

NeuralSky: Deep Learning-Based Weather Prediction Using Cloud Images

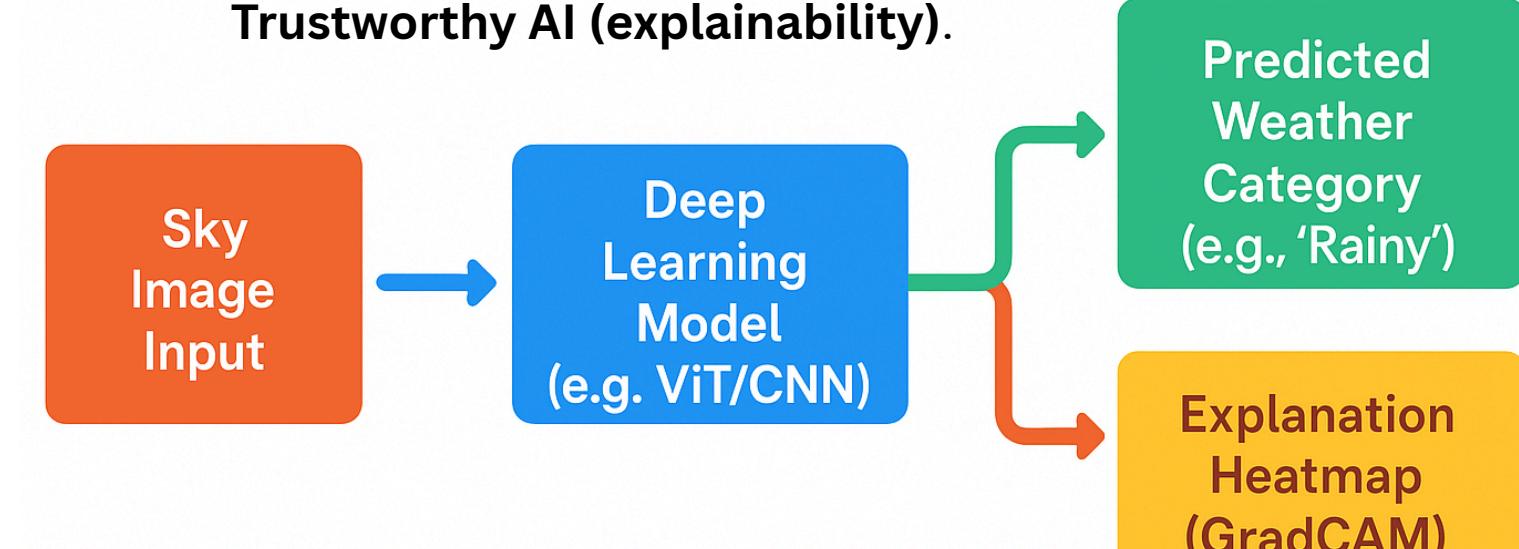
Pranav Dwivedi | Prabhjot Kaur | Charity Gwese | AJ De Vera

1. Executive Summary / Abstract

Accurate, localized weather prediction is crucial for disaster mitigation and precision agriculture. This project pioneers a **deep learning approach** to classify weather conditions (clear, cloudy, rainy, stormy) directly from ground-based sky images, bypassing expensive sensor networks. We merged heterogeneous cloud image datasets (CCSNv2, Howard-Cloud-X) and trained multiple architectures, with **Vision Transformer (ViT)** achieving **70% test accuracy** – a 10% improvement over baseline CNNs. Crucially, **Grad-CAM** visualizations revealed model reliance on physically meaningful cloud features (e.g., stratocumulus patterns for 'cloudy' predictions), enhancing interpretability. The system was deployed as a **containerized Flask app on Google Cloud Run**, demonstrating real-world viability for accessible, explainable weather forecasting.

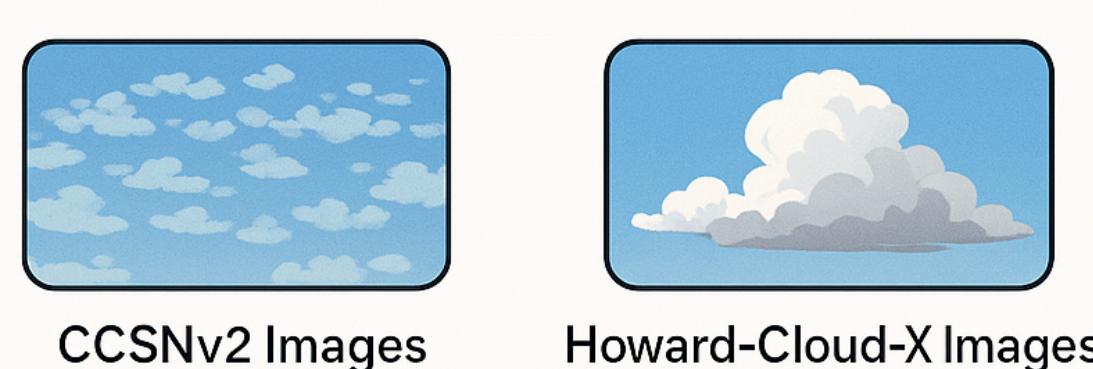
2. Introduction / Motivation

- Problem:** Need for automated, accessible weather prediction using readily available visual data (**cloud images**). Limitations of manual observation and predictions in remote areas.
- Goal:** Develop an ML model to **classify weather conditions from cloud images** and **explain why** it makes a prediction.
- Importance:** Potential for **localised forecasting**, climate monitoring assistance, research tools. Need for **Trustworthy AI (explainability)**.



