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HYBRID DEEP LEARNING-BASED WEATHER CLASSIFICATION SYSTEM USING SATELLITE IMAGES

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Abstract— The accessibility of satellite images has significantly improved due to the advancements in remote sensing technologies. To effectively apply remote sensing in various real-world scenarios, it is crucial to explore efficient and scalable strategies for extending its applications to new domains. Deep Learning (DL) techniques play a crucial role in Remote Sensing Imaging, aiding in achieving rapid analysis and accurate classification goals. This research focuses on classifying weather conditions using relevant satellite images, which often pose challenges such as poor quality and uneven data distribution. Despite the widespread use of Convolutional Neural Networks (CNNs) in image classification, they suffer from poor performance, mainly due to their limited global representational capabilities and reliance on local receptive fields. In addressing this issue, we introduce CNN-T, a network architecture that combines the Transformer encoder and CNN features. The CNN-T network, with its robust global modeling capabilities and high inductive biases, emerges as a powerful solution. The CNN extracts local and low-level features from the images, while the transformer encoder captures abstract and high-level semantic information by globally modeling these features. Subsequently, the multilayer perceptron (MLP) classifier receives the data to make the final decision. To assess the recognition performance of satellite images, this study compares the proposed CNN-T model against various DL models, including ResNet-18, AlexNet, and GoogLeNet. Each model's effectiveness is evaluated using a diverse set of measures. Experimental results demonstrate that the CNN-T model outperforms other models on the Large-Scale Cloud Image Database for Meteorological Research (LSCIDMR) dataset, achieving an impressive classification accuracy of 99%. This indicates the effectiveness of the proposed hybrid model in handling challenges associated with satellite image classification.
Keywords— Deep Learning, Weather Classification, Transformer, Convolutional Neural Network, Satellite Images,

I. INTRODUCTION

People require more accurate weather forecasts to function in their daily lives. Obtaining trustworthy weather forecasts has been a top priority for all parties engaged in ensuring the safety of aircraft and passengers [1]. The aviation industry is continuously seeking improved techniques for creating accurate predictions as the problem remains unsolved. Severe weather poses the most significant threat to planes and passengers, as it can cause damage [2]. Despite advances in theories, observation methods, and prediction tools over the last decade, effectively predicting weather remains a challenge characterized by nonlinearity, complexity, and time variation [3]. Few industries rely as heavily on satellite image analysis and categorization as the aviation industry, including marine, agriculture, military, and architecture [4]. Currently, there exist hundreds of forecast models, each tailored to achieve a distinct aim. Simultaneously, weather forecasting enabled by DL has piqued the interest of many academic communities, finding several practical applications in computer vision.

As a result, the satellite image analysis research community has primarily focused on satellite image classification techniques. According to the article [5], data for the LSCIDMR is collected by the Himawari-8 satellite, with no other freely available benchmark cloud dataset for meteorological research known to the author. Analyzing satellite cloud images with the aid of weather satellites allows us to learn more about clouds, the sky, and the oceans. Weather satellites play an essential role in weather analysis and alerts, primarily monitoring Earth's weather conditions.

DL networks encounter limitations in their application to remote sensing image categorization, frequently facing issues with datasets exhibiting class imbalance or excessive similarity across classes. In this paper, we propose a hybrid DL model to enhance the classification accuracy of satellite images.

II. LITERATURE SURVEY

The recent work on remote satellite images for different categorization task is discussed in this section. The article [6] proposes a Deep Convolutional Neural Network (DCNN) with multiple layers for categorizing downscaled satellite cloud images. After training on cloud images, the DCNN achieves remarkably high prediction accuracy. Training a deep convolutional network with a substantial number of instances from a suitable dataset reduces the delivery time for test images while increasing prediction accuracy. The Meteorological and Oceanographic Satellite Data Archival Centre provides satellite cloud images of the Indian subcontinent and the world. These images were obtained from this facility. The DCNN design enhances the prediction accuracy of the proposed cloud image categorization method. The study [7] introduces a new residual network called SnapResNet, comprising dropout layers, fully connected layers, Batch Normalization (BN), L2 regularization, data augmentation, and a dense layer. Architectural changes eliminate the issue of class similarity, while data augmentation corrects imbalances. To reduce over fitting and enhance network performance, the snapshot ensemble technique is also employed. Utilizing the most complex LSCIDMR data with ten classes and thousands of high-resolution images to classify, the proposed SnapResNet152 model outperforms existing DL-based methods (such as EfficientNet, ResNet101, VGG-19, and AlexNet).

