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Comparative Study of Traditional Convolutional Neural Network (CNN) And MobileNet Architecture for Weather Detection

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Abstract:

This research is a comparative study of Traditional Convolutional Neural Network (CNN) and MobileNet architecture for effective weather condition detection. An open-source dataset of high-quality weather images captured from different weather conditions was used for this study. The method adopted in this study involves the training and validation of CNN and MobileNet models to classify weather conditions such as cloudy, foggy, rainy, snowy, and sunny. The research objective is to compare the performance of CNN and MobileNet models in accurately classifying weather conditions and identifying the strengths and limitations of each approach using metrics such as precision, recall and f1-score. The results indicate that while both CNN and MobileNet models achieved high overall accuracy in weather classification, there were differences in their performance across specific weather classes. CNN with augmented images demonstrated superior speed and efficiency in inference, with an average accuracy of 96% across the various weather classes, thereby making it well-suited for deployment on resource-constrained devices. However, MobileNet models exhibited incredibly low accuracy, especially in detecting or properly classifying weather conditions when inputting new images. These findings provide insights into the suitability of CNN and MobileNet architectures for weather classification tasks and offer guidance for future research and application development in this area.

Keywords — **Weather classification, Convolutional neural networks, MobileNet, Image classification, Machine learning, Deep learning.**

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I. INTRODUCTION

Weather conditions are an important aspect of everyday life. It is involved in different areas including agriculture, transportation, emergency management and urban planning. The ability to accurately detect and identify weather conditions is essential for ensuring safety, optimizing resource allocation, and mitigating potential risks associated with adverse weather events. Over the years, advancements in technology and data science have facilitated the development of sophisticated methods for weather condition detection and identification, leveraging diverse datasets and innovative algorithms [1]. Weather condition classification plays a crucial role in various applications such as transportation systems, outdoor activities scheduling, and agriculture [2, 3, 4].

This paper is focused on the detection and identification of weather conditions using a deep-learning approach. The main aim is to contribute to the existing body of knowledge by exploring the use of Convolutional neural networks and Transfer learning from pre-trained MobileNet networks. This approach helps to accurately recognize and classify different weather phenomena, thereby enhancing the understanding of atmospheric dynamics and improving the reliability of weather forecasting systems.

Accurate detection and identification of weather conditions are crucial for several reasons. Primarily, they aid in improving public safety by providing timely warnings and alerts about severe weather events. Additionally, these techniques play a significant role in optimizing various sectors' operations, such as transportation planning, where knowledge of weather conditions can help mitigate risks and enhance efficiency. Moreover, weather condition detection contributes to scientific research by providing valuable insights into atmospheric processes and climate patterns. Detecting and identifying weather conditions pose several challenges due to the complex and dynamic nature of atmospheric processes. One of the primary challenges is the inherent variability and unpredictability associated with weather patterns, which can lead to uncertainties in observation and prediction. Additionally, the presence of various atmospheric phenomena, such as clouds, precipitation, and wind patterns, further complicates the task of weather condition detection.

Furthermore, the quality and coverage of available data sources can significantly impact the accuracy of weather detection algorithms. While traditional weather monitoring systems provide valuable information, they may suffer from spatial and temporal limitations, especially in remote or underserved regions. Moreover, the integration of heterogeneous data sources, including satellite imagery, ground-based sensors, and numerical weather models, requires sophisticated data fusion techniques to ensure robust and reliable detection of weather conditions. Detecting weather conditions from images poses unique challenges due to the inherent complexity and variability of atmospheric phenomena. Factors such as lighting conditions, cloud formations, and visibility levels can significantly affect the interpretation of images. Moreover, distinguishing between different weather conditions, such as identifying fog from clouds or discerning between various levels of cloud cover, requires robust feature extraction and classification algorithms.

However, the availability of high-resolution imagery, coupled with advancements in machine learning techniques, presents exciting opportunities for improving weather condition detection accuracy. By leveraging deep learning models and convolutional neural networks (CNNs), researchers can extract intricate patterns and features from images, enabling more precise classification of weather conditions.

Weather condition detection and identification are vital tasks in meteorology, impacting various sectors such as transportation, agriculture, and disaster management. With the advent of advanced technology and the availability of diverse datasets, researchers are continuously striving to improve the accuracy and efficiency of weather prediction models. In this paper, we focus on the detection and identification of weather conditions using a dataset comprising images captured in Rome under five distinct weather conditions: Sunny, Rainy, Cloudy, Foggy, and Snowy.