3. Datasets & Preprocessing

- Data Sources:** Merged **CCSN_v2** and **Howard-Cloud-X** datasets.
- Preprocessing:** **Resizing (224x224)**, **Normalisation**.
- Splitting:** Data divided into **Training**, **Validation**, and **Test** sets.



CCSNv2 Images Howard-Cloud-X Images

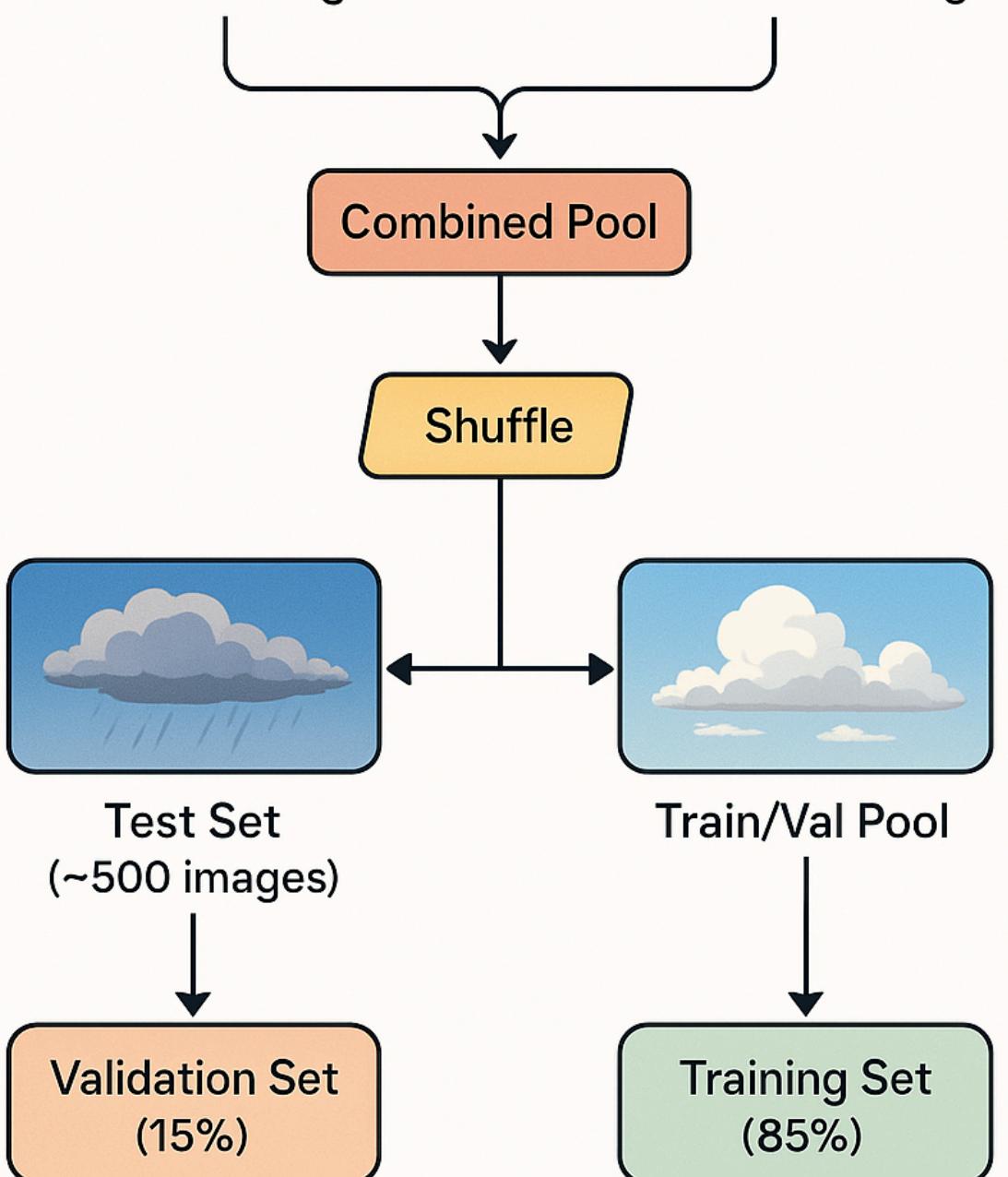


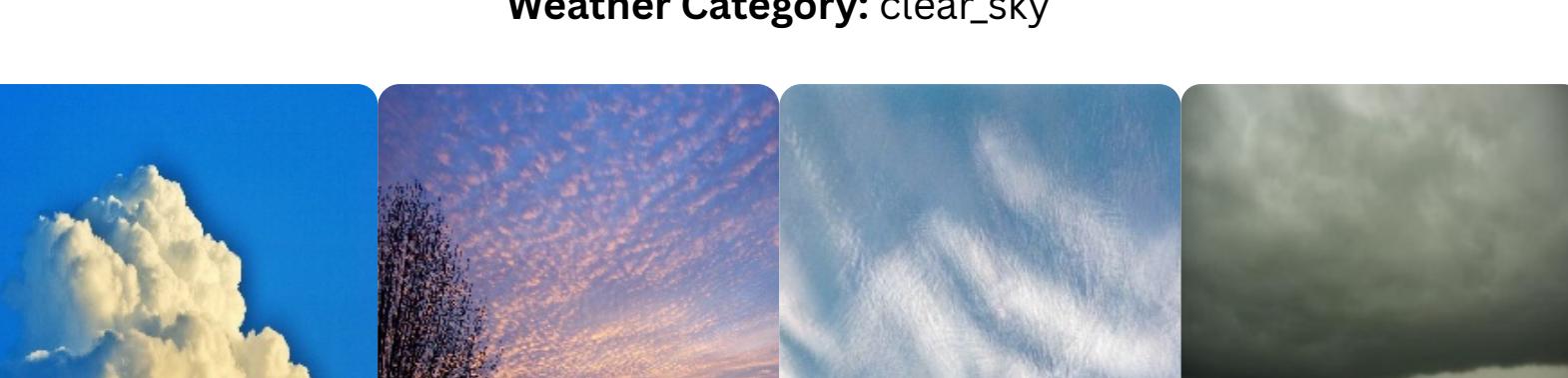
Image Count Per Category	Train	Validation	Test
Clear Sky	662	95	199
Cloudy	1415	277	244
Rainy	583	93	104
Stormy	280	54	33
Total images	3959		

Dataset References:

- Mario. "Cirrus Cumulus Stratus Nimbus (CCSN) Database." Kaggle.com, 2021, www.kaggle.com/datasets/mmicheilli/cirrus-cumulus-stratus-nimbus-ccsn-database.
- Saha, Bikram. "Howard-Cloud-X." Kaggle.com, 2022, www.kaggle.com/datasets/imbikramsha/howard-cloudx. Accessed 14 Apr. 2025.



