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Attention-Guided Deep CNN for Robust Image-Based Weather Phenomena Classification

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***Abstract*—The rapid growth of computer vision applications has opened new possibilities for automated environmental monitoring and weather forecasting. Accurate recognition of weather phenomena from images is crucial for supporting climate research, improving situational awareness, and enhancing the reliability of intelligent systems in real-world conditions. However, the diverse visual characteristics of natural weather events, such as rain, snow, fog, frost, hail, lightning, etc., make this task highly challenging. In this research, we focus on developing a robust framework for automatically detecting weather phenomena from images. For this purpose, a comprehensive dataset of labeled weather-condition images was used to ensure balanced representation across multiple categories. We present a custom CNN architecture integrated with a Convolutional Block Attention Module, which enhances feature learning by adaptively refining both spatial and channel-wise representations. The proposed CBAM-CNN framework demonstrates superior performance in capturing subtle visual cues associated with different weather phenomena. Experimental evaluation shows that the model achieves a highest accuracy of 87.61%, significantly outperforming baseline CNN models. This study highlights the effectiveness of attention-guided approaches for environmental perception tasks and underscores their potential for advancing intelligent weather monitoring systems.**

***Index Terms*—Weather Classification, Convolutional Neural Network, Convolutional Block Attention Module, Deep Learning**

I. INTRODUCTION

THE growing integration of artificial intelligence (AI) into environmental and meteorological applications has opened new avenues for automated weather understanding and analysis [1]. Among these developments, weather classification has become a vital research area, enabling systems to recognize and interpret atmospheric conditions such as sunny, cloudy, rainy, foggy, snowy, e.t.c. scenes from visual data [2]. Accurate weather recognition plays a critical role across domains such as intelligent transportation, autonomous navigation, climate observation, and outdoor scene interpretation. By leveraging visual cues from the environment, AI-based systems can enhance situational awareness, improve safety, and support real-time decision-making across multiple applications [3]. Traditional weather recognition techniques primarily relied on handcrafted features, such as color histograms, edge descriptors, or texture patterns, which often struggled under varying lighting, seasonal transitions, and overlapping visual conditions. The recent integration of deep learning methods, particularly Convolutional Neural Networks (CNNs), has addressed many of these challenges by automatically learning discriminative spatial representations directly from images [4] [5]. However, despite their success, CNNs tend to emphasize dominant local patterns while neglecting subtle contextual relationships that are critical for distinguishing visually similar weather scenes (e.g., cloudy vs. foggy). To overcome these limitations, attention mechanisms have gained prominence for their ability to adaptively focus on informative regions and features within an image [6]. Building upon this idea, the Convolutional Block Attention Module (CBAM) offers an efficient means of refining feature maps through both channel and spatial attention, thereby enhancing the representational power of CNNs without significant computational overhead. Motivated by this, the present study introduces a CBAM-CNN framework to enhance the accuracy and generalization of weather classification under diverse visual and environmental conditions. The proposed architecture integrates spatial and channel-wise attention mechanisms into the convolutional backbone, enabling the model to focus on weather-relevant features while suppressing irrelevant information. A balanced dataset of diverse weather images was collected from publicly available sources to train and evaluate the model under real-world conditions. `The main contributions of this study` can be summarized as follows: A CBAM-CNN framework is proposed for effective weather classification, leveraging attention mechanisms to enhance feature discrimination and robustness under variable environmental settings. To enhance interpretability, a Grad-CAM visualization was employed to highlight discriminative regions that influence model predictions, providing valuable insights into the decision-making process. The proposed model's performance was thoroughly evaluated using standard metrics such as accuracy, precision, recall, and F1-score, and compared against state-of-the-art baselines. `The remainder of this paper` is structured as follows. Section II reviews existing literature on weather classification by deep learning methods. Section III outlines the dataset preparation and proposed methodology. Section IV details the experimental setup and implementation. Section V presents the results, followed by a discussion of findings and comparative analysis. Finally, Section VI concludes the paper with insights and directions for future research.

