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Classification of Weather Phenomenon with a New Deep Learning Method Based on Transfer Learning

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Abstract – Recognition of weather conditions, which have an important effect on the planning of our daily lives, affects many events from transport to agriculture. Even on an ordinary day, the weather affects many events, from taking children to the market to taking a walk. In addition, in many commercial areas such as agriculture and animal husbandry, many issues from planting and planting time to production are directly or indirectly related to weather conditions. For these reasons, automatic analyses and classification of aerial images will provide significant convenience. New technologies based on deep learning are needed to minimize the errors of experts working in the towers established to monitor weather conditions. Deep learning based systems are preferred because they bring a new perspective to feature extraction and classification approaches in classical machine learning technologies. With deep learning based systems, it is possible to classify by obtaining distinctive features from different weather conditions. In this paper, a pre-trained architecture-based deep learning model is proposed to classify a dataset containing 6877 images of 11 weather conditions. In order to measure the effect of the proposed model on the performance, a comparison with the basic model is performed. The weather classification accuracy of the proposed model in the test set is 88%. This performance result shows that the model is competitive with its competitors. At this point, eleven different weather images can be automatically classified. As a result of the mentioned procedures, this study can be a reference for future weather classification studies.

Keywords –Deep Learning, Weather, Transfer Learning, Resnet152v2, Classification

I. Introduction

People need to have information about the weather to plan their lives. For example, people plan their lives according to the weather in different events in daily life such as picking up their children from school, going to the market, going to the grocery store, going on holiday, walking, playing football, taking their children to the park.

Planned living has an important effect on people's lives. In order to support this effect, it is necessary to have information about the weather. Many actions and events in which people are involved affect the weather. Many activities carried out during the day are carried out according to the weather. Observation stations developed to monitor weather events that vary from region to region are managed by experts and effective devices [1]. Artificial intelligence-supported decision support systems are needed to prevent human-based errors in an ordinary way.

Weather events can be classified based on human observation, which is one of the classic classification methods. However, it is also possible to make mistakes in such classification due to fatigue or low attention during visual discrimination. For these reasons, there is a great need for high-precision, efficient systems that automatically classify weather images. In the literature, Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), ResNet50, DenseNet, VGG16, InceptionV3 based deep learning models are used to classify weather images [1]–[6]. In addition, it is also seen that multiple sensors are used in weather classification [7]. However, deep learning and computer vision-based solutions are needed due to the difficulty of installation and maintenance of sensors and the need for more manpower. In contrast to the disadvantages of manual feature extraction, deep learning-based methods are quite good in semantic classification without extracting discriminative features [3]. CNN-based methods automatically extract more detailed features than the features extracted using classical machine learning-based methods [8].

The following sections of the article consist of four sections. In the first section, studies similar to the work carried out in this paper are listed. In the second section, the data set used in the paper and the proposed method are mentioned. In the third section, the performance results obtained from the proposed method are shared. In the fourth section, the study is concluded with the results obtained.

II. Related Works

The advancement of artificial intelligence technology every day facilitates weather forecasts [9]**.** There are studies in the literature on the classification of images of different weather types based on deep learning architectures, which is a sub-branch of artificial intelligence.

Elhoseiny et al. classified two different types of weather images using both pre-trained ImageNet weights and a CNN model [10]. At this point, it is seen that the performance results of both models are shared in the study developed to analyses the layer behavior of the CNN model. An et al. classified weather images with a deep learning model that combines AlexNet and ResNet architectures [11]. They used a multi-class SVM structure at the classification layer stage. Guerra et al. categorised the images of the data set created using weather images from in-car cameras [12].

Kalkan et al. performed accurate classification of weather images using deep learning architectures to prevent incorrect weather forecasts in meteorological institutions [13]. They have developed a deep learning system that classifies image data taken from the ground showing clear and cloudy weather conditions. It is seen that four pre-trained deep learning models are used here to reduce misprediction due to human errors. DenseNet201, ResNet152, VGG16, MobileNet V2 are used in the study. The VGG16 architectural model is stated to give the best classification result among them. The importance of preferring deep learning based models instead of meteorologists collecting and analyzing image data on a weekly basis is mentioned. In models based on deep learning, it is emphasised that models whose training data are expanded by increasing the size of the data set with aerial images improve the performance criteria [13].

