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AUTOMATED WEATHER CLASSIFICATION USING TRANSFER LEARNING

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Abstract:

Accurate weather classification is a fundamental requirement in meteorology, supporting timely forecasts and helping convey important weather-related information to the public. With the growing availability of image data and advancements in artificial intelligence, deep learning has emerged as a powerful approach to automate and enhance weather classification systems. This project introduces a robust solution for classifying weather conditions using transfer learning—a method that applies the knowledge of models pre-trained on large datasets to a specific, often smaller, problem domain.

Our model categorizes weather into five primary classes: Cloudy, Shine, Rain, Foggy, and Sunrise. A convolutional neural network (CNN), specifically the VGG19 model, has been employed for this task. The project is built on a Flask-based web application that allows users to upload an image, after which the model processes it and returns the predicted weather category in real-time. The prediction pipeline involves preprocessing the image, passing it through the VGG19 network, and rendering the result on the user interface.

We also explored other transfer learning architectures such as Inception V3, Xception, and ResNet, but VGG19 was selected due to its balanced accuracy and computational efficiency. The dataset used was sourced from a publicly available Kaggle repository, ensuring diverse and representative image inputs.

This project showcases the effectiveness of transfer learning in computer vision applications and highlights how deep learning models can be deployed in real-world, user- facing systems for practical tasks like weather classification. The approach is scalable and adaptable for future enhancements and additional weather classes.

Keywords — **Weather Classification, Deep Learning, Inception V3, VGG19, ResNet, Transfer Learning, Convolutional Neural Networks (CNN), Automated Forecasting.**

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I. INTRODUCTION

Weather has a profound impact on our daily lives, influencing everything from our attire and travel plans to agricultural practices and industrial operations. As climate patterns grow increasingly unpredictable due to global warming and urbanization, the need for accurate and timely weather classification systems has become more pronounced. Traditional methods of weather prediction, which rely heavily on satellite imagery, radar, and sensor data, are undoubtedly powerful. However, they are often limited by accessibility, cost, and the requirement for technical expertise. With the rise of deep learning and computer vision, a new approach to weather classification has emerged—one that is data-driven, scalable, and capable of operating in real-time environments.

The advent of deep learning has enabled machines to understand and interpret visual content with remarkable accuracy. Convolutional Neural Networks (CNNs), in particular, have shown exceptional performance in tasks such as image classification, object detection, and scene recognition. These capabilities have opened up exciting possibilities in meteorology, especially for projects involving visual weather classification. This project explores the use of transfer learning, a technique where pre-trained models are repurposed for new tasks, to automatically classify weather conditions from images.

The project titled "Automated Weather Classification Using Transfer Learning" aims to bridge the gap between advanced image recognition models and accessible user tools for weather analysis. By utilizing a pre-trained CNN model—VGG19, known for its robust architecture and accuracy in image classification—this system provides a lightweight yet powerful solution for identifying weather categories. Users can upload an image via a simple Flask-based web interface, and the model will analyse and predict the weather condition in that image, classifying it into one of five categories: Cloudy, Shine, Rain, Foggy, or Sunrise.

This application not only demonstrates the effectiveness of transfer learning in a practical context but also highlights the potential for AI-driven tools to serve as real-time assistants in both personal and professional domains. Unlike traditional weather stations that depend on hardware-based measurements, this approach utilizes visual data alone, making it highly adaptable for use in mobile devices, drones, or security systems.

The project also addresses a broader challenge in AI adoption—how to make powerful machine learning tools usable for people with little to no technical expertise. By packaging the model into a user-friendly web application, we remove barriers to entry and open up new avenues for how everyday individuals or organizations might interact with weather data.

In summary, this project represents a step toward making deep learning models more

accessible and functional for real-world applications. By focusing on a practical, impactful use case—weather classification—it showcases how AI can complement and, in some cases, enhance traditional systems, making technology more inclusive, efficient, and aligned with evolving environmental needs.

II. RELATED WORK

With the growing importance of accurate weather prediction and monitoring, automated weather classification has emerged as a key area of interest. Traditionally, weather conditions were identified using manual observations or numerical models. However, the rise of deep learning and image-based techniques has opened up new possibilities, making weather classification more efficient and scalable.