II. LITERATURE REVIEW

Extensive research using deep learning and computer vision techniques has been prompted by the growing need for precise weather classification. These approaches aim to classify diverse atmospheric conditions under varying illumination and environmental factors, contributing to advance-

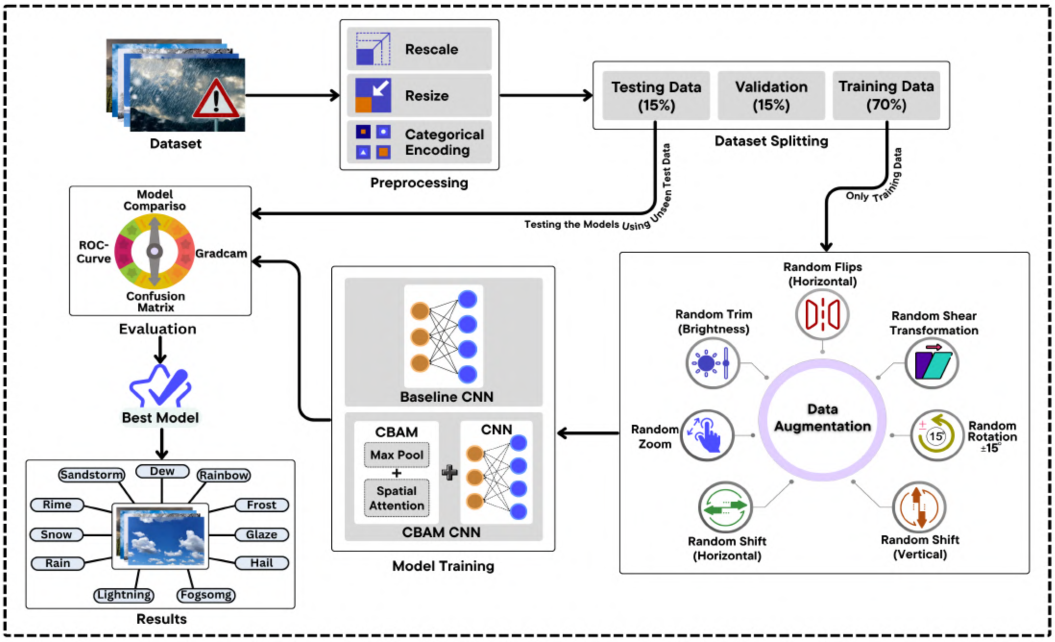

Fig. 1. The Proposed workflow diagram for Weather Phenomenon Classification

ments in automated monitoring and intelligent transportation systems. To better understand the progress and methodologies in this domain, several notable studies on weather classification are reviewed. For instance, *H. Tarwani et al.* [7] conducted research on weather classification using transfer learning with several CNN architectures, including ResNet50V2, EfficientNetB5, and EfficientNetV2S. Their models were trained across multiple weather conditions such as snow, lightning, and haze, demonstrating strong adaptability and robustness through fine-tuning strategies. *S.A. Amiri et al.* [8] focused on improving weather classification performance by systematically enhancing pretrained deep learning models like ResNet50 and EfficientNet variants. Their architectural modifications, involving the use of Global Average Pooling and dropout layers, aimed to reduce overfitting and strengthen generalization across multiple weather categories. *V. Madaan et al.* [9] based their research on weather classification using a fine-tuned VGG19 model trained on multiple visual weather categories. Their approach leveraged transfer learning and optimized hyperparameters to effectively capture distinct visual cues present in different weather conditions. *V. Afxentiou et al.* [10] developed a structured evaluation methodology for weather classification using CNN-based architectures. Their study analyzed various models and datasets to assess classification performance under different adverse weather conditions, particularly for autonomous driving systems. *S. Singh et al.* [11] proposed a deep learning-based weather forecasting model designed to classify and predict meteorological phenomena such as temperature, precipitation, and wind patterns. Their work compared data-driven deep learning models with traditional forecasting techniques to highlight improvements in accuracy and adaptability. *Y. Lv et al.* [12] introduced a hybrid weather classification framework that combined ResNet50-based deep feature extraction with PCA and SVM. This approach effectively captured complex weather patterns and improved classification in visually challenging scenarios. *L. Sivaraman et al.* [13] focused their research on enhancing weather classification in low-light and nighttime environments through a novel framework combining CycleGAN-based domain adaptation and contrastive learning. Their model addressed illumination inconsistencies by transforming nighttime images into day-like representations while preserving weather-specific features. *N. Shelke et al.* [14] developed a deep learning framework using a Fully Convolutional Network combined with Long Short-Term Memory (FCN-LSTM) for real-time weather classification. Their method integrated spatial and temporal features from image sequences to predict weather conditions effectively. Overall, these studies demonstrate significant progress in weather classification through transfer learning, hybrid deep learning architectures, and domain adaptation techniques. However, challenges remain in ensuring model generalization across unseen environments, reducing computational complexity, and maintaining consistent performance under varying visual and environmental conditions.