The paper [8] employs a newly created, scaled-up CNN called EfficientNet as the encoder and UNet as the decoder to classify cloud organization patterns. This aids experts in understanding how clouds will impact future climates. These networks perform feature extraction, reconstruction of fine-grained feature maps, and classification. The application of a segmentation network in a classification challenge demonstrates the dataset's effective use with a suitable encoder and UNet. The final assessment metric, the dice coefficient, yields reasonable results on the Kaggle competition's public and private. The study [9] employs various image fusion approaches, including Pyramid-Based Fusion (PF) methods, PF paired with CNN, and a hybrid strategy using various pyramid decomposition techniques in conjunction with CNN. Image quality, fusion metrics, and categorization accuracy are measured using an optimized 2D-CNN-based DL classifier. PF with CNN preserves both visual quality and precise structural information while combining two pyramid decomposition algorithms with CNN retains both types of information. The study's 2D-CNN-based DL classifier's hyper-parameters are optimized using a Bayesian technique. Vertical-vertical polarized images demonstrate better classification accuracy when using fused images generated by PF with CNN.

In the study [10], the channel-dilation-concatenation network (CDC-Net) is created for meteorological satellite image categorization. CDC-net, a modification of the standard convolution approach, uses depth-wise convolution for feature extraction. Additionally, a Feature Copy operation is used instead of a half-convolution procedure. Employing a local importance-based pooling layer and retrieving high-dimensional features, CDC-net reduces inference time, parameter count, and network depth. The CDC-net proved effective in weather research, providing highly accurate results with minimal GPU inference time. The proposed CDC-net is evaluated on data with multiple labels and found to be the optimum structure in studies with meteorological satellite image datasets containing both single and multi-label information. In our study [11], we integrate images with weather data containing five types of labels: month, season, date stamp, geographic latitude, and longitude. We present a unique framework for satellite image categorization called the Multimodal Auxiliary Network (MANET), efficiently utilizing these multiple modalities to recognize clouds and weather systems. MANET comprises three major components: CNN-based image feature extraction, perceptron-based weather information feature extraction, and a layer-level multimodal fusion module. MANET successfully incorporates multimodal data, such as meteorological components and satellite images. According to experimental outcomes, MANET more accurately classifies land cover and weather systems using satellite images.

III. METHODOLOGY

This study introduces a Hybrid CNN-T model for categorizing satellite images based on weather systems. To enhance processing efficiency, images extracted from the LSCIDMR database are converted to grayscale. Noise reduction filters are applied to improve the data quality of these satellite images, known for their inherent noise [12]. Due to the natural imbalance in the collected images, balancing methods are employed to ensure proper representation of different weather groups. The processed images are then input into the proposed Hybrid CNN-T model. Additionally, three well-known DL models, ResNet-18, GoogleNet, and AlexNet, are utilized for comparison. The models' performance is assessed using key parameters, including the F1 score, specificity, accuracy, precision, and sensitivity. Through the comparative analysis of model performances, the most effective model is identified. The proposed Hybrid CNN-T model demonstrates superior performance in accurately identifying weather conditions from satellite images when compared to the competing models. Figure 1 visually presents the entire workflow of the proposed system, delineating the data pre-processing, model training, and evaluation stages.