Weather Category: clear_sky



Weather Category: cloudy



Weather Category: rainy

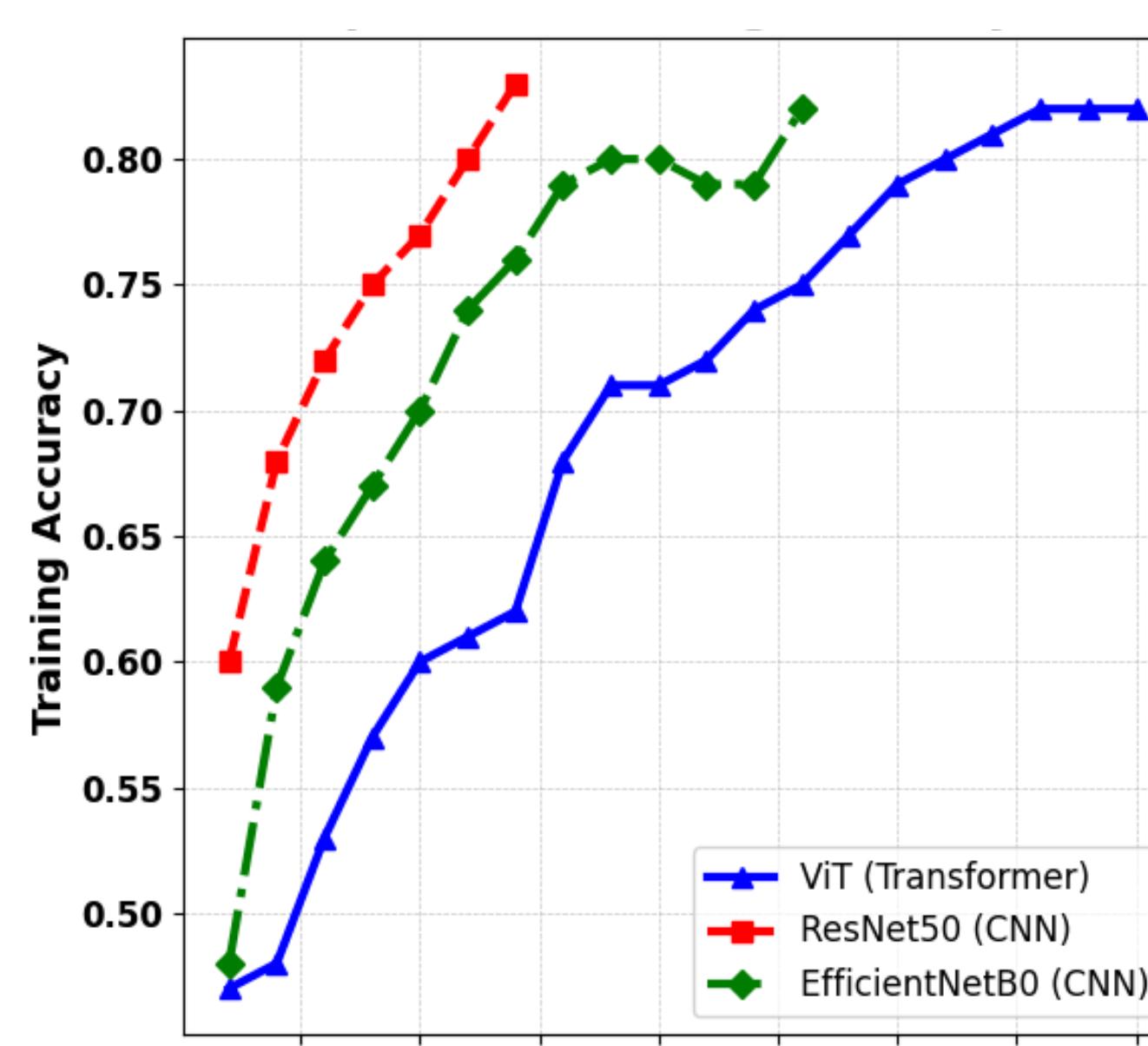
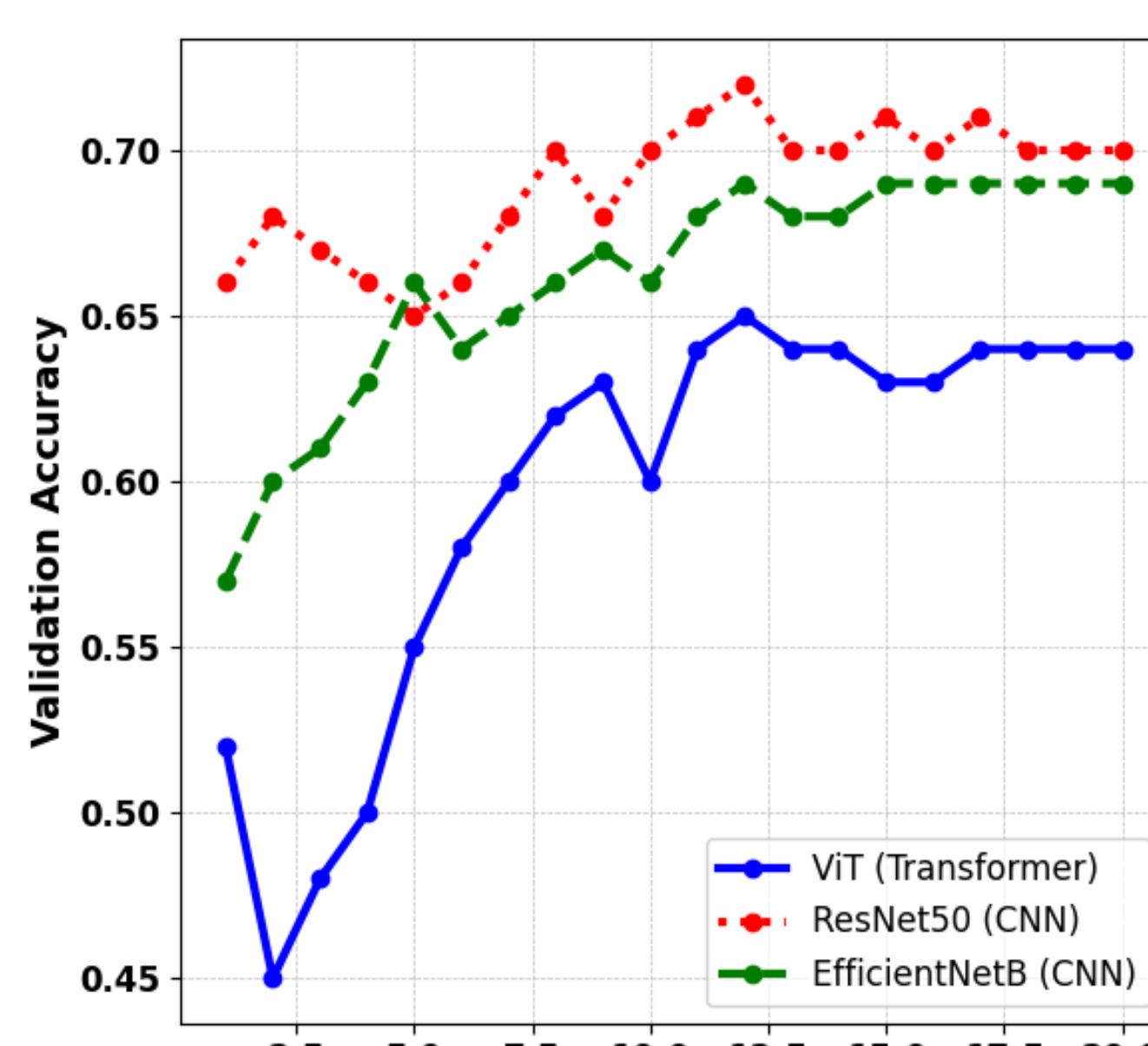


