Image-Based Multiclass Classification of Weather Conditions using Machine Learning

M. Manchukonda Mounika[1], Bujjayola Saivamshi Goud[2], L. V. Sai Prashanth[2], Therati Uma Devi[2], Bandi Rakesh[2]

[1]Assistant Professor, [2]UG Student, [1,2]Department of Computer Science and Engineering (AI & ML)

[1,2]Malla Reddy Engineering College and Management Science, Kistapur, Medchal-50140l, Hyderabad, Telangana, India

ABSTRACT

Image-based multiclass classification of weather conditions plays a crucial role in various applications, including autonomous vehicles, surveillance systems, and weather forecasting. Accurate weather condition classification helps self-driving cars adjust their behavior and make informed decisions based on road conditions, visibility, and potential hazards. Weather classification aids surveillance cameras in detecting adverse weather conditions, enabling real-time alerts and improved security measures. Automatic weather classification from images enhances the accuracy of weather forecasting models by incorporating visual data into predictions. Identifying weather conditions through images aids in monitoring climate change and its impact on the environment. Therefore, this study proposes a two-stage machine learning approach for weather condition classification. Utilize ML models to extract high-level features from a pretrained model. This step aims to capture rich representations from the input images, minimizing the need for a large, annotated dataset. Build an ML classifier on top of the extracted features, which helps to improve classification accuracy and robustness. Finally, the proposed ML model classifies the sunny, rainy, snowy, and haze classes. Additionally, it reduces the risk of overfitting and enhances the model's generalization capabilities.

Keywords: Weather forecasting, Machine learning, Image processing, Classification.

1. INTRODUCTION

The image-based multiclass classification of weather conditions using machine learning is a significant and technologically advanced application in the field of computer vision and meteorology. Weather conditions significantly impact our daily lives, from determining what we wear to influencing transportation, agriculture, and disaster management. Accurately categorizing weather conditions from images is essential for both everyday decision-making and more complex scenarios like climate research and disaster preparedness [1]. This task involves using machine learning techniques to analyze images and classify them into distinct weather categories, such as sunny, cloudy, rainy, snowy, or foggy, among others [2]. The primary objective is to automate the process of weather condition identification, which traditionally relied on human observers or weather stations. Machine learning models, powered by convolutional neural networks (CNNs) and deep learning algorithms, are capable of learning intricate patterns and features within images, making them adept at discerning various weather conditions based on visual cues like cloud cover, precipitation, and lighting [3].

The motivation behind this endeavor is multifaceted. Firstly, automating weather condition classification can improve the accuracy and timeliness of weather forecasting. Meteorological agencies can utilize such models to enhance their ability to provide real-time weather updates and severe weather alerts, ultimately benefiting public safety and disaster management. Additionally, industries like agriculture, renewable energy, and transportation can optimize their operations by having access to precise and up-to-date weather information. Moreover, image-based multiclass classification of weather conditions serves as a valuable tool for climate research and monitoring [4]. Long-term data collection using this approach can contribute to our understanding of climate change and its effects, as well as help assess regional weather patterns over time. Furthermore, the integration of machine learning into weather monitoring systems can support the development of smart cities and efficient energy management systems, as well as facilitate autonomous vehicle navigation in diverse weather conditions [6].

In conclusion, image-based multiclass classification of weather conditions using machine learning represents a cutting-edge application that merges computer vision and meteorology. Its potential to revolutionize weather forecasting, enhance various industries, and advance climate research underscores the significance of this field. As machine learning algorithms continue to evolve and datasets grow, the accuracy and applicability of these models in understanding and predicting weather conditions will only become more pronounced [7].

The motivation for image-based multiclass classification of weather conditions using machine learning is grounded in the profound impact of weather on our daily lives and society as a whole. Weather conditions influence a wide range of activities, from determining what we wear to shaping critical decisions in agriculture, transportation, and disaster management. The core motivation lies in addressing several key challenges:

Firstly, improving the accuracy of weather forecasting is a primary goal. Weather predictions are essential for various sectors, including agriculture, tourism, and outdoor events. By employing machine learning to analyze images and classify weather conditions, we can enhance the precision and reliability of forecasts [8]. This, in turn, allows individuals and industries to make better-informed decisions, whether it's planning a farming schedule, scheduling flights, or preparing for a storm. Secondly, enhancing public safety is a significant driver. Severe weather events, such as hurricanes, tornadoes, and floods, can have devastating consequences. Machine learning-based weather classification can aid in the early detection and prediction of these events, providing valuable lead time for evacuation and emergency response. This technology has the potential to save lives and reduce property damage during extreme weather incidents [9]. Thirdly, optimizing resource management is a critical aspect. Industries such as agriculture and renewable energy rely heavily on weather conditions. Accurate weather classification enables farmers to make informed decisions about planting and harvesting, helps energy providers manage renewable energy sources more efficiently, and allows construction companies to plan projects effectively. This optimization translates into cost savings, increased productivity, and reduced environmental impact [10].