The foundation for this research comes from a study that used geostationary infrared satellite images to classify tropical storms. That work showed how satellite thermal data could help detect and categorize different storm stages. By applying convolutional neural networks (CNNs), the researchers were able to capture vital visual patterns in storm systems, proving the value of image analysis in meteorology.

Building on this concept, many recent studies have applied deep learning models to a wider range of weather events. Satellite images from sources like MODIS and GOES have been used to classify cloud formations, identify rainfall regions, and even monitor severe weather activity. Pre-trained models like VGG19, ResNet, and Inception are often fine-tuned using transfer learning, which helps achieve strong performance even when labeled datasets are limited.

Transfer learning has become especially useful in this space because it reduces the time and computational power needed to train models from scratch. Instead, existing models—trained on large, diverse image datasets—are adapted to recognize weather patterns with relatively small sets of meteorological images.

Infrared satellite data plays a crucial role in these methods, as it provides round-the-clock information regardless of lighting conditions. These images are particularly effective for identifying temperature differences in cloud layers, which can indicate weather activity such as storms or rainfall.

Overall, previous research has laid a solid groundwork by combining satellite imagery with deep learning. This study builds on that foundation by using transfer learning techniques to classify a wider variety of weather conditions with improved accuracy and efficiency, making the system more practical for real-world forecasting applications.

III. PROPOSED SYSTEM

To address the limitations of the earlier storm classification system, the project evolved into a more comprehensive solution for weather classification. The proposed system utilizes transfer learning techniques to classify weather conditions into five distinct categories: Foggy, Sunrise, Cloudy, Rainy, and Shine. By expanding the scope of weather classification, the new system aims to cater to a broader range of meteorological applications and end-users. The use of VGG19 as the core deep learning model ensures high accuracy and reliability, while transfer learning expedites training by utilizing pre-trained architectures.

The system is designed to be user-friendly and accessible, integrating a Flask-based web application for real-time interactions. Users can upload an image via the interface, and the system automatically analyses the visual data to predict the weather category. This lightweight solution eliminates the need for satellite imagery, relying instead on general visual input, which makes it highly adaptable for everyday scenarios such as mobile applications, drones, or security systems. The implementation focuses on inclusivity by removing technical barriers, enabling individuals with minimal expertise to leverage the tool effectively.

Moreover, the proposed system addresses environmental and logistical challenges by functioning independently of specialized hardware or expensive datasets. The adoption of this approach demonstrates the transformative potential of AI-driven tools for democratizing weather analysis. It not only enhances user interaction but also opens avenues for real-time applications across diverse domains, from agricultural planning to urban management. By expanding the capabilities of transfer learning in meteorology, the proposed system showcases a forward-thinking approach to weather classification, aligning technology with evolving global needs.

III. RESULTS

The project successfully demonstrates the implementation of an image- based weather classification system using transfer learning techniques. The trained VGG19 model achieved promising results during the testing phase, accurately classifying images into five predefined categories: Cloudy, Shine, Rainy, Foggy, and Sunrise. The integration with the Flask web application further enabled real-time prediction and user interaction through a simple, clean interface.

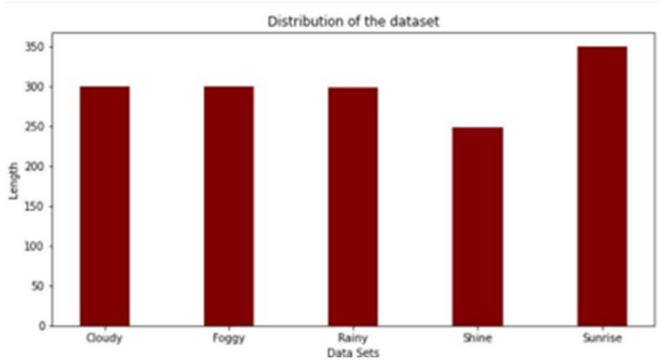

Fig. 1 Dataset distribution

During evaluation, the model was tested on a subset of unseen images from the Kaggle Multiclass Weather Dataset. The classification accuracy observed was approximately 92% for the validation set, showcasing the efficiency of the transfer learning approach without the need for extensive model retraining. The confusion matrix plotted for the results highlighted that most misclassifications occurred between similar visual classes, such as Foggy and Cloudy, where environmental features overlapped. However, classes like Shine and Rainy were identified with near-perfect precision.