Weather Category: stormy

4. Methodology

4.1 Model Training & Selection

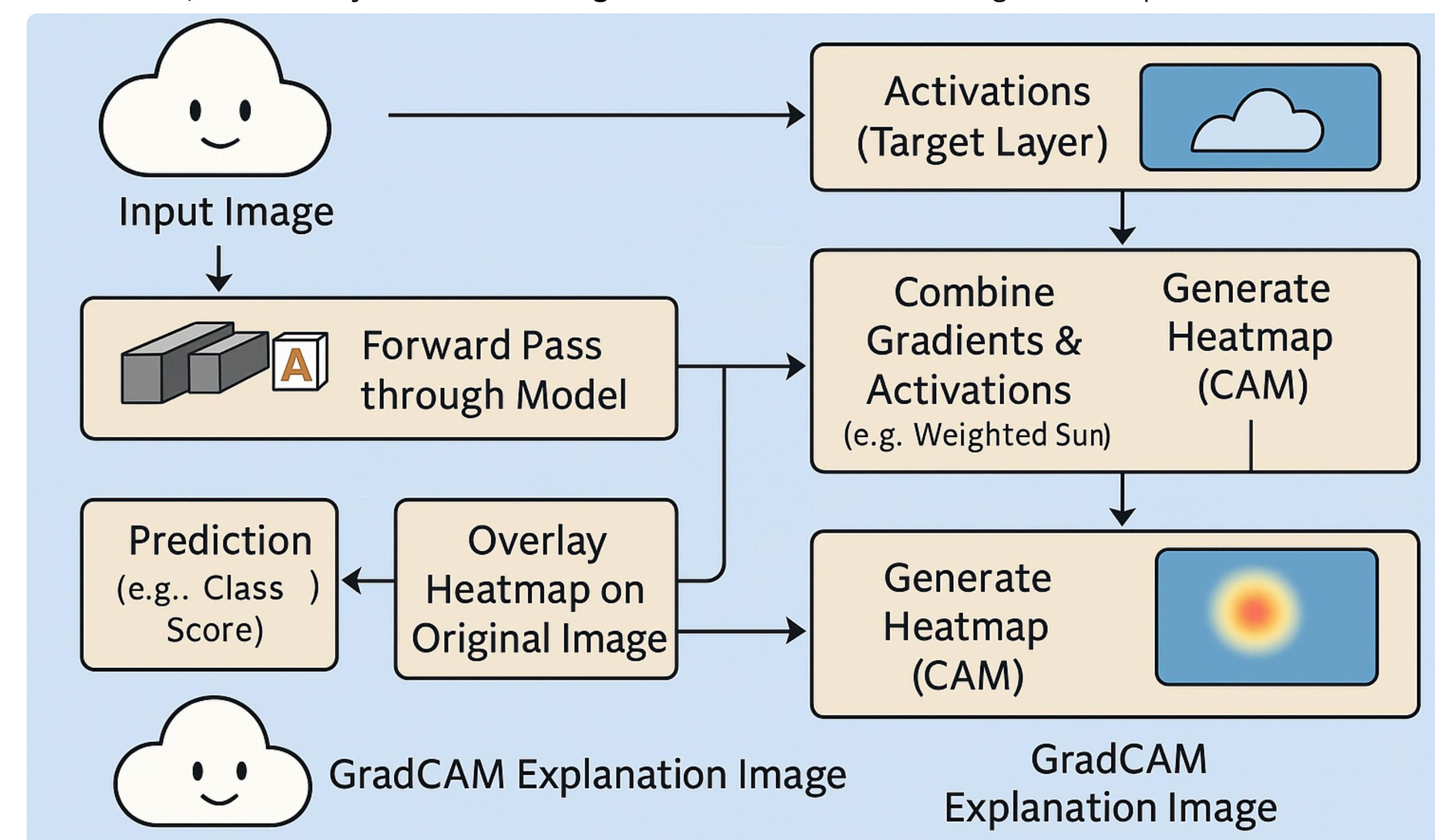
- Architectures Tested:** Vision Transformer (ViT-Base), ResNet50, EfficientNetB0. Utilised transfer learning with pre-trained weights.
- Task:** 4-Class Weather Classification.
- Training:** AdamW optimizer, CrossEntropyLoss, Early Stopping based on validation accuracy.



Model	Architecture	Epochs Trained	Final Train Accuracy	Final Validation Accuracy	Test Accuracy
ViT	Transformer	20	0.8156	0.6705	0.6980
ResNet50	Convolutional (CNN)	7	0.8241	0.6455	0.6880
EfficientNetB	Convolutional (CNN)	13	0.8153	0.6455	0.6660

4.2 Explainability: GradCAM

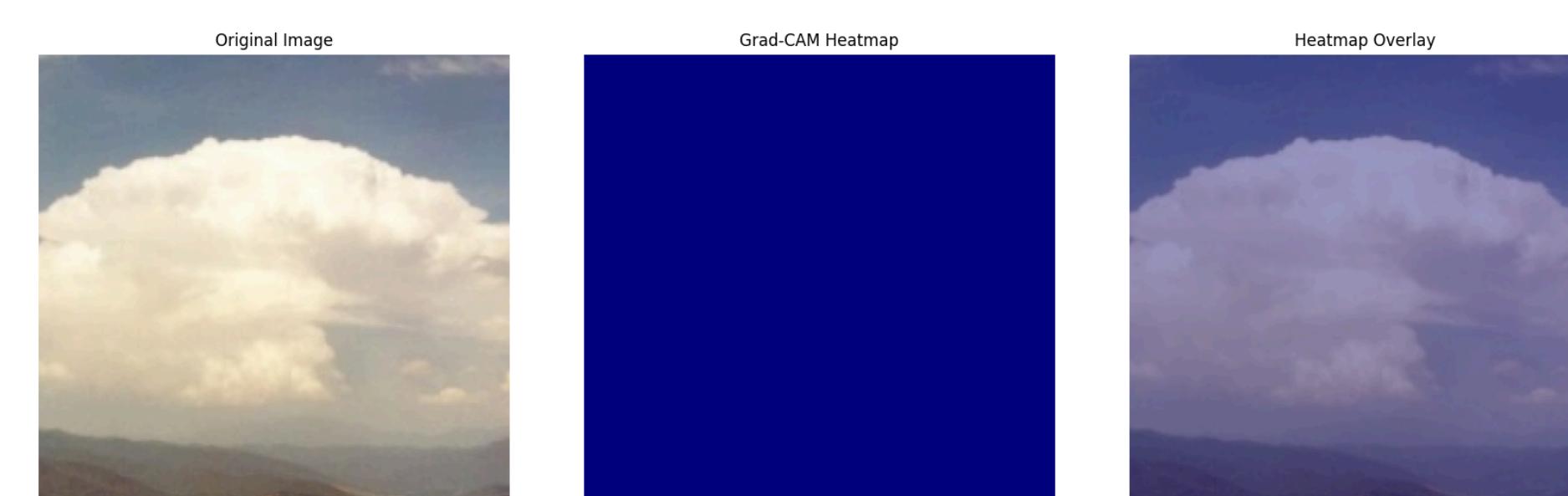
- Technique:** Gradient-weighted Class Activation Mapping (GradCAM) used to visualize model focus.
- Implementation:** Adapted for both **CNN** and **ViT** architectures, targeting relevant layers (e.g., last conv layer for CNNs, last norm layer for ViT). Hooks gradients and activations during backward pass.