III. Materials and Methods

This section outlines the research methodology adopted for the weather classification task. The overall process involves dataset preparation, image preprocessing, data augmentation, and the development of the proposed CBAM-CNN model. An overview of the workflow is illustrated in Fig. 1

A. Dataset

The "Weather phenomenon database," collected from The Harvard Dataverse [15], was employed in this study. The dataset comprises high-quality images representing 11 distinct weather conditions, including dew, fog, frost, glaze, hail, lightning, rain, rainbow, storm, and snow scenes. The author of this dataset collected weather images from various online sources to capture real-world visual diversity and ensure robustness in model training. The dataset consists of a total of 6,862 images. For the experiments, it was divided into 70%

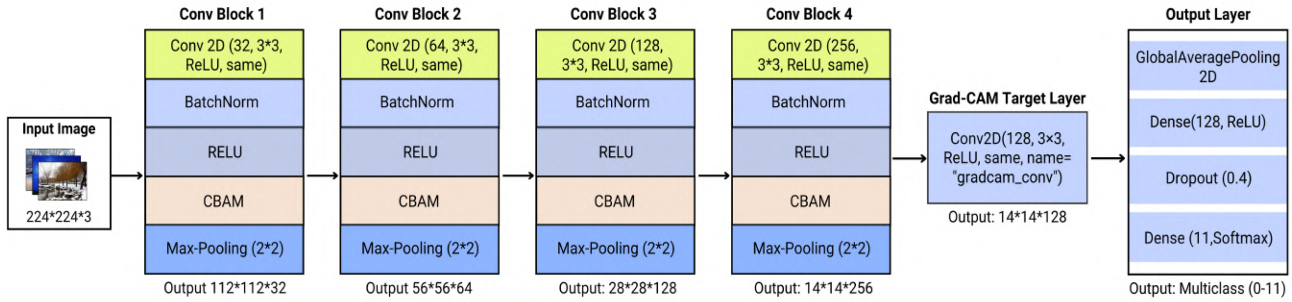

Fig. 2. The architecture of the Proposed CBAM-CNN Model illustrates the sequential architecture for multiclass weather classification, utilizing four Convolutional Blocks (with CBAM for spatial and channel attention) to extract robust features. The network integrates a Grad-CAM target layer for interpretability and culminates in a final Softmax layer for prediction across 11 classes (0-10)

training, 15% validation, and 15% testing subsets, resulting in 4,731 training images, 1,023 validation images, and 1,041 testing image, while maintaining an even class distribution throughout the dataset. A sample images from each class shown in Fig. 3,

(a) Dew (b) Fog-smog (c) Frost (d) Glaze

(e) Hail (f) Lightning (g) Rain (h) Rainbow

(i) Rime (j) Sandstorm (k) Snow

Fig. 3. Sample images representing different weather phenomenon from the Weather phenomenon database.

B. Data Preprocessing and Augmentation

The dataset contained images in multiple formats, including JPG, PNG, and JPEG. To maintain consistency, all files were converted to the JPG format, which is well-suited for CNN and attention-based architectures. Each image was then resized to 224 × 224 pixels and rescaled to a [0, 1] range to normalize pixel values and improve model convergence. To enhance generalization, data augmentation was performed using the `ImageDataGenerator` function. The training generator applied rescaling (1./255), brightness variation (0.8–1.2), random zoom (±0.1), horizontal flipping, and small width and height shifts (±0.1), simulating real-world variability. For validation and testing, only rescaling was applied to ensure an unbiased evaluation. Finally, the preprocessed dataset was loaded into `TensorFlow.Keras` pipelines preserve class balance and enable efficient batch-wise training and evaluation.