Weyn et al. developed a CNN-based deep learning model for weather prediction [14]. Schultz et al. discusses whether weather forecasting can be done with deep learning in their study [15]. Zhang et al. aimed to classify clouds, which are very effective in world energy balance, climate, and weather, based on deep learning [16]. Using a ten-category dataset of cloud-type images, a deep learning-based model called CloudNet was developed. Sharma and Ismail developed a CNN-based model to predict four different weather conditions [17]. Al-Haija et al. classified weather types using ResNet-18 [18]. Weather images are classified in different ways for traffic communication, afforestation, and regulation of environmental problems [19]. CNN based methods and machine learning based methods have been used together to obtain high accuracy performance results. Yildirim et al. developed a method to classify a dataset consisting of shine, rainy, foggy, cloudy, cloudy, sunrise type weather images [20]. In this method, they developed a hybrid model using DenseNet, MobileNet, and EfficientNet architectures, which are pre-trained architectures. By removing the classification layers in the top layers of these models, they extracted only the features from the weather images. Then, they classified the extracted features with the algorithm called Support Vector Machine (SVM). It is reported that combining the features obtained by using pre-trained architectures together improves performance.

III. Material and Methods

A. *Material*

In supervised learning, separated and labelled images are needed. The quality and nature of the data set to be analyzed can affect the classification performance [21]. To improve the performance metrics of the proposed deep learning model, the data separated as training and test should be of high quality as a whole [16]. While determining the data set to be studied within the scope of this article, a data set that meets these criteria has been searched.