GradCAM Paper:
Selvaraju, Ramprasaath R., et al. "Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization." International Journal of Computer Vision, vol. 128, no. 2, Feb. 2020, pp. 336–359, https://doi.org/10.1007/s11263-019-01228-7.

4.3 GradCAM Explanations

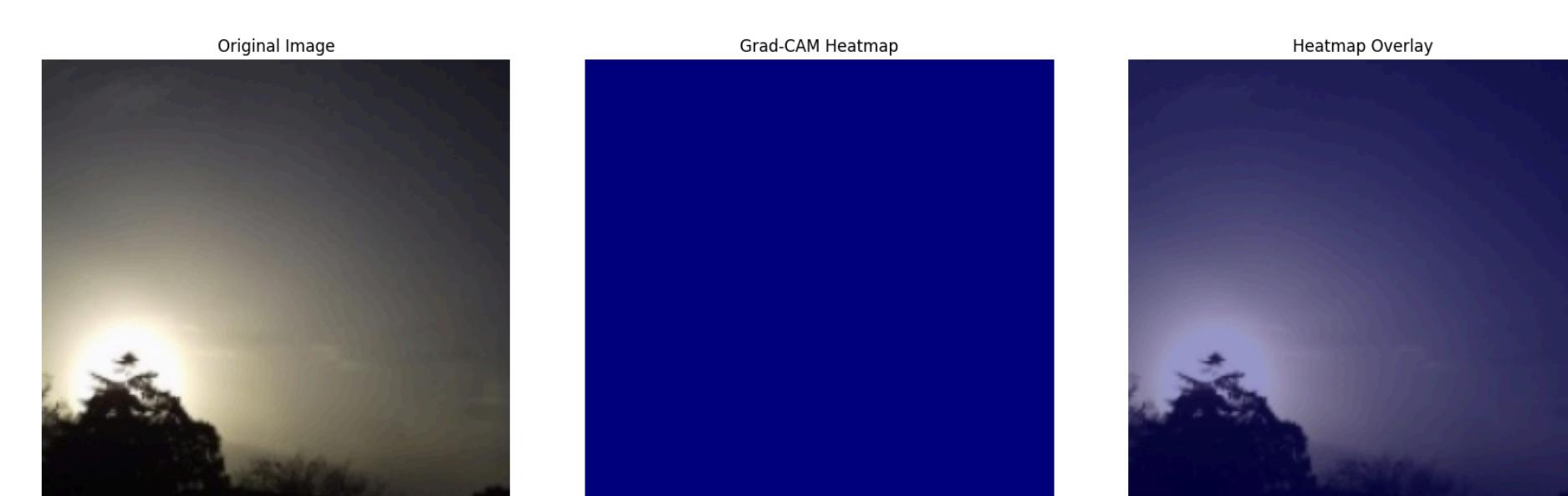
Case 1: True: stormy | Prediction: stormy (0.85) [Correct]



Explanation:

- Correct 'stormy' prediction (high confidence).
- Uniform blue GradCAM heatmap lacks local region focus.
- Common in Vision Transformers
- Suggests global context reliance or final-layer gradient averaging.

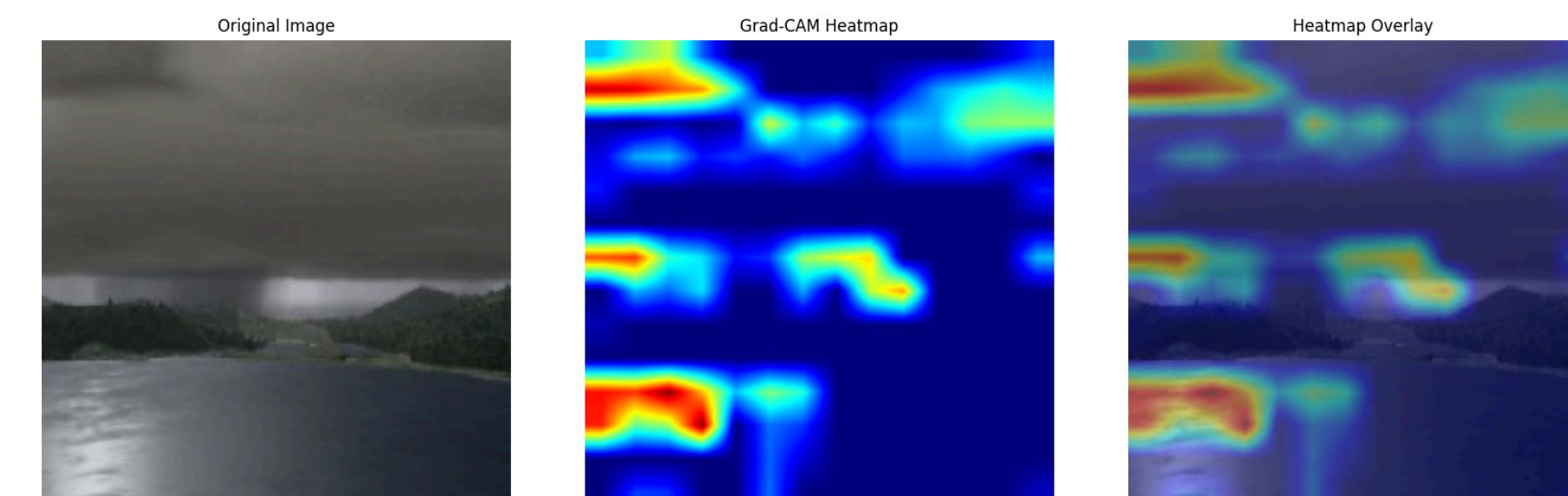
Case 2: True: clear_sky | Pred: stormy (0.47) [Incorrect]