C. Proposed CBAM-CNN Model

In this study, we propose a CBAM-CNN architecture designed to enhance the accuracy and interpretability of weather image classification by integrating attention mechanisms into a convolutional backbone. The model is constructed from four sequential convolutional blocks, each followed by batch normalization, a CBAM (Convolutional Block Attention Module), and max-pooling for progressive spatial downsampling. The first, second, third, and fourth blocks employ 32, 64, 128, and 256 filters, respectively, with 3×3 kernels and ReLU activation, enabling the network to effectively extract hierarchical visual features. The embedded CBAM modules refine feature representations through channel and spatial attention, allowing the network to emphasize weather-relevant visual cues (such as cloud texture, lighting, or precipitation patterns) while suppressing redundant background information.

Following the final block, an additional convolutional layer with 128 filters, denoted as `gradcam_conv`, serves as the Grad-CAM target layer to facilitate visual interpretability through class activation maps. The extracted features are then aggregated via global average pooling and passed through a fully connected layer of 128 neurons with ReLU activation and a dropout rate of 0.4 to reduce overfitting. The final output layer employs a softmax activation function to classify images into 11 distinct weather categories. The model was trained from scratch using the Adam optimizer with a learning rate of 0.0001 and categorical cross-entropy loss, enabling efficient end-to-end optimization for multi-class weather recognition. The overall architecture of the proposed CBAM-CNN model is illustrated in Fig. 2.

IV. Experimental Setup and Implementation

The experimental work for this study was conducted using a hybrid computational setup, combining a local machine with a cloud-based platform to manage the demanding workload. The local system, a 64-bit Windows 11 PC, was configured with an Intel® Core™ i5 8th Generation processor, 12 GB of DDR4 RAM, and an NVIDIA GeForce MX250 GPU with 2 GB of VRAM. For more computationally intensive operations like image preprocessing, model training, and evaluation, we leveraged Kaggle Notebooks, which provided dual NVIDIA Tesla T4 GPUs to significantly speed up the process. This combined approach allowed us to efficiently handle the resource-heavy tasks, with the complete training and evaluation of the proposed CBAM-CNN model taking just over three hours.

A. Training Setup

The proposed CBAM-CNN model was trained to classify weather images into 11 distinct categories. All input images were resized to 224x224x3 and normalized before training to ensure uniformity and improve convergence. The dataset was randomly split into training, validation, and test sets with an 70:15:15 ratio, ensuring class balance across all splits. To enhance generalization and reduce the risk of overfitting, various data augmentation techniques were applied, including random horizontal flips, rotations, and zooms. The model was trained for 100 epochs using a batch size of 32, which was chosen to balance computational efficiency with stable convergence given the dataset size and available hardware resources.

B. Parameter Setting

The proposed model was optimized using the Adam optimizer with a learning rate of $1{\times}10^{-4}$ and categorical cross-entropy loss to handle the multi-class classification task. Early stopping was applied with a patience of 20 epochs, automatically restoring the best-performing weights once validation performance ceased to improve. Additionally, a learning rate scheduler reduced the learning rate by a factor of 0.5 whenever the validation loss did not improve for 10 consecutive epochs. This parameter configuration ensured stable optimization, faster convergence, and improved generalization performance on unseen test data.

C. Evaluation Metrics

To evaluate the efficacy of our models, we employed several standard metrics, including the confusion matrix (CM), accuracy, precision, recall, and the F1-score. The CM provides a granular view of the model's performance by detailing correct and incorrect predictions for each class. The key metrics and their mathematical definitions are summarized in Table I. True Positives (TP) and True Negatives (TN) represent successful predictions, while False Positives (FP) and False Negatives (FN) denote misclassified instances.

TABLE I
PERFORMANCE EVALUATION METRICS

Metric	Formula	Description
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	The proportion of all correct predictions out of the total number of samples.
Precision	$\frac{TP}{TP+FP}$	The fraction of positive predictions that were genuinely positive; indicates prediction reliability.
Recall	$\frac{TP}{TP+FN}$	The fraction of all actual positive cases that were correctly identified by the model.
F1-Score	$2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}$	The harmonic average of precision and recall; a balanced measure that considers both false positives and false negatives.

D. Grad-CAM

To enhance the model's interpretability, we used Gradient-weighted Class Activation Mapping (Grad-CAM) to visually inspect which regions of an input image were most influential in the model's prediction. Grad-CAM generates a heatmap by computing the gradient of the predicted class score with respect to the feature maps of the final convolutional layer, specifically the `gradcam_conv` layer. This heatmap, which highlights discriminative areas, is then resized to match the original image resolution and overlaid to create a visual explanation. This process allows us to confirm that the model is correctly focusing on weather-relevant cues, such as cloud formations, lighting conditions, or precipitation patterns, rather than irrelevant background information. These visualizations provide strong qualitative evidence of the model's reasoning and enhance the trustworthiness of its classification results.