II. Literature Review

There has been similar research conducted in the artificial intelligence domain for classifying weather conditions. In previous research [2], Weather image classification was conducted using CNN with Transfer Learning. The aim was to classify weather images with four CNN architectures. Xception achieved the best accuracy of 90.21% with 10,962 seconds. MobileNetV2 had the fastest training time of 2,438 seconds with 83.51% accuracy. Hence, there is room for improvement in the accuracy. Also, the model was limited to 50 epochs due to training time constraints. Automated weather classification has been conducted from outdoor images using deep neural networks. The Framework is based on transfer learning for efficient weather image classification. InceptionV3 model with Logistic Regression yielded 97.77% accuracy [3]. The limitation of this work is the processing power and large datasets needed for CNN training.

ResNet152V2 architecture was used in weather classification involving a Dataset with 6877 images of eleven weather conditions. The model uses pre-trained ImageNet weights and performs batch normalization. The model achieved 88% accuracy in weather classification which serves as a reference for future weather classification research. The train accuracy results are not remarkably high which means there is room for improvement in the model's layer structure and enhancement of feature extraction layers [4]. Research on the RFS Dataset with rain, snow, and fog images was conducted by carrying out data augmentation with Super pixel masks and different Convolutional Neural Networks for feature extraction of the Diverse nature of weather conditions. An Overall mAP for models is between 68 and 81 while ResNet 50 architecture performs best in all settings. The major challenge of this method is the absence of discriminate features among weather conditions [5].

Weather classification based on cloud imagery using Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) (PCA + LDA) achieved 96% accuracy. The feature extraction made use of Euclidean Distance. However, the classification only considered a limited number of weather conditions namely bright, cloudy, and rainy [6]. Self-supervised Spatiotemporal Contrastive Learning for weather system classification was used to address the challenges of lack of labels and inaccurate similarity measures. It was observed that the SCL model outperforms traditional classification methods [7]. In another research in 2022 [8], Support Vector Machine (SVM) and Logistic Regression (LR) was used to create a multi-class classification system for weather forecasting. More importantly, two strategies, One-Against-One (OAO) and One-Against-All (OAA), are evaluated within the SVM and LR frameworks to predict weather conditions. In addition to SVM and LR, the study also considers the effectiveness of Random Forest (RF) and k-Nearest Neighbours (k-NN) algorithms for weather prediction. The linear SVM model under the OAO strategy emerges as the most successful, achieving high levels of Accuracy, Precision, Recall, F-Measure, and Area Under Curve (AUC) for weather condition forecasting [8]. In another work, different weather conditions are classified based on visual effects using features like autocorrelation of pixel intensities and rain/snow streak lengths, showing effective classification results in outdoor video analysis and computer vision [9], this tends towards real-time analysis of weather condition as opposed to prediction.

III. METHODOLOGY

Figure 1 shows the methodological approach. The weather condition detection methodology begins with data curation. Data representation of different weather conditions was gathered from an open-source database. This includes pictures that were previously captured in the city of Rome showing five different weather conditions such as:

i. Sunny
ii. Rainy
iii. Cloudy
iv. Foggy
v. Snowy

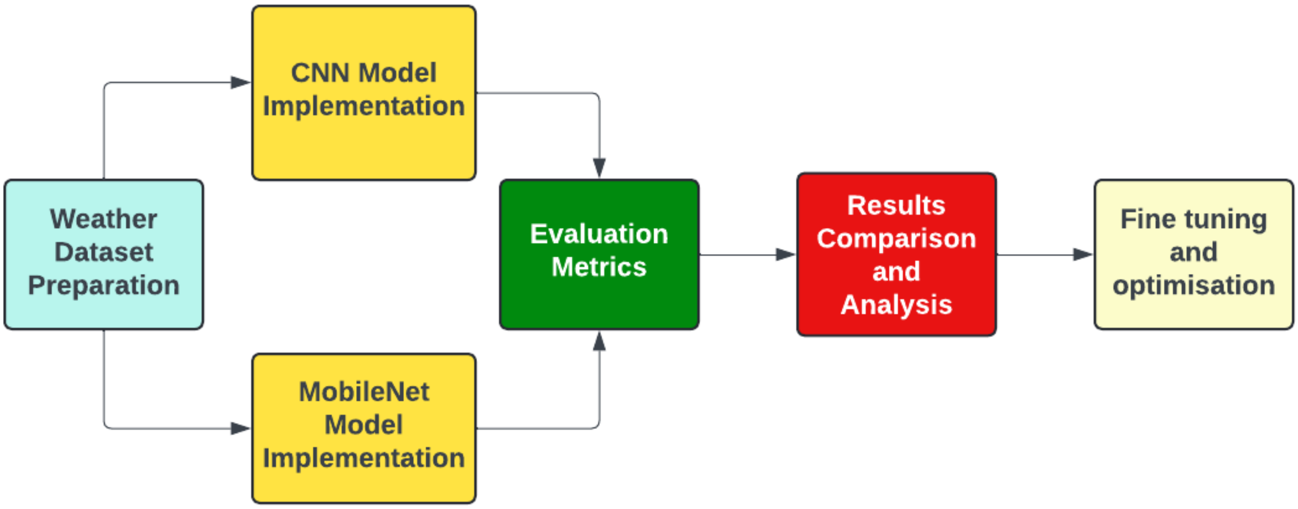

Fig.1. Methodology for Weather Condition Classification

The dataset is organized into separate directories for each class. The dataset is then split into distinct groups of training, validation, and test sets. This helps to ensure a balance in the image distribution across the various classes of weather conditions. Also, the original image dataset contains a total of 250 images, each class having fifty images. However, data augmentation approaches were used to increase the number of images to 2450 images in total. The augmentation is achieved by modifying original images through rotation, shifting (height and width), shearing, zooming, horizontal flipping, and filling. The ImageDataGenerator python library was used as it has the capability of carrying out image augmentation by generating new images.

A. *CNN Model Implementation*

A Convolutional neural network (CNN) is implemented for learning features in the weather image dataset. The CNN makes use of convolutions to understand different classes of predetermined weather conditions. The model is built using Python TensorFlow. The directories of the images are defined. The batch size is also defined to depict the number of image samples to be processed before updating the model during training, this was set at 32. The target size for the images is set at 64 x 64 since the original images have varying dimensions, hence this helps to ensure uniformity. The model class mode is set to categorical since the weather condition detection is a multi-class problem. Image data generation is implemented within the model to augment the images. This is done at the preprocessing stage. Batches of image data are generated from the training images for training and validation. Eighty percent of the image is used for training and 20% for validation.

The architecture of the CNN model is sequential. Convolutional layers with ReLU activation are used in the architecture, followed by max-pooling layers to trim the feature maps. The output of the convolutional layers is passed through a dense fully connected layer also with ReLU activation. For predicting the final weather condition, a softmax activation function is used. Adam optimiser is used to compile the model and save it in .Keras extension format. In other words, the CNN model is trained and validated using performance metrics such as F1 score, precision, recall and confusion matrix. In addition, hyperparameters of the CNN model such as learning rate, batch size, and number of layers, are tuned to optimize performance. The model summary is seen in Table 1.

TABLE 1. CNN MODEL DESCRIPTION FOR WEATHER CLASSIFICATION

Model component	Description
Architecture	Convolutional Neural Network (CNN)
Input Size	64x64 pixels
Classes	[List of classes]
Activation	ReLU
Optimizer	Adam
Loss Function	Categorical Cross-Entropy
Metrics	Accuracy
Training Data	Augmented Images
Validation Data	Separate Validation Set
Data Augmentation	Random rotation, shearing, zooming, horizontal flipping
Batch Size	32
Epochs	20

B. Transfer Learning with MobileNet

MobileNet is a pre-trained neural network that has been trained on large-scale image datasets like ImageNet. To adapt to MobileNet, the top classification layers of the pre-trained MobileNet model are removed and replaced with new dense layers. Also, we freeze the convolutional layers of the pre-trained models to retain the learned features and prevent overfitting. Next, we train the modified pre-trained models using the training set and fine-tune the top layers while keeping the convolutional layers frozen. Finally, validation of the performance of the pre-trained MobileNet model is done using the validation set and hyperparameters are adjusted as needed.

C. Evaluation Metrics

Evaluation of the performance of both the CNN model and the MobileNet-based transfer learning model is done using appropriate evaluation metrics such as accuracy, precision, recall, and F1-score. A comparison of the performance of the models across different weather condition classes and several images is done to assess their robustness and generalization ability.

IV. RESULTS AND DISCUSSIONS

A. CNN Model Original Dataset

The original data set of 250 images was used to train the CNN model and the training/validation progression is seen in Figure 2.