2. LITERATURE SURVEY

Fraiwan, et al. [11] proposed a Multiclass classification of grape diseases using deep artificial intelligence. The work aims at utilizing a ubiquitous technology to help farmers in combatting plant diseases. Particularly, deep-learning artificial-intelligence image-based applications were used to classify three common grape diseases: black measles, black rot, and fusariosis leaf spot. In addition, a fourth healthy class was included. A dataset of 3639 grape leaf images (1383 black measles, 1180 black rot, 1076 isariopsis leaf spots, and 423 healthy) was used.

Osipov, et al. [12] proposed a Deep-learning method for the recognition and classification of images from video recorders in difficult weather conditions. This work proposes a way to improve the accuracy of object identification by using the Canny operator to exclude the damaged areas of the image from consideration by capturing the clear parts of objects and ignoring the blurry ones. Only those parts of the image where this operator has detected the boundaries of the objects are subjected to further processing.

Hao, et al. [13] proposed an effective classification method by combining CNN and SVM by taking advantage of their respective advantages. At the same time in the weather scene, the brightness of the image is also a point of concern. Hue, Saturation, Value (HSV) color model can visualize the brightness of the image, so the paper experiments on both RGB and HSV images to find which pattern of colour space can achieve better results.

Batchuluun, et al. [14] proposed the Deep learning-based plant classification using nonaligned thermal and visible light images. The proposed network extracted features from each thermal image and corresponding visible light image of plants through residual block-based branch networks, and combined the features to increase the accuracy of the multiclass classification. Additionally, a new database was built in this study by acquiring thermal images and corresponding visible light images of various plants.

Kukreja, et al. [15] proposed a novel approach for the detection and multi-classification of weather conditions using an amalgamated deep learning (DL) model of Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs). The proposed model is evaluated on a dataset of 10,000 self-collected images consisting of five different weather conditions: sunny, rainy, windy, snowy, and cloudy. Our approach demonstrates a high level of accuracy and robustness in identifying different weather conditions.

Alsubai, et al. [16] proposed a Hybrid Deep Learning with an Improved Salp Swarm Optimization-based Multi-class Grape Disease Classification (HDLISSA-MGDC) model. The proposed HDLISSA-MGDC model focuses on the classification of grape leaf images into four distinct classes such as black measles, black rot, Isariopsis leaf spot and healthy. Initially, the Median Filtering (MF) technique is applied for image pre-processing, which eliminates the noise present in the images. Hybrid deep learning with improved Salp swarm optimization based multi-class grape disease.

3. PROPOSED METHODOLOGY

3.1 Overview

The multi-class weather classification task involves image preprocessing to prepare the data, training a LGBM model to learn patterns in the images, and making predictions on new images to classify them into one of the predefined weather categories. This workflow has practical applications in various domains where weather condition recognition is valuable. Figure 4.1 shows the proposed system model. The step wise analysis as follows:

Step 1. Image Preprocessing: Image preprocessing is a crucial initial step in a multi-class weather classification task. It involves several key components:

- Data Collection: A dataset of images depicting various weather conditions, including cloudy, rainy, shine, and sunrise, is collected. These images serve as the raw input for the classification task.
- Data Augmentation: To improve model robustness and generalize well to different scenarios, data augmentation techniques may be applied. This can include random rotations, flips, brightness adjustments, and cropping. Augmented images provide a more diverse training dataset.
- Image Resizing: The images are resized to a consistent resolution to ensure uniformity in the input data. Common resolutions are 224x224 or 256x256 pixels.