V. EXPERIMENTAL RESULT ANALYSIS AND DISCUSSION

This section details the experimental findings for the proposed CBAM-CNN model in multi-class weather image classification. We quantify the performance gains by comparing it directly against a baseline CNN that omits the CBAM attention mechanism. Evaluation relies on standard metrics, accuracy, precision, recall, and F1-score, to comprehensively gauge overall classification quality and performance across the distinct weather classes. Furthermore, we provide visual evidence of the model's behavior through learning curves, ROC curves, confusion matrices, confidence scores, and Grad-CAM visualizations to fully interpret its decision-making process and feature selection.

A. Result Analysis

Fig. 4 illustrates the learning curves of the proposed CBAM-CNN model over 100 epochs, showing both accuracy and loss curves. The accuracy plot shows rapid initial learning, with validation accuracy stabilizing around 88% after approximately 60 epochs, maintaining a small, consistent gap from the training accuracy, which approaches 95%. This stability is mirrored in the loss plot, where both training and validation losses decrease sharply before reaching a low, steady state. The overall convergence behavior, characterized by stable validation performance and a minimal gap between curves, indicates that the model is robust and generalizes well to unseen data without significant overfitting.

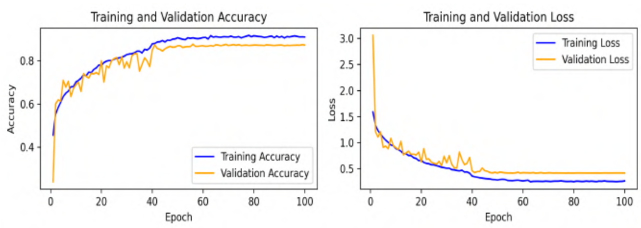

Fig. 4. Training and validation accuracy and loss curves of the proposed CBAM-CNN model.

Table II presents the performance metrics of the baseline CNN model for weather image classification. The model achieved an overall accuracy of 81.75%, with a weighted average F1-score of 0.82. The results show strong performance across several classes, particularly for "Dew" (F1-score of 0.90) and "Lightning" (F1-score of 0.93), but weaker performance on others, such as "Frost" (F1-score of 0.59) and "Glaze" (F1-score of 0.66). These variations indicate that while the model generalizes well across most classes, its ability to correctly identify less frequent or more challenging categories is limited.

Table III summarizes the performance metrics for the proposed CBAM-CNN model, highlighting its enhanced classification capabilities. The model achieved a notable overall accuracy of 87.61% and a weighted average F1-score of 0.87, demonstrating a significant improvement over the baseline CNN model. The results show strong performance across most weather classes, with particularly high F1-scores for

TABLE II
PERFORMANCE OF THE BASELINE CNN MODEL

Class	Precision	Recall	F1-Score	Support
Dew	0.93	0.88	0.90	106
Fogsmog	0.86	0.88	0.87	129
Frost	0.72	0.50	0.59	72
Glaze	0.60	0.73	0.66	97
Hail	0.85	0.79	0.82	90
Lightning	0.92	0.95	0.93	58
Rain	0.81	0.85	0.83	80
Rainbow	1.00	0.75	0.86	36
Rime	0.85	0.87	0.86	174
Sandstorm	0.89	0.89	0.89	105
Snow	0.69	0.77	0.73	94
Weighted Avg	**0.82**	**0.82**	**0.82**	**1041**
Overall Accuracy: 0.8175				

"Lightning" (0.97), "Rainbow" (0.93), "Dew" (0.92), and "Sandstorm" (0.92). While performance on "Frost" remains the lowest (F1-score of 0.72), the model shows improved generalization across all classes, reflecting the effectiveness of the integrated CBAM attention mechanism in refining key features.