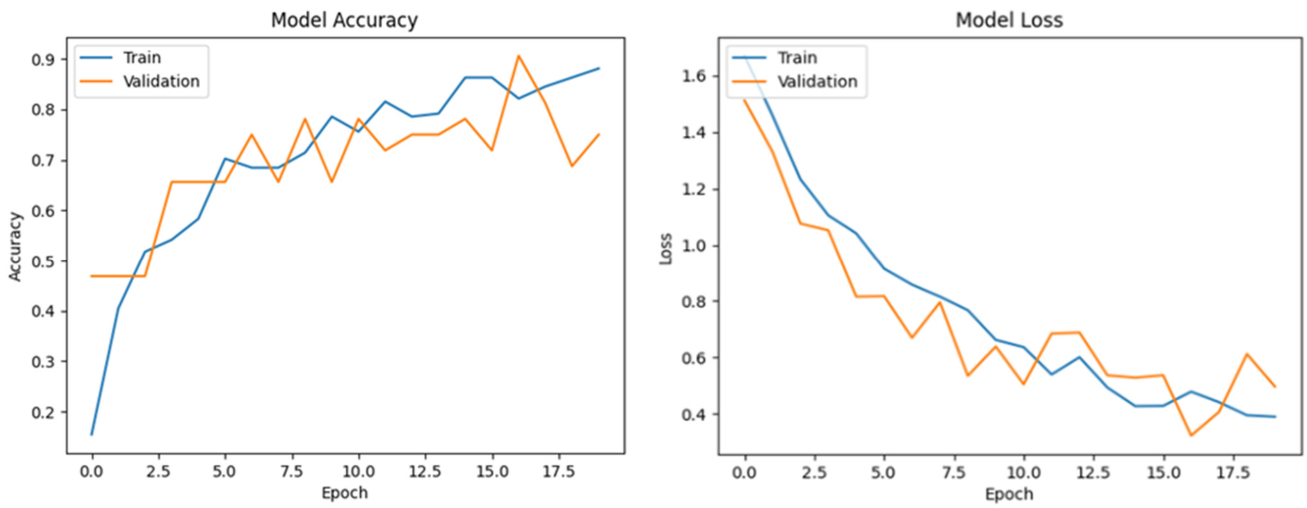

Fig.2. CNN Model Training and Validation on The Original 250 Dataset

Table 2 fully gives the details of the CNN model's performance on fifty images for each weather category, revealing distinct patterns in precision, recall, F1-score, and support metrics. Precision values indicate the model's accuracy in identifying positive instances within each weather class, with notable strengths observed in Foggy (0.91), Rainy (0.97), Snowy (0.87), and Sunny (0.87) conditions. On the contrary, Cloudy conditions exhibit lower precision at 0.69, suggesting potential challenges in classification.

TABLE 2. EVALUATION METRIC FOR CNN MODEL ON ORIGINAL 250 DATASET

Class	Precision	Recall	F1-score	Support
Cloudy	0.69	0.84	0.76	50
Foggy	0.91	0.98	0.94	50
Rainy	0.97	0.58	0.72	50
Snowy	0.87	0.92	0.89	50
Sunny	0.87	0.90	0.88	50
Accuracy			0.84	250
Macro avg	0.86	0.84	0.84	250
Weighted avg	0.86	0.84	0.84	250

Additionally, recall values highlight the model's ability to capture all relevant instances of a given class, with Foggy (0.98), Snowy (0.92), and Sunny (0.90) conditions demonstrating robust performance. However, recall for Rainy conditions is notably lower at 0.58, indicating difficulties in accurately identifying rainy weather instances. This fact is buttressed by the representation of the confusion matrix as seen in Figure 3. These findings underscore the unique characterisation of the model's performance across different weather categories, emphasizing areas for improvement and providing valuable insights for further refinement in weather classification tasks.

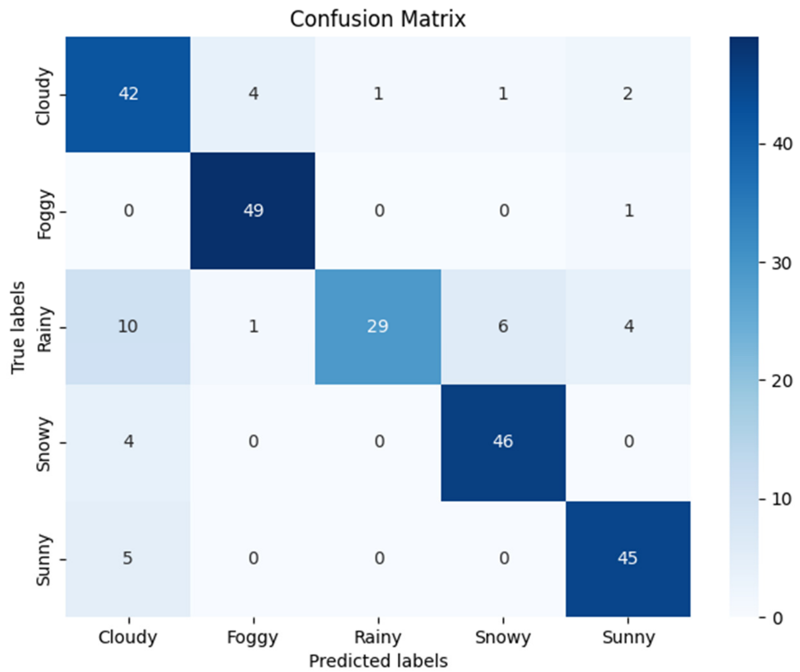

Fig.3. Confusion Matrix of CNN Model on Original 250 Dataset

B. CNN Model Augmented Dataset

Here, new datasets were generated from the original dataset to increase the number of images to 2500 Using the designed CNN, the model accuracy and loss graph is represented in Figure 4.