Explanation:

- Incorrect 'stormy' prediction (low confidence).
- Uniform blue GradCAM: no localized features for prediction.
- Common in ambiguous inputs (e.g., glare) or diffuse gradient signals.
- Suggests weak activation patterns at the target layer.

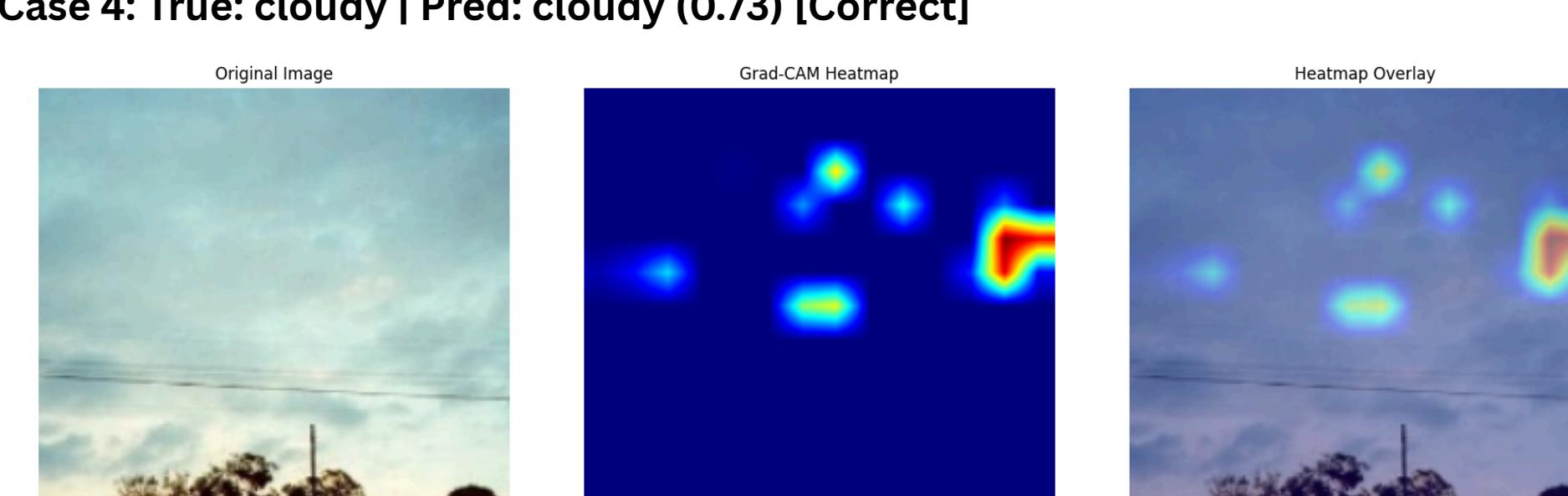
Case 3: True: rainy | Pred: rainy (0.48) [Correct]



Explanation:

- Correct 'rainy' prediction (moderate confidence).
- GradCAM highlights dark horizon clouds & water texture.
- Model prioritizes typical rainy-weather features.
- Demonstrates focused activation on relevant visual cues.

Case 4: True: cloudy | Pred: cloudy (0.73) [Correct]



Explanation:

- Correct 'cloudy' prediction (high confidence).
- GradCAM highlights scattered sky clouds, strong activation on upper-right formation.
- Multiple cloud regions identified as evidence.
- Reflects robust feature recognition for class-specific traits.

5. Key Findings

- The **ViT-Base** architecture demonstrated the **highest classification accuracy** 70% on the unseen test set.
- Grad-CAM visualizations successfully **highlight discriminative cloud features** relevant to the predicted weather category (e.g., dark, turbulent areas for 'Stormy', thin wisps for 'Clear Sky').
- The model and explanation system were successfully **containerised using Docker** and **deployed scalably** on Google Cloud Run.
- Validation split and **early stopping** were effective in **preventing overfitting** during training.