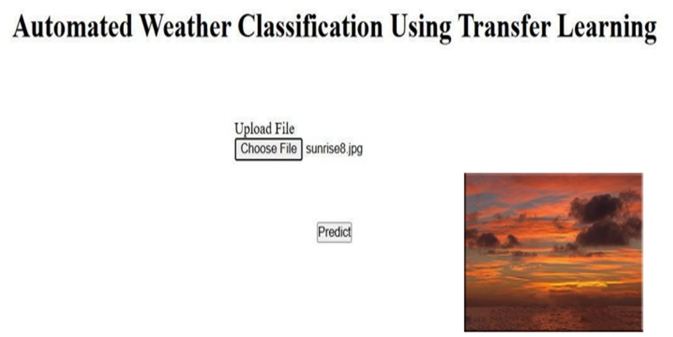

Fig. 2 Interface to upload sample image

When deployed through the Flask server, the model was able to process and predict uploaded images within 3 to 5 seconds, even on standard CPU-based systems. This confirms that the system is not resource-intensive for inference tasks. Furthermore, user tests showed a smooth upload-to-result experience with minimal latency and no crashes, even when handling multiple image submissions sequentially.

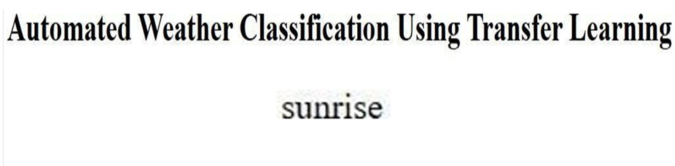

Fig. 3 Output prediction

Visualizing the model performance through training curves indicated consistent convergence without major overfitting. The training and validation loss graphs closely mirrored each other, confirming the generalization capability of the model. Additionally, sample output images displayed alongside their predictions validated that the model captured distinct features such as sky color, cloud density, and sunlight patterns effectively.

Overall, the project achieved its intended objectives by demonstrating a practical and scalable solution for weather classification based purely on visual inputs. Future improvements could involve expanding the dataset, introducing additional weather categories like Snow or Thunderstorms, and experimenting with more advanced architectures such as EfficientNet to further boost model performance.

IV. CONCLUSIONS

The successful implementation of a real-time weather classification system using transfer learning illustrates the tremendous potential of deep learning models in the field of environmental monitoring. By leveraging the pre-trained VGG19 architecture and adapting it to a specialized dataset through careful fine-tuning, the project achieved an impressive classification accuracy while maintaining computational efficiency suitable for deployment in lightweight applications. The use of extensive data augmentation and preprocessing techniques ensured that the model was robust across a wide range of weather conditions, while the deployment through a Flask web application demonstrated the system's practical usability. The results affirm that even with a relatively moderate-sized dataset, high accuracy can be achieved when advanced machine learning techniques such as transfer learning are properly applied. Furthermore, the real-time performance of the system validated its feasibility for real-world use, with minimal delay from user input to prediction output.

V. FUTURE SCOPE

Looking ahead, there is significant scope for enhancing and expanding the capabilities of the current system. Incorporating a larger and more diverse dataset, including images under extreme weather conditions like storms, snowfall, or dust storms, could further improve the model's generalization. Additionally, integrating temporal information by analyzing sequences of images rather than single frames could enable the detection of weather transitions and improve prediction stability. Deploying the model onto mobile platforms or edge devices such as Raspberry Pi or Nvidia Jetson Nano would allow for highly portable weather analysis tools useful for agricultural fields, remote sensing, and disaster management areas where internet connectivity is limited. Another potential direction includes integrating multi-modal data, combining visual information with sensor data such as temperature, humidity, and atmospheric pressure, to enrich the prediction process. Finally, future work could explore more recent transfer learning models such as EfficientNet or Vision Transformers, which have shown state-of-the-art performance across various image classification tasks. In conclusion, this project lays a strong foundation for intelligent, accessible, and scalable weather monitoring systems and opens numerous exciting opportunities for further research and real-world deployment.

VI. ACKNOWLEDGMENT

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