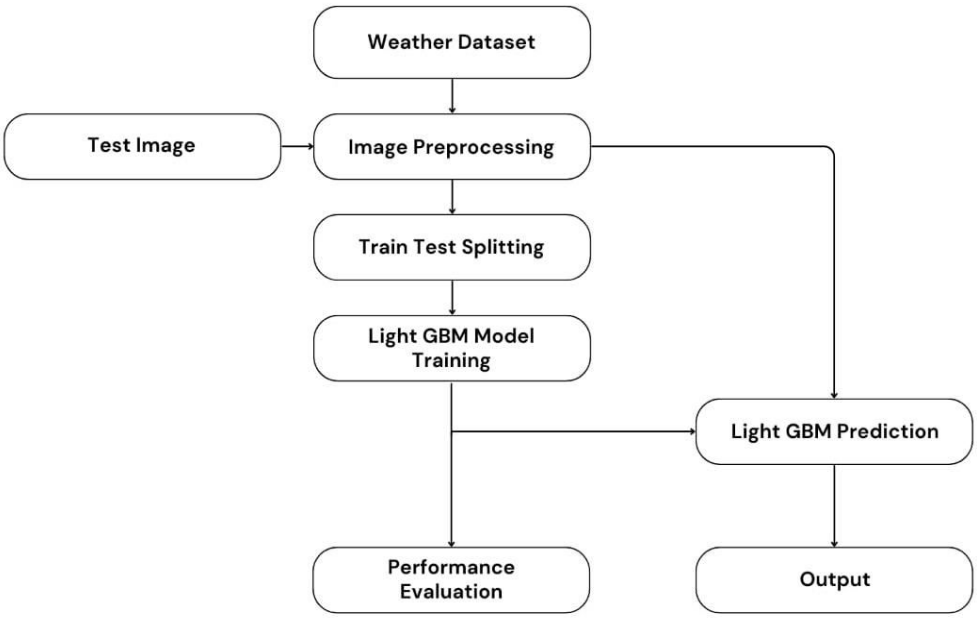
- Normalization: Normalizing pixel values is essential to make the input data suitable for machine learning models. Normalization typically involves scaling pixel values to a standardized range, such as [0, 1] or [-1, 1].
- Data Splitting: The dataset is split into training, validation, and test sets. The training set is used to train the model, the validation set helps in hyperparameter tuning, and the test set is used to evaluate the final model's performance.

Step 2. LGBM Training: Once the image preprocessing is complete, the next step involves training a machine learning model, in this case, the LGBM (Light Gradient Boosting Machine) algorithm, for multi-class weather classification:

- Feature Extraction: In the context of image data, deep learning models (such as Convolutional Neural Networks or CNNs) are typically used to extract features automatically from the preprocessed images. These features can capture patterns and characteristics relevant to weather classification.
- Model Selection: LGBM is a gradient boosting algorithm known for its efficiency and effectiveness in handling tabular and structured data. In this case, it can be employed as the classifier for weather classification.
- Hyperparameter Tuning: The LGBM model may require tuning of hyperparameters to optimize its performance. Parameters like learning rate, number of trees (boosting rounds), and depth of trees are adjusted using techniques like grid search or random search.

Step 3. Prediction: After the LGBM model is trained, it can be used for making predictions on new or unseen images:

- Image Preprocessing for Predictions: Before feeding new images into the trained model, the same image preprocessing steps (resizing, normalization) applied to the training data are also applied to these images to ensure compatibility.
- Inference: The preprocessed images are input into the trained LGBM model. The model predicts the weather class for each image based on the patterns it has learned during training.



3.2 Data Preprocessing

Image preprocessing is a critical step in computer vision and image analysis tasks. It involves a series of operations to prepare raw images for further processing by algorithms or neural networks. Here's an explanation of each step in image preprocessing:

Step 0. Image Read: The first step in image preprocessing is reading the raw image from a source, typically a file on disk. Images can be in various formats, such as JPEG, PNG, BMP, or others. Image reading is performed using libraries or functions specific to the chosen programming environment or framework. The result of this step is a digital representation of the image that can be manipulated programmatically.

1. Image Resize: Image resize is a common preprocessing step, especially when working with machine learning models or deep neural networks. It involves changing the dimensions (width and height) of the image. Resizing can be necessary for several reasons:

- Ensuring uniform input size: Many machine learning models, especially convolutional neural networks (CNNs), require input images to have the same dimensions. Resizing allows you to standardize input sizes.
- Reducing computational complexity: Smaller images require fewer computations, which can be beneficial for faster training and inference.
- Managing memory constraints: In some cases, images need to be resized to fit within available memory constraints.