TABLE III
PERFORMANCE OF THE PROPOSED CBAM-CNN MODEL

Class	Precision	Recall	F1-Score	Support
Dew	0.93	0.91	0.92	106
Fogsmog	0.88	0.92	0.90	129
Frost	0.82	0.64	0.72	72
Glaze	0.77	0.74	0.75	97
Hail	0.94	0.86	0.90	90
Lightning	0.97	0.97	0.97	58
Rain	0.82	0.94	0.88	80
Rainbow	0.94	0.92	0.93	36
Rime	0.85	0.94	0.89	174
Sandstorm	0.93	0.91	0.92	105
Snow	0.86	0.84	0.85	94
Weighted Avg	**0.88**	**0.88**	**0.87**	**1041**
Overall Accuracy: 0.8761				

Fig. 5 presents the confusion matrix for the CBAM-CNN model, providing a detailed view of its classification performance across 11 weather classes. The diagonal elements show the number of correctly classified images, indicating high true positive counts for "Rime" (163), "Fogsmog" (119), and "Sandstorm" (96), among others. The off-diagonal values represent misclassifications, such as a few "Fogsmog" images being incorrectly classified as "Sandstorm" (5) and "Glaze" images being mistaken for "Rime" (11). The heatmap's darker shades along the diagonal confirm the model's strong performance and its ability to correctly identify the majority of instances for most weather types.

Fig. 6 displays the Receiver Operating Characteristic (ROC) curve for the CBAM-CNN model, highlighting its high-performance multi-class classification ability. The plot shows the trade-off between the True Positive Rate and the False Positive Rate for each of the 11 weather classes, with each class achieving an Area Under the Curve (AUC) between 0.98 and 1.00. The micro-average AUC of 0.99 indicates that the model demonstrates excellent overall discriminative power, significantly outperforming a random classifier (represented by the dashed gray line). The curves' proximity to the top-left corner of the graph confirms the model's high

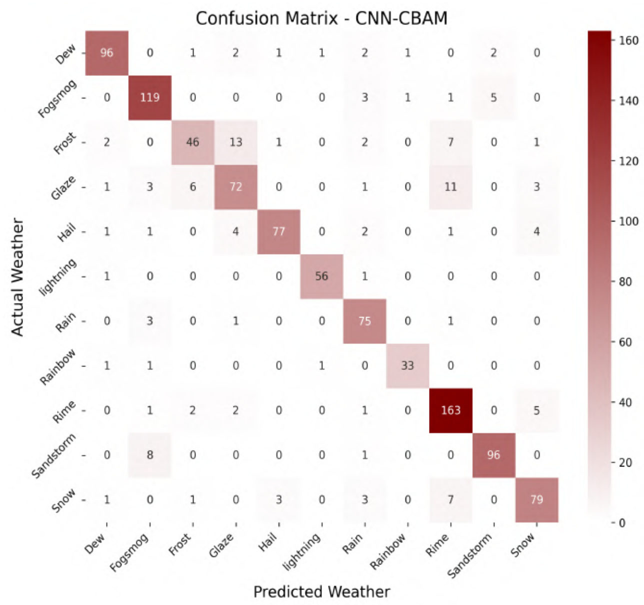

Fig. 5. Confusion matrix of the proposed CBAM-CNN model

true positive rates and low false positive rates, indicating a robust and reliable performance.

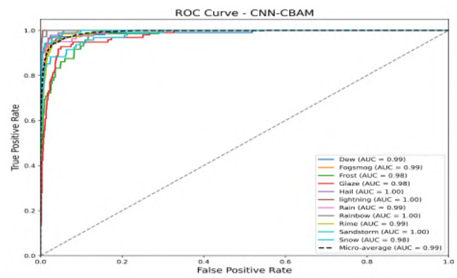

Fig. 6. ROC curve of the proposed CBAM-CNN model

Fig. 7 displays Grad-CAM heatmaps generated by the CBAM-CNN model across various weather images. Each set of three images (Original Image, Grad-CAM Heatmap, and Grad-CAM Overlay) visually confirms that the model is effectively focusing on weather-relevant cues, such as snow texture, frost patterns, rainbow arcs, and lighting conditions, to make its classifications. The red and yellow regions in the heatmaps precisely highlight the most discriminative visual evidence, providing qualitative proof of the model's interpretability and reliability.