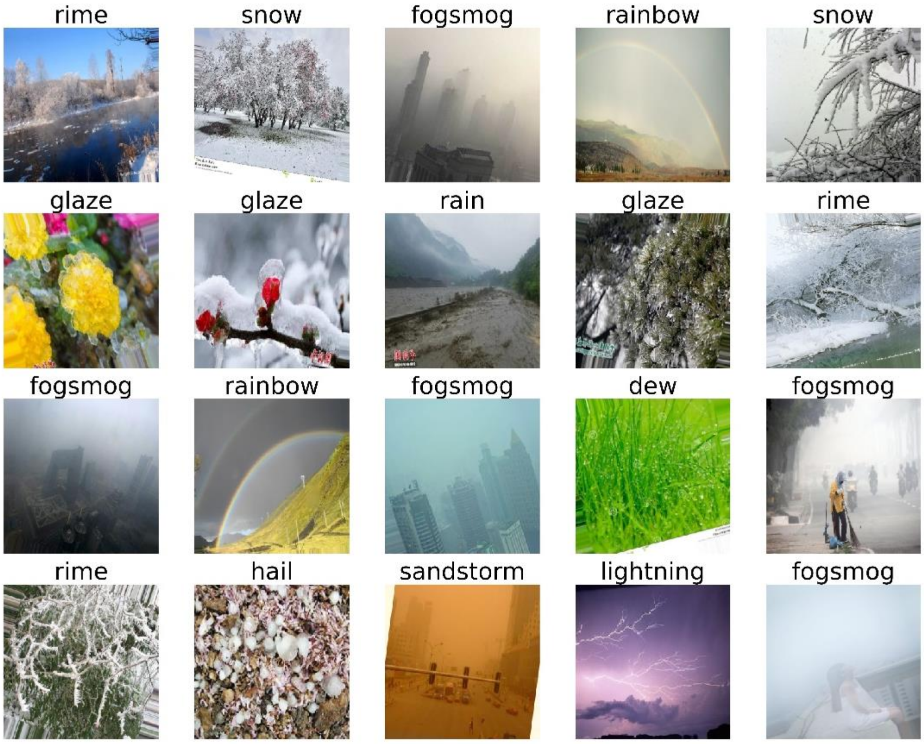

Fig. 1. Some of the weather images in the dataset

As a result of the investigation, a data set was identified that contained a large number of images with different weather events in 11 categories [22]. This dataset contains 6877 images. The 11 categories in the dataset consist of classes named rime, fog/smog, frost, sandstorm, ligtning, rain, rainbow, snow, hail, dew, glaze, respectively. The classes named rime, fog/smog, frost, sandstorm, ligtning, rain, rainbow, snow, hail, dew, glaze consist of 1.160, 855, 475, 692, 378, 527, 238, 621, 592, 700, 639 images respectively.

Some of the images in the dataset are shown in Fig. 1. In this figure, weather types that are frequently encountered in our daily lives are presented.

B. *Methods*

There is no ResNet152V2 based study using the dataset studied in this paper. In order to fill this gap, a deep learning model is proposed based on the ResNet152V2 architecture, which is one of the pre-trained architectures. The ResNetV2 architecture is a CNN architecture consisting of convolution layers. It performs batch normalisation before each weight layer. ResNet, deep neural networks are architectures with skip connections in order not to forget their features. With this feature, it has made a great contribution to the literature.

In the proposed ResNet152V2 model to classify weather images, 10 layers are added on top of the basic ResNet152V2 architecture. In the first layer, max-pooling is performed with a 3x3 window size kernel with 32 filters. In the second layer, a dropout layer with a dropout rate of 0.3 neurons is applied. In the third layer, a dense layer with 512 neurons and ReLU activation was used. In the fourth layer, batch normalization was applied. In the fifth layer, a dropout of 0.4 was added. In the sixth layer, a 256 neurone dense layer with ReLU activation function was applied. In the seventh layer, batch normalisation was applied for interlayer normalisation. In the eighth layer, a dropout of 0.3 was added. In the ninth layer, a fully connected layer is defined, which is given by combining the features and strengthening them with the classification layer. In the last layer, a classifier with 11 outputs and a softmax activation function was added to be equivalent to the number of classes.

IV. Results and Discussion

The experimental studies carried out within the scope of this article were carried out on a computer with a NVIDIA RTX 3060 graphics card with a Windows 10 64-bit operating system. Using Tensorflow [23] and Keras [24] libraries, which are the two most widely used libraries of artificial intelligence, the proposed model was run in 50 epochs. The dimensions of the input images are 256x256x3. The training and test performance results obtained from the data trained using the Adam [25] optimisation method are presented in Figs. 2-6.

Table 1. Performance results obtained in experimental studies

Model	Train accuracy	Train loss	Validation accuracy	Validation loss
ResNet152V2	0.95	0.12	0.87	0.57
Proposed Model	0.96	0.08	0.88	0.62

The performance results shown in Table 1 are shown graphically in Figs. 2-6. Fig. 2. shows two train accuracy performance accuracy graphs close to each other.