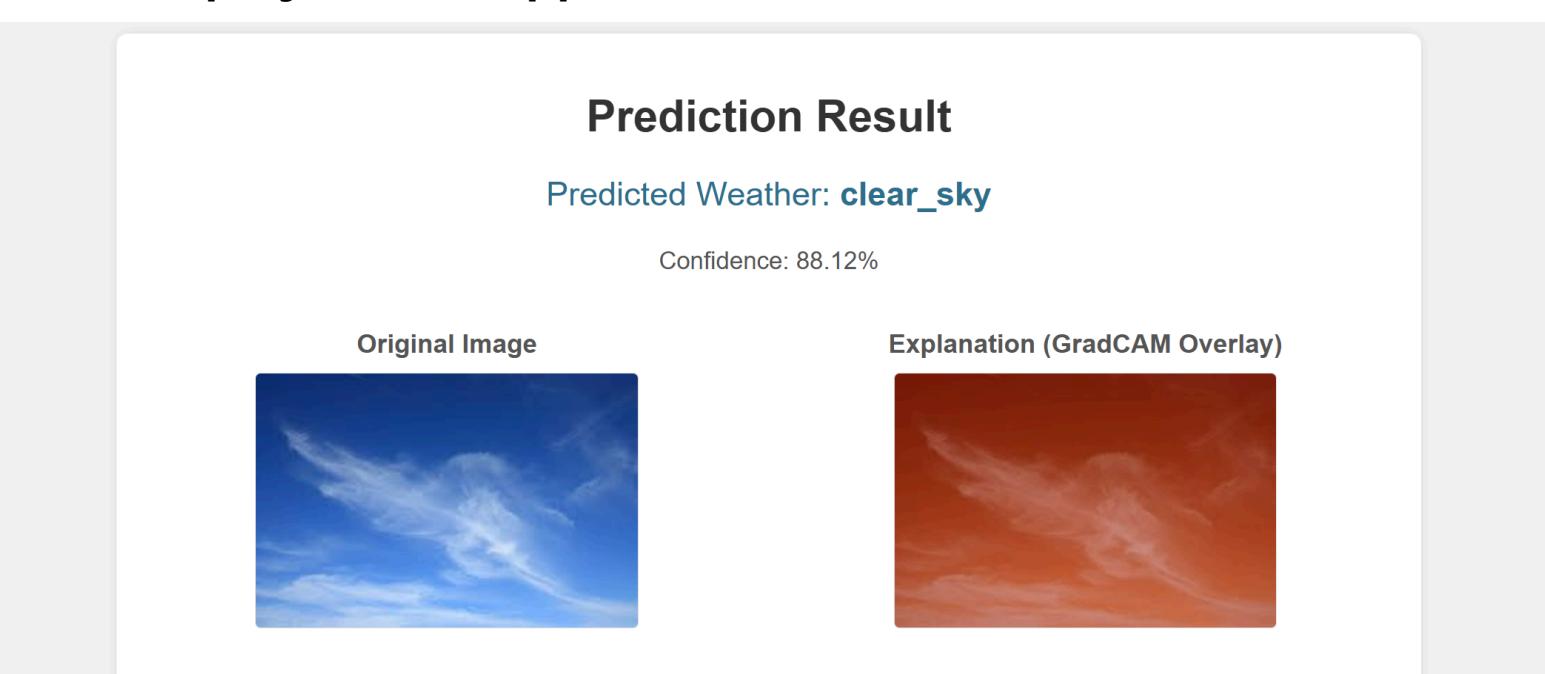
6. Results

6.1 Classification Performance

- Best Model:** Vision Transformer (ViT-Base)
- Test Accuracy:** 70%

clear_sky	80	35	2	2
cloudy	13	190	26	15
rainy	6	41	52	5
stormy	0	4	2	27

6.3 Deployed Web Application



- User Uploads Image:** The user navigates to the site (via an initial upload page, not shown here) and uploads an image containing clouds or sky.
- Backend Processing:** The uploaded image is sent to the backend (the deployed Flask application running in Cloud Run/Docker).
 - The application **preprocesses the image** to the format expected by the trained machine learning model.
 - It **feeds** the image to the loaded **ML model**.
 - The model **predicts the weather category** ("clear_sky" in this example) and **calculates a confidence score** (88.12%).
 - The application then runs the **GradCAM** algorithm to **generate a visual explanation** (heatmap) showing which **parts** of the image **most influenced** the model's prediction.
- Result Display:** The backend renders this "Prediction Result" page, sending back the results:
 - The **predicted weather category** and **confidence score** are displayed as text.
 - The **original image** uploaded by the user is shown.
 - The **GradCAM explanation** is visualized as a **heatmap overlay** on the original image, providing insight into the model's decision process.
 - A "Try another image" link allows the user to return to the upload page to analyse a different picture.

7. Conclusion & Future Work

- Successfully developed and deployed an end-to-end, explainable deep learning system for weather prediction from cloud images.
- Demonstrated the feasibility of using **ViT/CNN** models and **GradCAM** for this task.

Future Work:

- Incorporate larger, more diverse datasets.
- Explore time-series analysis using sequences of images.
- Investigate other explainability techniques (e.g., LIME, SHAP).
- Optimize model size for faster inference (quantization, pruning).
- Integrate with real-time camera feeds.

8. Acknowledgements

- Unit Conveners:** We appreciate the guidance, framework, and support provided by our Unit Conveners.
- Sponsor:** Our sincere thanks go to our project sponsor, Mrs. Jansi Sankar, for providing us with this challenging and engaging project opportunity.
- Mentor:** We would like to express our heartfelt thanks to our mentor, Mr. James Ireland, for his dedicated guidance and invaluable support throughout this project.
- Team Members:** Finally, a special thanks to the entire project team.

Try out the website for yourself!!