When resizing, it's essential to maintain the aspect ratio to prevent image distortion. Typically, libraries like OpenCV or Pillow provide convenient functions for resizing images.

2. Image to Array: In this step, the image is converted into a numerical representation in the form of a multidimensional array or tensor. Each pixel in the image corresponds to a value in the array. The array is usually structured with dimensions representing height, width, and color channels (if applicable).

For grayscale images, the array is 2D, with each element representing the intensity of a pixel. For color images, it's a 3D or 4D array, with dimensions for height, width, color channels (e.g., Red, Green, Blue), and potentially batch size (if processing multiple images simultaneously).

The conversion from an image to an array allows for numerical manipulation and analysis, making it compatible with various data processing libraries and deep learning frameworks like NumPy or TensorFlow.

3. Image to Float32: Most machine learning and computer vision algorithms expect input data to be in a specific data type, often 32-bit floating-point numbers (float32). Converting the image array to float32 ensures that the pixel values can represent a wide range of intensities between 0.0 (black) and 1.0 (white) or sometimes between -1.0 and 1.0, depending on the specific normalization used.

This step is essential for maintaining consistency in data types and enabling compatibility with various machine learning frameworks and libraries. It's typically performed by dividing the pixel values by the maximum intensity value (e.g., 255 for an 8-bit image) to scale them to the [0.0, 1.0] range.

4. Image to Binary: Image binarization is a process of converting a grayscale image into a binary image, where each pixel is represented by either 0 (black) or 1 (white) based on a specified threshold.

Binarization is commonly used for tasks like image segmentation, where you want to separate objects from the background.

The process involves setting a threshold value, and then for each pixel in the grayscale image, if the pixel value is greater than or equal to the threshold, it is set to 1; otherwise, it is set to 0.

Binarization simplifies the image and reduces it to essential information, which can be particularly useful in applications like character recognition or object tracking, where you need to isolate regions of interest.

4. RESULTS AND DISCUSSION

Dataset description

The dataset contains total of 4946 images with 1356 images in Cloudy class, 1260 images in Rain class,1350 images in Shine class and 980 images in Sunshine class

Table 1: Dataset description.

S. No.	Number of images	Class type
1	1356	Cloudy
2	1260	Rain
3	1350	Shine
4	980	Sunrise

..	67491	67492	67493	67494	67495	67496	67497	67498	67499	Target
..	0.098402	0.080850	0.084774	0.109206	0.093225	0.098424	0.104651	0.088480	0.101404	0
..	0.163113	0.066473	0.030661	0.204392	0.095487	0.055853	0.194917	0.078189	0.035085	0
..	0.090544	0.084703	0.151186	0.108156	0.104161	0.154694	0.419241	0.416855	0.449252	0
..	0.060633	0.009888	0.037692	0.073603	0.022858	0.050662	0.074392	0.023647	0.051451	0
..	0.001911	0.002092	0.001496	0.000061	0.000125	0.000317	0.000139	0.000045	0.001117	0
..	...	...	...	...	...	...	...	...	...	...
..	0.337671	0.299463	0.062129	0.327231	0.293843	0.073827	0.347965	0.315976	0.089761	3
..	0.338140	0.406279	0.060684	0.311429	0.369744	0.036610	0.334290	0.381876	0.042596	3
..	0.310458	0.337905	0.136824	0.260982	0.288433	0.084632	0.326134	0.353585	0.149781	3
..	0.736872	0.628875	0.399515	0.783501	0.681540	0.450167	0.746286	0.647801	0.414691	3
..	0.081073	0.069310	0.004152	0.133459	0.122273	0.046628	0.137255	0.129385	0.047085	3

Figure 1: Dataset after preprocessing image for weather condition monitoring using ML model.

Figure 2: Sample images from dataset with Cloudy class.

Figure 3: Sample images from dataset with Sunrise class.