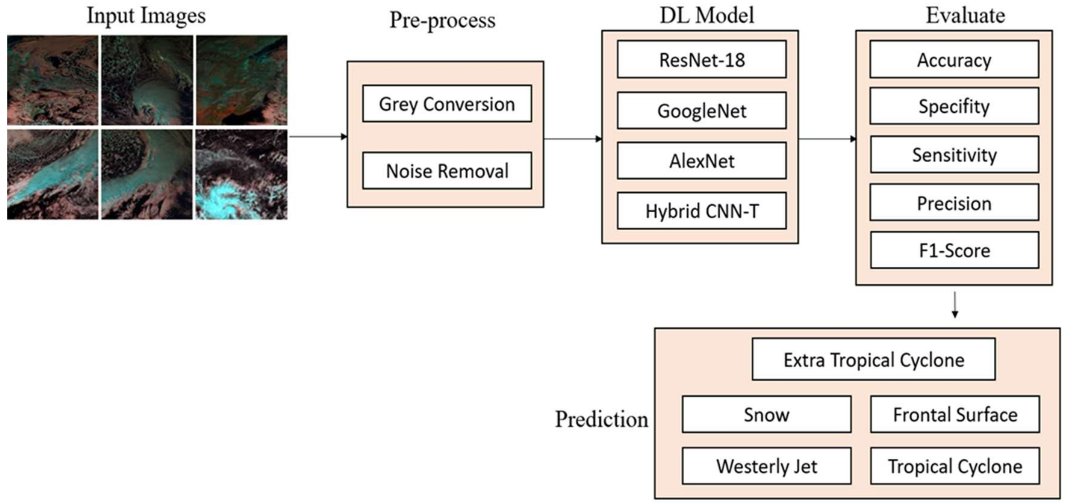

Fig. 1. Proposed method framework on weather classification from satellite images.

A. Data Collection and Processing

The LSCIDMR dataset explores all scene categories in the current weather system, integrating them with weather events captured in satellite cloud images and meteorological expert judgments to provide ten majorly utilized scene categories. These categories can be classified as: 1) Weather, 2) Terrestrial, and 3) Cloud systems. The most prominent types of weather systems in LSCIDMR are tropical cyclones, extra-tropical cyclones, frontal surfaces, westerly jets, and snow. The research focused on weather systems, and sample images from each category are displayed in Figure 2.

From the dataset, the Extra-tropical Cyclone category consists of 4,984 images, snow contains 7,631 images, Westerly Jet holds 628 images, Frontal Surface contains 634 images, and Tropical Cyclone holds 3,305 images. The dataset exhibits a high level of imbalance. To address this imbalance, 1000 images from each category is selected. However, due to the limited data in the Westerly Jet and Tropical Cyclone categories (less than 650 images), augmentation is performed for these two categories. Consequently, after augmentation, a consistent count of 1000 images in each category is ensured. The 800, 100, and 100 images from each category within the weather system are taken for the training, validation, and testing sets, respectively. Detailed information regarding the data distribution is provided in Table 1. Additionally, various processing techniques, such as color conversion [13] and noise reduction [14, 15], are applied to enhance the quality of the dataset.

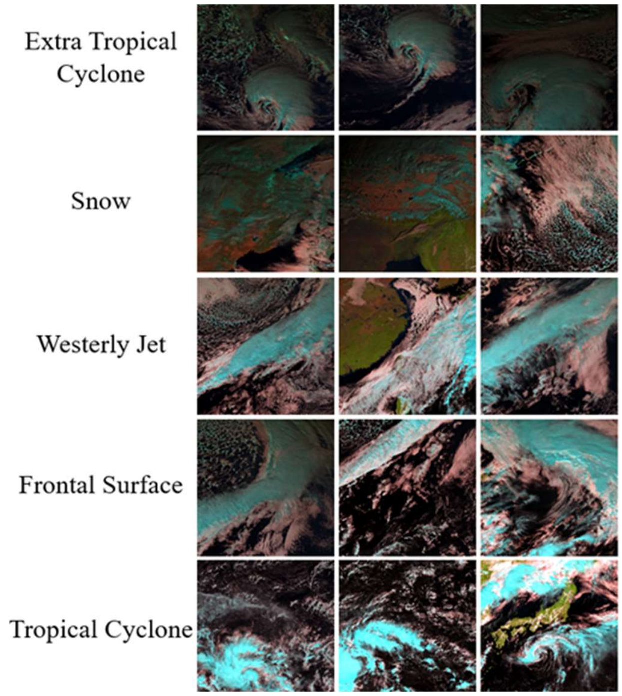

Fig. 2. Sample images from the LSCIDMR dataset.

Table. 1. Weather Data Distribution.

Data	Count	Taken	Augmented	Train	Validate	Test
Extratropical Cyclone	4984	1000	1000	800	100	100
Snow	7631	1000	1000	800	100	100
Westerly Jet	628	600	1000	800	100	100
Frontal Surface	634	600	1000	800	100	100
Tropical Cyclone	3305	1000	1000	800	100	100
Total	17182	4200	5000	4000	500	500

B. Hybrid DL Model

The architecture and working of the proposed hybrid CNN-T model are detailed in this section.