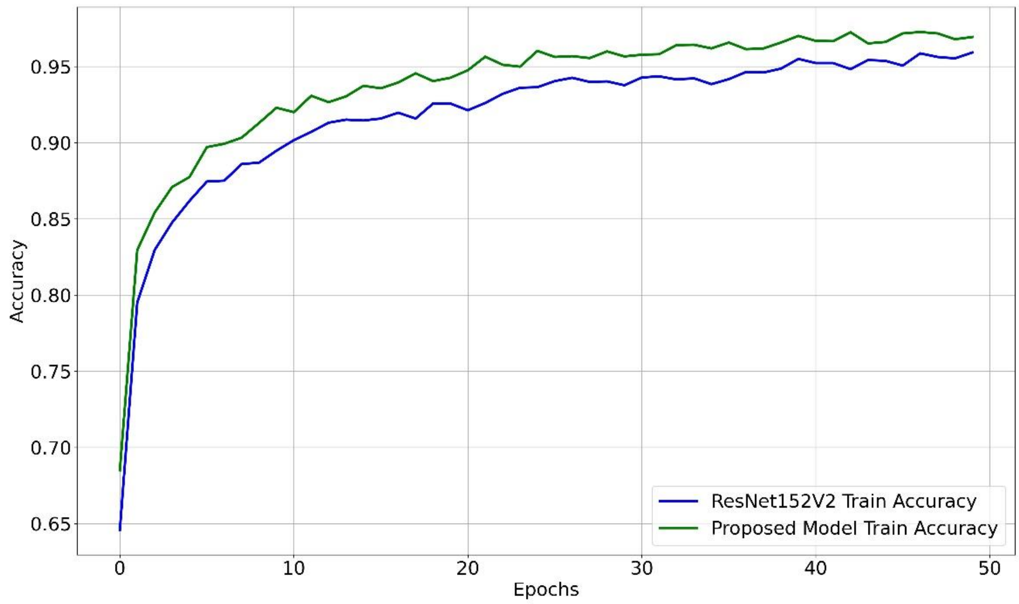

Fig. 2. Train accuracy performance graph in weather classification

Fig. 3. shows the loss values of the two models that give similar results. The proposed model gives a slightly lower loss value. The higher the accuracy of the train, the lower the loss value.

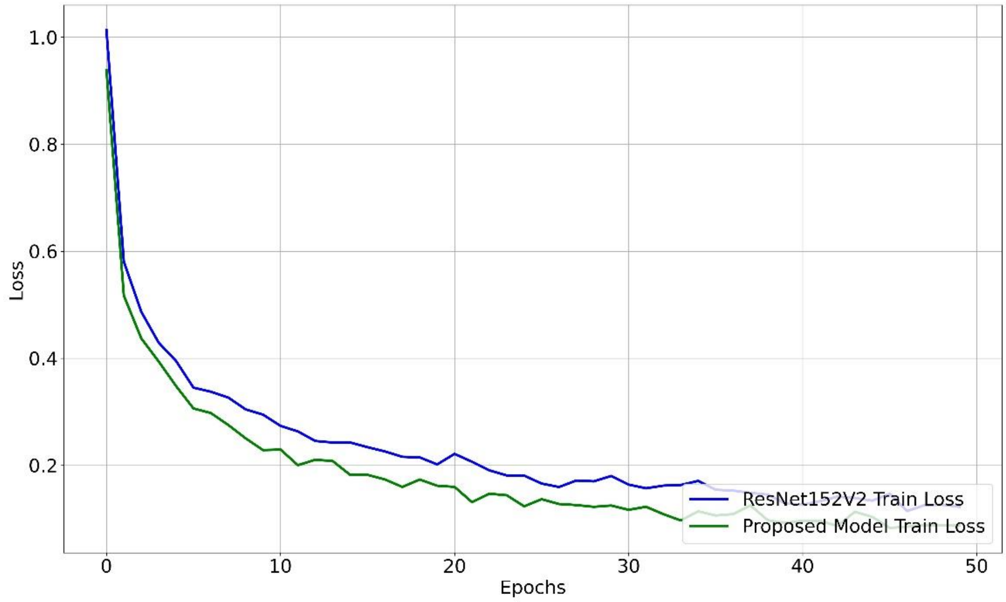

Fig. 3. Train loss performance graph in weather classification

Fig. 4 shows that the validation accuracy values of both models are very close to each other. Both models obtained a result of 0.88. To obtain a better result, the model needs to be improved.