	0	1	2	3	4	5	6	7	8	9	...	67490	67491	67492	67493	67494
0	0.964491	0.588875	0.175885	0.965719	0.591133	0.189581	0.960490	0.594155	0.196179	0.970811	...	0.057548	0.098402	0.080850	0.084774	0.109206
1	0.974672	0.590359	0.155065	0.978194	0.593881	0.158586	0.985106	0.600921	0.165562	0.985524	...	0.050390	0.163113	0.066473	0.030661	0.204392
2	0.619648	0.617410	0.713268	0.171908	0.194709	0.414944	0.130480	0.187307	0.476146	0.145099	...	0.144373	0.090544	0.084703	0.151186	0.108156
3	0.043373	0.051216	0.102196	0.043373	0.051216	0.102196	0.043373	0.051216	0.102196	0.043163	...	0.040208	0.060633	0.009888	0.037692	0.073603
4	0.327076	0.161610	0.215032	0.325749	0.161608	0.220142	0.344374	0.174018	0.226181	0.367774	...	0.021617	0.001911	0.002092	0.001496	0.000061
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
548	0.204554	0.380349	0.611828	0.214684	0.382061	0.614731	0.226105	0.390777	0.620331	0.235487	...	0.067170	0.337671	0.299463	0.062129	0.327231
549	0.891809	0.907496	0.919260	0.904641	0.920327	0.932092	0.921857	0.937543	0.949308	0.932444	...	0.069961	0.338140	0.406279	0.060684	0.311429
550	0.266667	0.427451	0.631373	0.266667	0.427451	0.631373	0.266667	0.427451	0.631373	0.266667	...	0.075984	0.310458	0.337905	0.136824	0.260982
551	0.349469	0.622248	0.823410	0.345990	0.600646	0.788109	0.373358	0.607443	0.778064	0.369482	...	0.385025	0.736872	0.628875	0.399515	0.783501
552	0.678732	0.655942	0.694850	0.650139	0.638184	0.665840	0.632965	0.624359	0.645512	0.633535	...	0.034528	0.081073	0.069310	0.004152	0.133459

553 rows × 67500 columns

Figure 4: data frame of input images after preprocessing

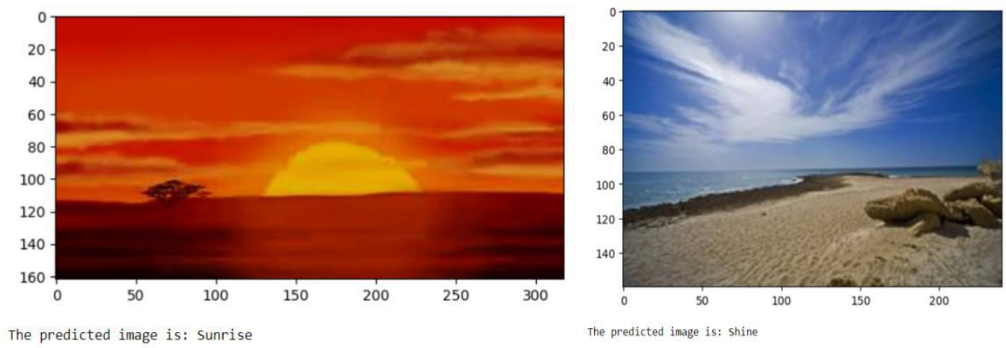


Figure 5: Sample prediction on test data using proposed ML model.

	precision	recall	f1-score	support
0	0.95	0.86	0.91	147
1	0.82	0.82	0.82	138
2	0.49	0.52	0.51	75
3	0.50	0.57	0.53	83
accuracy			0.74	443
macro avg	0.69	0.69	0.69	443
weighted avg	0.75	0.74	0.74	443

Figure 6: Classification report for Light BGM classifier Model

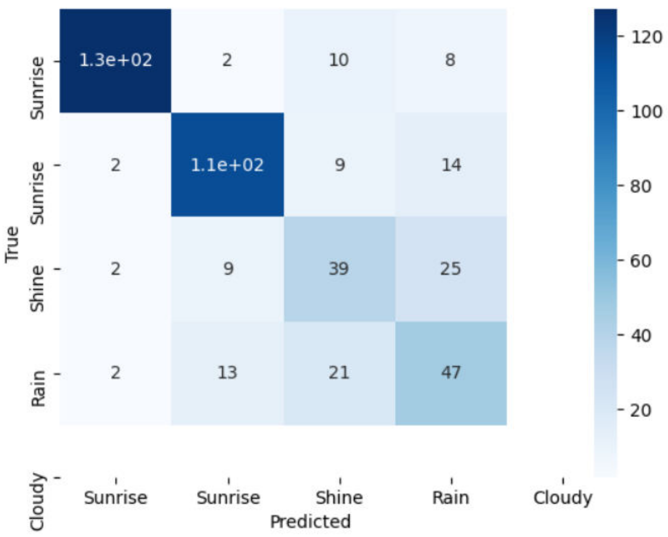


Figure 7: Obtained confusion matrix with actual and predicted labels using Light BGM Classifier.