CNN: CNNs have experienced remarkable growth in recent years, driven by rapid breakthroughs in deep learning and significant advances in computer power and data storage technology [16]. Benefits of CNNs include autonomous weight change and non-linear mapping. Convolutional Layers (CL), Pooling Layers (PL), and Fully Connected Layers (FCL) are the standard building blocks of CNNs [17]. In complex neural networks, the multilayer non-linear structures known as CL and PL make up the hidden layers. Because of convolution and pooling, the network can automatically extract visual features. In CLs, convolution kernels are essential for feature extraction from input images. Convolution is a method for improving object images by filtering incoming data while keeping important features. Through feature map compression and parameter minimization, the PL minimizes the computational work.

The advantages of CL and PL, such as translation invariance and weight collaboration, have led to the widespread and successful usage of CNNs in image categorization. However, their limitations are evident. The receptive field of CNNs is constrained by the convolutional kernel size, restricting their ability to model connections beyond neighboring pixels [18]. To address the constraints of CNNs, this study employs the attention strategy to generate global pixel-to-pixel relationships.

Vision Transformer: The first system to employ a pure Transformer design, ViT, surpassed CNNs in image classification [19]. ViT comprises three main parts: an encoder, a Patch Embedding (PE), and an MLP classifier [20]. The PE is made up of conv2d (16 x 16, stride = 16) and reshaping operations. Multiple layers of the Transformer are stacked vertically to form an encoder. The MLP consists of normalized and FCL. During execution, the ViT network splits the input image (224 × 224 pixels) into 16 × 16 non-overlapping patches using PE. These patches are then converted into one-dimensional tokens. The tokens are merged and supplied into the encoder, along with a categorization token and position embedding. Finally, the MLP Classifier receives these tokens for weather classification.

ViT, leveraging the self-attention process [21], can be globally modeled and performs exceptionally well on the ImageNet data. Transformer networks, such as ViT, lack the inherent bias of CNNs, but they still need a lot of data to operate as well as CNNs [22]. Data protection is crucial, given the abundance of data that poses a risk of privacy violations. Risks associated with the proliferation of massive data need to be considered. Based on the priority principle, it is not optimal to depend only on large datasets to improve performance; rather, the research proposes combining CNN and Transformer architectures.

Proposed Architecture: The analysis led to the conclusion that Transformer and CNN function well together. While Transformer excels at capturing global issues, CNN is proficient in capturing local ones. To achieve this purpose, the CNN and Transformer are integrated to create a CNN-T hybrid architecture. CNN-T comprises four components: the convolution module, the encoder, the PE, and the MLP classifier. The feature map of the image is obtained using the convolution module, and PE transforms images into token sequences. The encoder extracts high-level semantic information from these tokens, which include class tokens with positional encoding. Finally, the MLP makes weather predictions.

The convolution module contains four CLs, each with a 2x step size and a 3x convolution kernel. Each layer contains a different number of convolution kernels: 16, 32, 64, and 256. After each convolution, the activation method and BN are performed. BN provides control over the data distribution range, effectively preventing explosions and gradient dispersion. The PE comprises a reshape operation and a CL with the size of 1 × 1 and stride of 1. The encoder eliminates the batch size and converts the 128 × 14 × 128-3D feature map to a 196 × 128-2D shape due to its 2D input requirement. In the encoder, two stacks of Transformer layers are employed. A Transformer layer consists of twice as many sub-layers, with three layers of substructure: multi-head self-attention (MHSA), LayerNorm, and a residual structure. In this study, MHSA employs the internal Scaled Dot-Product Attention score mechanism. Building blocks like LayerNorm, MLP, and residual form the second sub-layer. The MLP is a FCL with an overlay of Gaussian Error Linear Units (GELU) and the dropout function.

Figure 3 depicts the process flow diagram for the CNN-T-based weather system classification. Initially, color images from the LSCIDMR collection are transformed into grayscale. The data is then transmitted to the CNN component for feature extraction. These features are then input into the PE component for convolution and reshaping. Ultimately, the MLP generates the weather prediction.