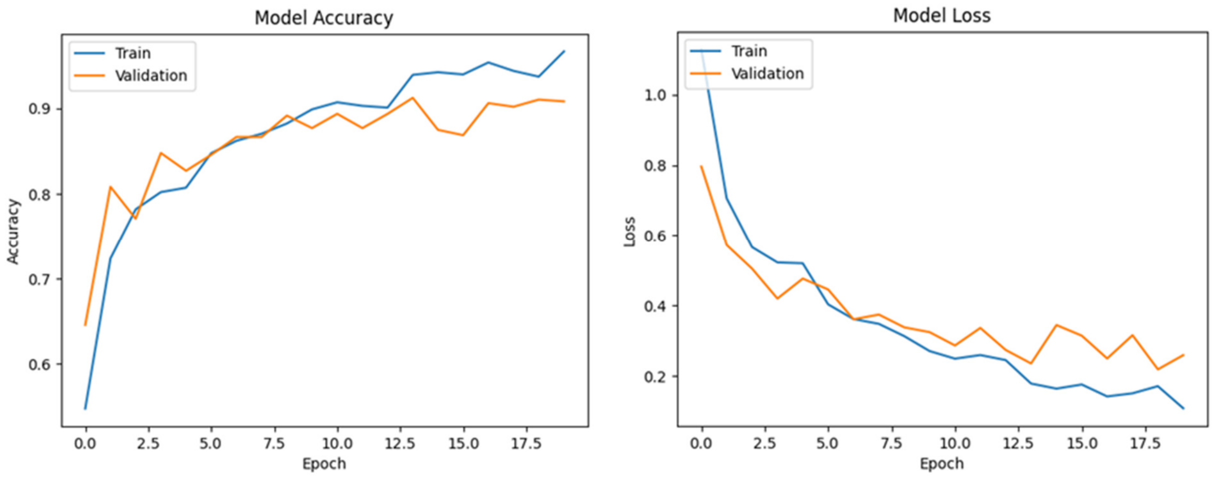

Fig.4. CNN Model Training and Validation on Augmented 2450 Dataset

Table 3 summarizes its performance across different weather conditions, indicating high precision, recall, and F1-score values for Cloudy (0.90, 0.97, 0.93), Foggy (0.99, 0.99, 0.99), Rainy (0.95, 0.93, 0.94), Snowy (0.99, 0.97, 0.98), and Sunny (0.99, 0.95, 0.97) conditions. The model achieves an overall accuracy of 0.96, with macro and weighted average scores also at 0.96, reflecting consistent performance across all classes.

TABLE 3. EVALUATION METRIC FOR CNN MODEL ON AUGMENTED 2450 DATASET

Class	Precision	Recall	F1-score	Support
Cloudy	0.90	0.97	0.93	488
Foggy	0.99	0.99	0.99	491
Rainy	0.95	0.93	0.94	492
Snowy	0.99	0.97	0.98	491
Sunny	0.99	0.95	0.97	488
Accuracy			0.96	2450
Macro avg	0.96	0.96	0.96	2450
Weighted avg	0.96	0.96	0.96	2450

These results demonstrate the model's effectiveness in accurately classifying various weather conditions, with minimal discrepancies between individual class performances. This is evident in the confusion matrix in Figure 5

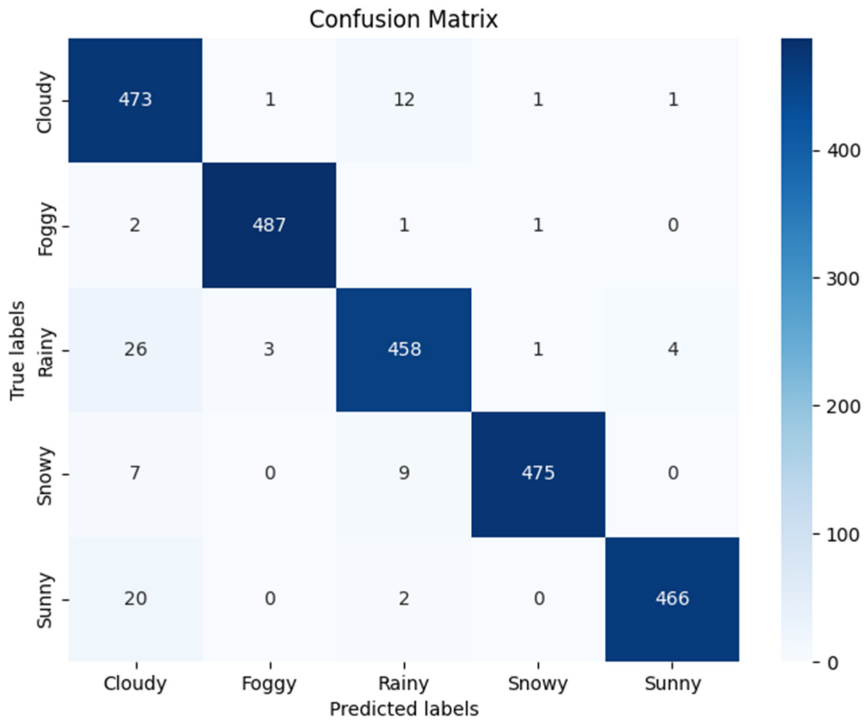

Fig.5. Confusion Matrix of CNN Model on Augmented 2450 Dataset

C. 4.3. MobileNet Model Original Dataset

Using the Original dataset of fifty images in each class on the MobileNet transfer learning approach, the model accuracy and loss are seen in Figure 6.