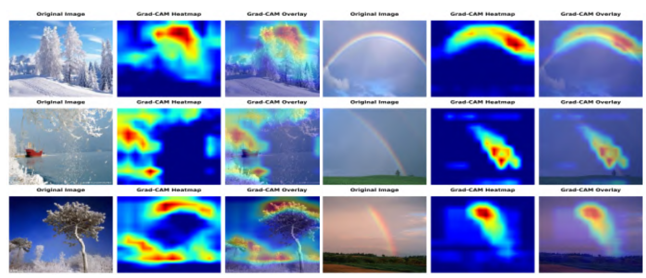

Fig. 7. Grad-CAM visualizations of the proposed CBAM-CNN model, highlighting key regions used to distinguish different types of weather conditions

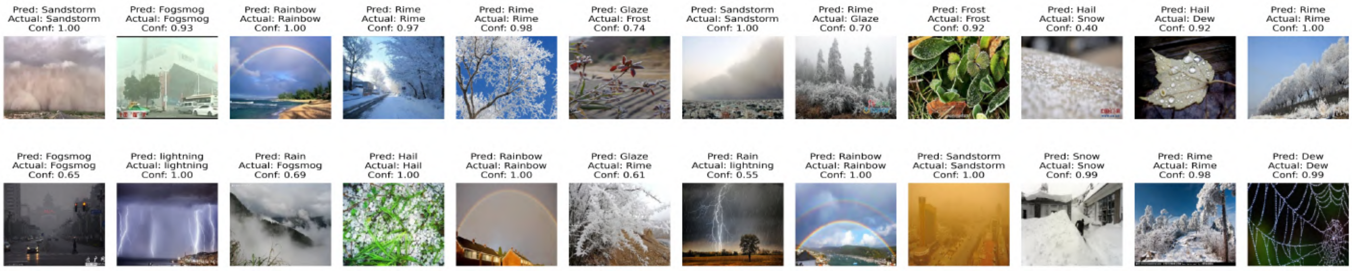

Fig. 8. Sample classification results of the proposed CBAM-CNN model with corresponding confidence scores, showcasing perfect detection of different weather condition images across diverse samples.

Fig. 8 presents sample classification results from the proposed CBAM-CNN model, accompanied by their corresponding confidence scores. The visualization showcases the model's high effectiveness in accurately classifying diverse weather conditions. For images that were correctly predicted (where Pred matches Actual), the model consistently exhibits high confidence scores (mostly 0.90 to 1.00). For instance, the model predicts "Sandstorm," "Rime," and "Lightning" with perfect confidence (1.00). The samples serve as qualitative evidence of the model's robust performance and its ability to correctly identify distinct weather features, demonstrating reliable performance across a variety of visual scenarios.

B. Discussion and Limitations

The comparative experimental analysis confirms that the proposed CBAM-CNN model reliably surpasses the baseline CNN architecture across all key quantitative metrics. This substantial performance leap is directly attributed to the integrated CBAM module, which enhances the model's feature extraction by selectively emphasizing critical weather-related visual cues. Given the critical nature of accurate weather monitoring for public safety and logistical planning, the improved robustness of the CBAM-CNN holds tangible real-world value. We chose to focus solely on the internal comparison against a structurally identical baseline to provide a clear, apples-to-apples validation of the attention mechanism's efficacy, rather than engaging in potentially inconsistent comparisons with external state-of-the-art methods that use disparate benchmarks. However, this study is not without limitations. First, training and validation were confined to a single, curated dataset, which may constrain the model's ability to generalize to real-time, noisy images captured under diverse geographic and sensor conditions. Second, the addition of the CBAM module introduces an inherent increase in parameter count and computational load, which could pose a challenge for deployment in low-power and edge-computing environments.

VI. Conclusion and Future Prospects

This study introduced the CBAM-CNN architecture for robust multi-class weather image classification, trained without leveraging pre-trained weights to ensure full control over feature learning. By incorporating the Convolutional Block Attention Module (CBAM) into the convolutional backbone, the model successfully enhances feature representation by selectively emphasizing weather-relevant visual cues and suppressing noise. This integration led to significant performance improvements over the baseline CNN across all metrics. The Grad-CAM visualizations affirmed the model's interpretability by confirming it focuses on semantically critical areas, such as cloud formations, lighting, and precipitation patterns, thereby increasing confidence in its classification outcomes. Future research will concentrate on three primary areas: evaluating the model's generalizability across diverse real-world weather datasets; optimizing the computational efficiency of the attention module for deployment in resource-limited, edge-computing scenarios; and analyzing the model's resilience to image perturbations and domain shifts to ensure long-term dependability in atmospheric monitoring systems.

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