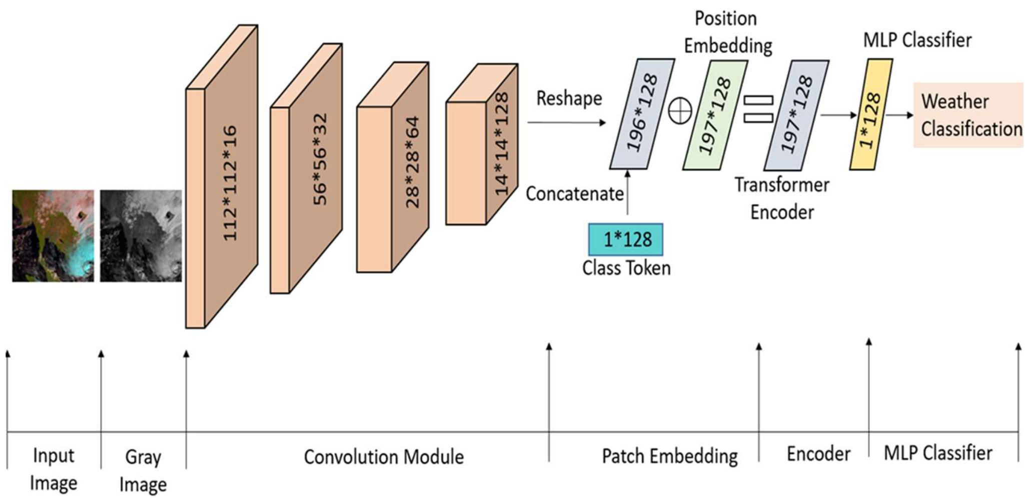

Fig. 3. Proposed CNN-T Architecture.

IV. EXPERIMENTAL OUTCOME

In this study, a Hybrid Deep Learning-Based Weather Classification System was constructed using satellite images, with a focus on identifying images depicting tropical cyclones, extra-tropical cyclones, frontal surfaces, westerly jets, and snow using the LSCIDMR dataset. The dataset was separated into 4000 images for training, 500 for validation, and the remaining 500 for testing. The proposed hybrid DL model was tested against three popular DL models: ResNet-18, GoogleNet, and AlexNet. Accuracy, specificity, sensitivity, precision, and F1 score were some of the evaluation metrics used to determine the models' effectiveness [23, 24]. Table 2 details the outcomes of the proposed approach and existing methods for classifying satellite images.

Table. 2. Performance comparison of weather classification system using satellite data.

Model	Accuracy	Specificity	Sensitivity	Precision	F1
CBB-T	**99**	**99.4**	**98.61**	**99.4**	**98.6**
ResNet-18	96.2	96.36	96.04	96.42	95.98
GoogleNet	97.4	97.79	97.02	97.8	97.01
AlexNet	98.1	98.59	97.62	98.6	97.6

The proposed hybrid model achieved outstanding prediction results, with an accuracy of 99%, specificity of 99.4%, sensitivity of 98.61%, precision of 99.4%, and an F1 score of 98.6%. In comparison, the AlexNet model achieved 98.1% accuracy, with specificity and sensitivity values of 98.59% and 97.62%, respectively. The F1 and precision scores are 97.6% and 98.6%, correspondingly. GoogleNet won in third place with 97.4% accuracy, 97.79% specificity, 97.02% sensitivity, 97.8% precision, and a 97.01% F1 score. Finally, ResNet-18 attained an accuracy of 96.2%, which is lower than the other models. The specificity, sensitivity, precision, and F1 scores are 96.36%, 96.04%, 96.42%, and 95.98%. These results show that the proposed hybrid model is superior at accurately identifying weather patterns.

Figure 4 depicts a detailed comparison of the performance indicators, revealing that the proposed model constantly beats the other DL models across all measured criteria. This illustration offers a clear overview of the model's effectiveness.