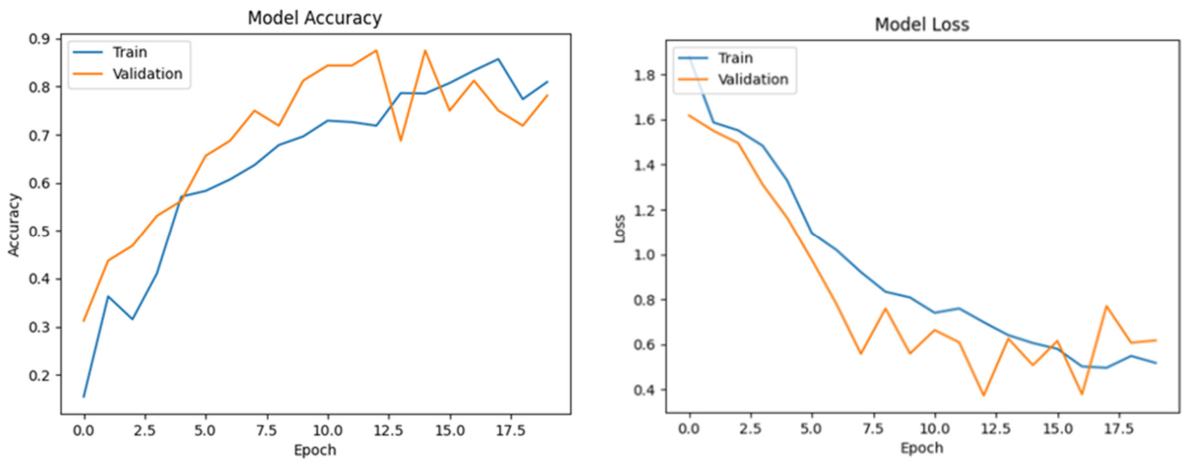

Fig.6. MobileNet Model Training and Validation on The Original 250 Dataset

Table 4 illustrates the model's performance across different weather conditions, showing precision, recall, and F1-score metrics. However, the results indicate low values for Cloudy (0.06, 0.10, 0.07), Foggy (0.11, 0.10, 0.11), Rainy (0.33, 0.10, 0.15), Snowy (0.17, 0.20, 0.18), and Sunny (0.38, 0.30, 0.33) conditions. The overall accuracy stands at 0.16, with macro and weighted average scores also at 0.16, suggesting limited performance across all classes. These findings highlight challenges in accurately classifying weather conditions, indicating areas for improvement in model training or dataset augmentation to enhance classification accuracy. The confusion matrix for this is seen in Figure 7.

TABLE 4. EVALUATION METRIC FOR MOBILENET MODEL ON ORIGINAL 250 DATASET

Class	Precision	Recall	F1-score	Support
Cloudy	0.06	0.10	0.07	10
Foggy	0.11	0.10	0.11	10
Rainy	0.33	0.10	0.15	10
Snowy	0.17	0.20	0.18	10
Sunny	0.38	0.30	0.33	10
Accuracy			0.16	50
Macro avg	0.21	0.16	0.17	50
Weighted avg	0.21	0.16	0.17	50

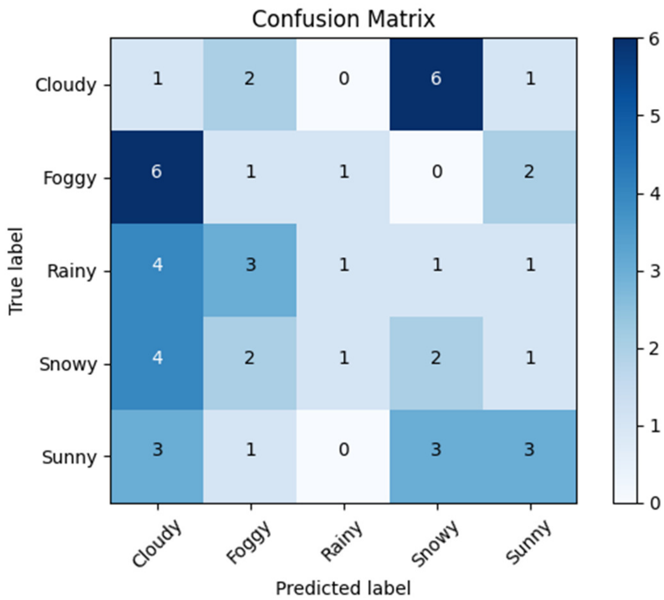

Fig.7. Confusion Matrix of CNN Model on Original 250 Dataset

D. MobileNet Model Augmented Dataset

Table 5 summarizes the performance metrics when the dataset is augmented to 2500?? across the different weather conditions. The training and validation progress is seen in Figure 8 depicting the model accuracy and loss.