Table 2: Overall performance comparison of proposed ML models.

Model name	Accuracy (%)	Precision (%)	Recall (%)	F1-score
Random Forest	65	69	69	69
Light BGM classifier	73	75	75	74

5. CONCLUSION

In conclusion, the multi-class weather classification task, encompassing image preprocessing, LGBM training, and prediction, represents a significant stride in the domain of computer vision and meteorology. The process begins by meticulously preparing a dataset of weather-related images, involving data augmentation, resizing, normalization, and data splitting to ensure robust model training and evaluation. The LGBM model, a powerful gradient boosting algorithm, emerges as an effective choice for classifying weather conditions based on the extracted image features. Through feature extraction and extensive hyperparameter tuning, the model is primed to recognize complex patterns and relationships in the images. The training process is monitored through validation, preventing overfitting and ensuring generalizability. Upon successful training, the model becomes capable of classifying new, unseen images into distinct weather categories. These predictions, once post-processed and visualized, offer valuable insights into current weather conditions, facilitating informed decision-making in various fields, including meteorology, agriculture, transportation, and event planning. As technology and data continue to advance, multi-class weather classification stands as a promising tool for enhancing our understanding of the environment and its implications on daily life.

REFERENCES

[1] Kirola, Madhu, et al. "Plants diseases prediction framework: A image-based system using deep learning." 2022 IEEE World Conference on Applied Intelligence and Computing (AIC). IEEE, 2022.

[2] Chakraborty, Kulendu Kashyap, et al. "Automated recognition of optical image based potato leaf blight diseases using deep learning." Physiological and Molecular Plant Pathology 117 (2022): 101781.

[3] Mishra, Shweta, Saurabh Kumar, and Vipin Kumar. "Multi-view Deep Learning for Weather Recognition." International Conference on Artificial Intelligence and Sustainable Engineering: Select Proceedings of AISE 2020, Volume 2. Singapore: Springer Singapore, 2022.

[4] Juyal, Amit, Sachin Sharma, and Priya Matta. "Multiclass Objects Localization Using Deep Learning Technique in Autonomous Vehicle." 2022 6th International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS). IEEE, 2022.

[5] Choi, Yeonjoo, et al. "Automated multi-class classification for prediction of tympanic membrane changes with deep learning models." Plos one 17.10 (2022): e0275846.

[6] Tiwari, Vaibhav, Rakesh Chandra Joshi, and Malay Kishore Dutta. "Deep neural network for multi-class classification of medicinal plant leaves." Expert systems 39.8 (2022): e13041.

[7] El Akhal, Hicham, et al. "A novel approach for image-based olive leaf diseases classification using a deep hybrid model." Ecological Informatics (2023): 102276.

[8] Li, Shanshan, et al. "Classification of Multi-Class Weather Image Data." 2023 9th International Symposium on System Security, Safety, and Reliability (ISSSR). IEEE, 2023.

[9] Habib, Shabana, et al. "X-ray Image-Based COVID-19 Patient Detection Using Machine Learning-Based Techniques." Computer Systems Science & Engineering 43.2 (2022).

[10] Lee, Sang-Heon, et al. "Accurate Ship Detection Using Electro-Optical Image-Based Satellite on Enhanced Feature and Land Awareness." Sensors 22.23 (2022): 9491.

[11] Fraiwan, Mohammad, Esraa Faouri, and Natheer Khasawneh. "Multiclass classification of grape diseases using deep artificial intelligence." Agriculture 12.10 (2022): 1542.

[12] Osipov, Aleksey, et al. "Deep learning method for recognition and classification of images from video recorders in difficult weather conditions." Sustainability 14.4 (2022): 2420.

[13] Hao, YuChen, and Yuxuan Zhu. "Weather Classification for Multi-class Weather Image Based on CNN." 2022 International Conference on Machine Learning and Intelligent Systems Engineering (MLISE). IEEE, 2022.

[14] Batchuluun, Ganbayar, Se Hyun Nam, and Kang Ryoung Park. "Deep learning-based plant classification using nonaligned thermal and visible light images." Mathematics 10.21 (2022): 4053.

[15] Kukreja, Vinay, Rishabh Sharma, and Rishika Yadav. "Multi-Weather Classification using Deep Learning: A CNN-SVM Amalgamated Approach." 2023 World Conference on Communication & Computing (WCONF). IEEE, 2023.