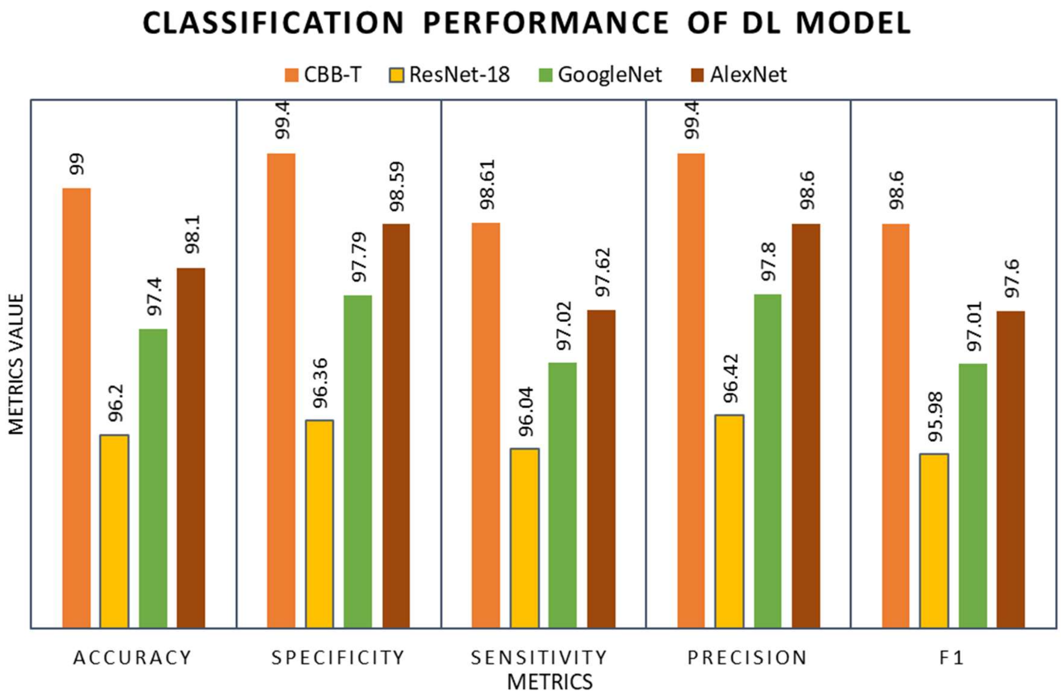

Fig. 4. Performance comparison of DL model on satellite images for weather classification.

Table 3 displays the proposed model's prediction performance across various weather categories. With notable accuracy involving 99% for Extra-Tropical Cyclone, Snow, and Tropical Cyclone, 99.5% for Westerly Jet, and 98.5% for Frontal Surface, the model demonstrated exceptional performance in accurately forecasting diverse weather systems. These results show that the proposed hybrid model is versatile and can handle many different types of weather. The output of the proposed hybrid DL model on weather categorization using satellite images is shown in Figure 5.

Table. 3. Outcome of the proposed hybrid CNN-T model

Weather	Accuracy	Specificity	Sensitivity	Precision	F1
Extra-Tropical Cyclone	99	100	98.03922	100	99.0099
Snow	99	99.0099	98.9899	98.9899	98.9899
Westerly Jet	99.5	99	100	99.0099	99.50249
Frontal Surface	98.5	98.9899	98.0198	99	98.50746

Tropical Cyclone	99	100	98.0198	100	99
Total	99	99.4	98.61	99.4	98.6

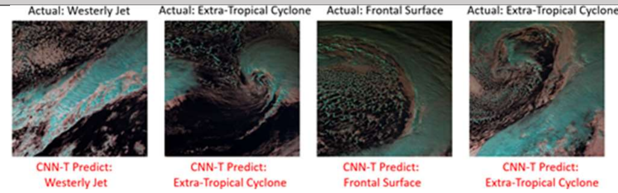

Fig. 5. Outcome of proposed hybrid CNN-T Model

V. CONCLUSION

Classifying satellite images of clouds is a crucial part of weather forecasting and climate research. For decades, remote sensing communities have focused on image categorization to limit the ecological harm caused by weather fluctuations. Classical CNNs are often used to classify satellite images. However, improving classification accuracy remains a challenge. In this study, a hybrid DL model called the CNN-T network is presented for weather categorization. This study makes use of the LSCIDMR dataset, which contains a large number of images, some of which are related to the weather system. Images are taken from five different categories and processed. After processing, the images are fed into DL models such as the proposed CNN-T network, ResNet-18, AlexNet, and GoogLeNet for classification. The results of the models are evaluated to determine which one performs better. The proposed approach surpasses conventional strategies, with 99% accuracy, 99.4% specificity, 98.61% sensitivity, 99.4% precision, and 98.6% F1 score.

The satellite images are delivered to the ground for further analysis, which can result in a time delay. To address this, in the future, plan to implement the analysis directly on the satellite. For this purpose, the Field Programmable Gate Arrays (FPGAs) will be used. FPGAs provide the advantage of programmable hardware acceleration, allowing for efficient and real-time processing of satellite images on board. This deployment approach aims to reduce latency and improve the overall efficiency of the weather categorization system by performing calculations closer to the data source, i.e., the satellite.

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