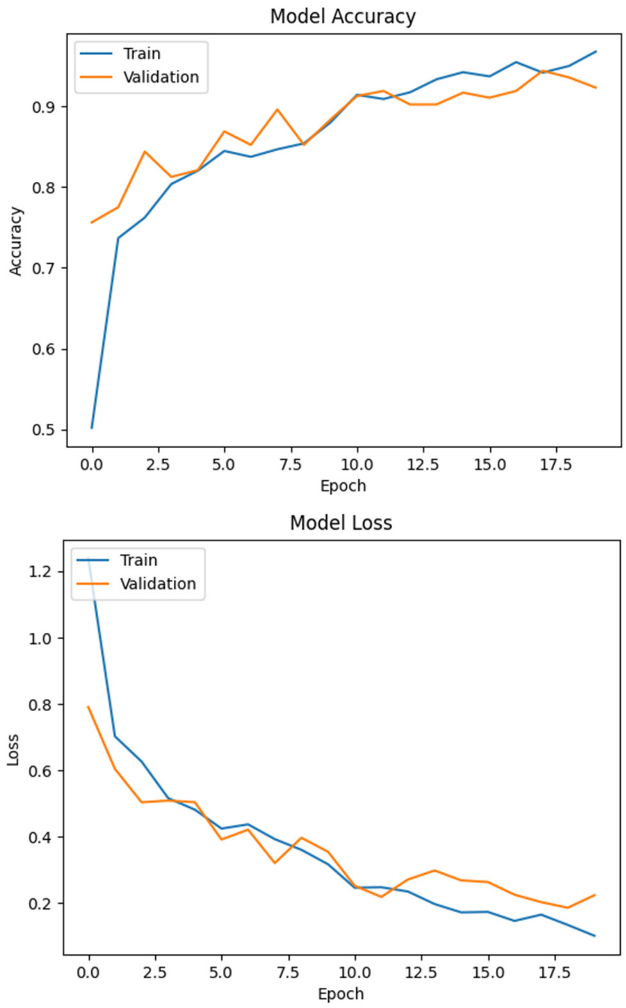

Fig.8. MobileNet Model Training and Validation on Augmented 2450 Dataset

Table 5 shows the metrics for different weather classes, including precision, recall, and F1-score, along with the support for each class. The precision values range from 0.17 to 0.21, indicating the proportion of correctly predicted positive instances within each class. Similarly, recall values range from 0.15 to 0.23, representing the proportion of relevant positive instances captured by the model.

The F1-score, a harmonic mean of precision and recall, ranges from 0.16 to 0.22, providing a balanced assessment of the model's performance. Despite variations across classes, the overall accuracy is reported at 0.19, reflecting the model's ability to correctly classify approximately 19% of instances across all classes. Both macro and weighted averages for precision, recall and F1-score align closely with the individual class metrics, indicating a consistent performance trend across the entire dataset. Figure 9 shows the confusion matrix. These findings underscore the model's limited effectiveness in accurately distinguishing between different weather conditions, suggesting potential areas for refinement or additional data collection to improve classification accuracy.

TABLE 5. EVALUATION METRIC FOR MOBILENET MODEL ON AUGMENTED 2450 DATASET

Class	Precision	Recall	F1-score	Support
Cloudy	0.17	0.15	0.16	97
Foggy	0.19	0.19	0.19	98
Rainy	0.21	0.23	0.22	98
Snowy	0.21	0.21	0.21	98
Sunny	0.17	0.15	0.16	97
Accuracy			0.19	488
Macro avg	0.19	0.19	0.19	488
Weighted avg	0.19	0.19	0.19	488

