracy quantify the performance of each algorithm. used colab for experimentation. we selected accuracy as our primary performance metric due to its intuitive interpretation, relevance to the image classification task, balanced evaluation across all classes, and widespread usage in classification tasks and benchmark evaluations. Accuracy is determined by the ratio of correctly classified instances to the total number of instances, offering a clear metric for assessing the model's success in predicting image categories . We choose accuracy because of; an accuracy is the most commonly used and often the primary choice for evaluating algorithm performance in classification tasks. However, despite its widespread use, accuracy may not be the most suitable performance metric in certain situations, particularly when the target variable classes in the dataset are imbalanced [15].

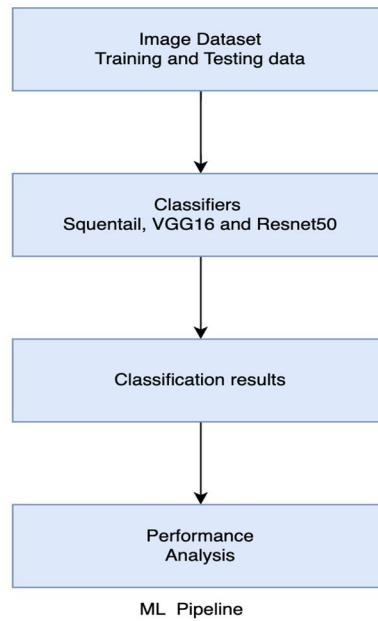


Figure 2. ML Pipeline

Figure 2 shows different phases like preparing and split image datasets for training and testing. Selecting classifiers like sequentials, VGG16, and ResNet50. Obtaing classification results from the chosen classifiers. And, analyze performance using metrics and visualizations.

Accuracy is a performance metric in machine learning that quantifies the proportion of correctly classified instances relative to the total instances in the dataset, offering a straightforward and intuitive gauge of model effectiveness.

$$\text{Accuracy} = (\text{Number of correct Predictions}) / (\text{Total Number of predictions})$$

OR

$$\text{Accuracy} = (\text{True Positive} + \text{True Negative}) / (\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative})$$

TABLE II. METHOD AND ACCURACY (MAKE IS RESULT TABLE)

Method	Accuracy
VGG16	92%
Sequential	96%
Resnet50	97%

As shown in TABLE II, the results indicate that all three algorithms achieved high classification accuracy, with ResNet50 demonstrating the highest accuracy of 97% , followed by Sequential at 96%, and VGG at 92%.

The superior performance of ResNet50 and Sequential compared to VGG suggests that deeper neural network architectures and advanced techniques such as skip connections contribute to improved classification accuracy.

While VGG achieved a lower accuracy compared to the other models, its performance is still commendable, indicating the effectiveness of its architecture in image classification tasks [16].

Further analysis of precision, recall, and will provide deeper insights into the algorithms' performance across different weather classes, enabling us to identify areas for improvement and optimization.

In conclusion, the experimental results underscore the effectiveness of deep learning algorithms, particularly ResNet50 and Sequential, in accurately classifying weather images. These findings pave the way for the development of robust weather classification systems essential for enhancing transportation safety and mitigating weather-related risks.

VI. SIGNIFICANCE

The advanced weather prediction models and safety protocols, that can be applied in real-world transportation scenarios to enhance safety and security. By addressing these challenges, we can improving transportation safety and minimizing the risks posed by adverse weather conditions.

VII. CONCLUSION

In summary, our research demonstrates the effectiveness of deep learning algorithms like VGG16, ResNet50 and Sequential in accurately classifying weather images. These models offer valuable insights for improving transportation safety and weather prediction. While our findings highlight challenges such as dataset size and model interpretability, they underscore the potential of deep learning in advancing transportation systems. Further exploration and optimization in this area hold promise for creating safer and more resilient transportation networks. In the future, leveraging advancements in intelligent transportation and computer vision, autonomous systems will seamlessly assess weather conditions from single images, revolutionizing safety measures in transportation worldwide. As research progresses, addressing the complexities of real-life data sources and licensing issues will be crucial for developing robust and universally applicable weather classification systems.

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