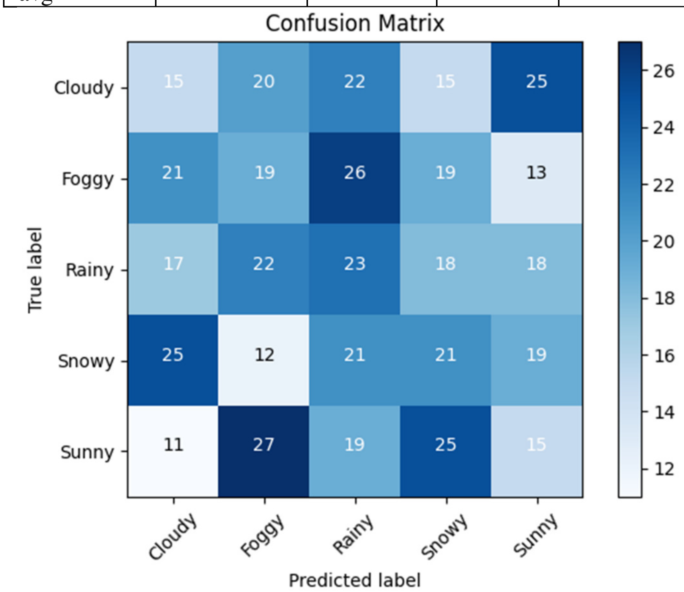

Fig.9. Confusion Matrix of CNN Model on Augmented 2450 Dataset

Table 6 shows a comparison of the different variations of experiments reported in this paper with both CNN and the transfer learning approach of the MobileNet model. The accuracy from the MobileNet training and validation was high but the metrics and confusion matrix shows otherwise. The interpretation of this is that the MobileNet does not generalise well on the dataset, it focuses too much on the training and might cause inaccurate classification or detection with new weather images. Meanwhile, the CNN model generalised well which is evident in the confusion matrix, precision, and recall. However, the best result achieved was with the Augmented-based CNN with 96% average precision.

TABLE 6. COMPARISON OF EVALUATION METRICS OF CNN AND MOBILENET MODEL

Model	Data amount	Average Precision	Average recall	Average F1 score
CNN	250	0.86	0.84	0.84
CNN	2450	0.96	0.96	0.96
MobileNet	250	0.21	0.16	0.17
MobileNet	2450	0.19	0.19	0.19

V. Conclusion

The convolutional neural network provided better results on the weather condition image dataset. Even more, there was a 96% accuracy on augmented images when compared to the 86% accuracy of the original image dataset with the same CNN. The MobileNet transfer learning model had good training and validation but poor recall and precision on both original images and augmented images. The confusion matrix also corroborates these findings. The CNN model is very accurate, hence useful for integration into real-life applications such as agriculture weather monitoring, transportation, construction, renewable energy, and emergency management amongst others. A previous research [2] conducted similar study on the dataset with 5-cross validation, but the best accuracy was 90.21%. Another research achieved 96% accuracy but involved the hybridisation of

Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) [4] with only three predicted classes. In contrast, the performance of Support Vector Machine (SVM) and Logistic Regression (LR) was studied in another weather classification research [8]. Comparison of the performance of neural networks and K-nearest neighbour in another research has also shown the efficacy and significance of comparative analysis of algorithms when it comes to choosing a machine learning method for weather detection [10].

The implementation of the new EfficientNet and Dual Attention Block model in another work achieved a high accuracy of 96.73% in classifying weather images using a dataset of 1530 images [11]. This further affirms the basis behind the increase in accuracy of our model when the number of datasets increases. Very severe weather conditions have also proven to be detected with deep learning techniques as such used in this research, especially with a high number of datasets [12]. There has also been evidence of weather classification systems without the use of manual labels. A method called Self-Supervised Spatiotemporal Contrastive Learning (SCL) outperformed traditional methods [13]. Beyond the usage of images, experiential deicison trees and C-SVM have also been able to classify weather conditions using outdoor video dataset [14]. In terms of practical implementation, a recent research used dashboard camera images to classify road conditions. However, it was limited by the lower classification accuracy of 80% accuracy for binary classification and 68% for three classes [15].

The major limitation of this work is the limited number of image datasets. Even though there were augmentations to increase the number of images to 2450 across the multiple classes, a large number of training and validation sets would have produced a more reliable result. Also, the dataset contains images from the same source, Rome to be specific, there is an uncertain expectation of how the model would respond if it were evaluated with images from a different location. It is therefore suggested that images from heterogeneous sources would be used in subsequent research on weather classification models. Also, it is recommended that preprocessing or image segmentation be done before training to separate the cloud from interfering objects to reduce noise levels.

This research is particularly important because it contributes to the field of AI application to weather understanding, intelligent machine integration and automation of engineering solutions. There is a need to provide machine learning solutions that are trusted and primarily applicable to everyday lives. CNN has proven to be useful for this purpose with a high level of accuracy. As weather conditions continue to impact various aspects of our daily lives, from outdoor events to infrastructure planning and healthcare delivery, the integration of weather condition detectors into decision-making processes becomes increasingly vital. By leveraging advanced technologies like CNNs and MobileNet, we can not only enhance our understanding of weather patterns but also proactively adapt to changing conditions, ensuring resilience and preparedness in the face of environmental challenges. Moving forward, continued research and innovation in weather classification methodologies hold the promise of further improving the accuracy and reliability of predictions, contributing to safer, more efficient, and more resilient communities worldwide.

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