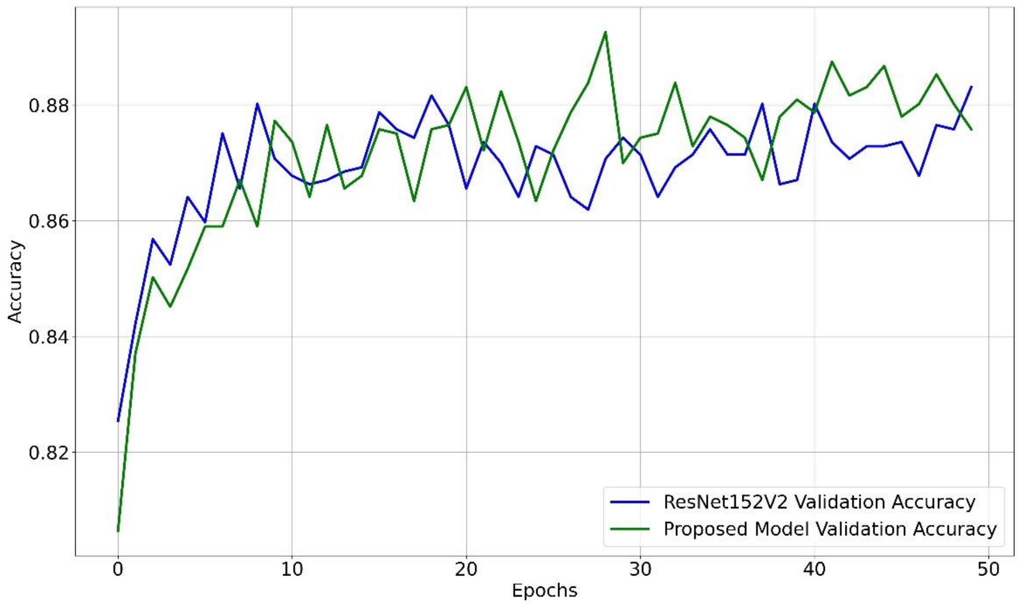

Fig. 4. Performance graph of validation accuracy for weather classification

Fig. 5, it is seen that the proposed model has a better loss value of 0.05 than the basic ResNet152V2 model.

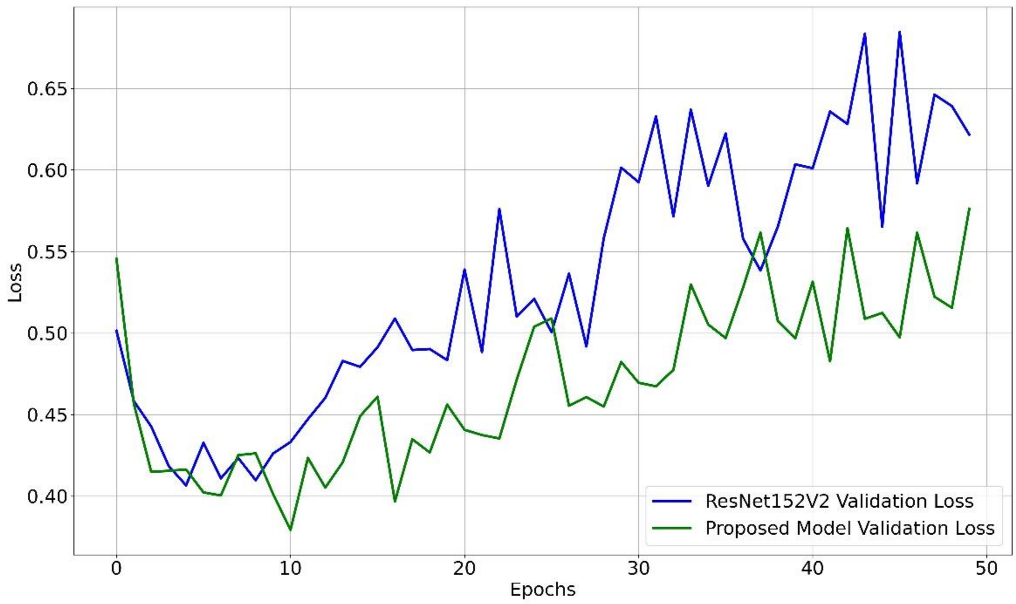

Fig. 5. Train loss performance graph in weather classification

As a result of the performance metrics obtained, the proposed model slightly outperforms the basic ResNet152V2.

However, the desired results are not very high. For better performance, the layer structure and feature extraction layers of the model can be improved.

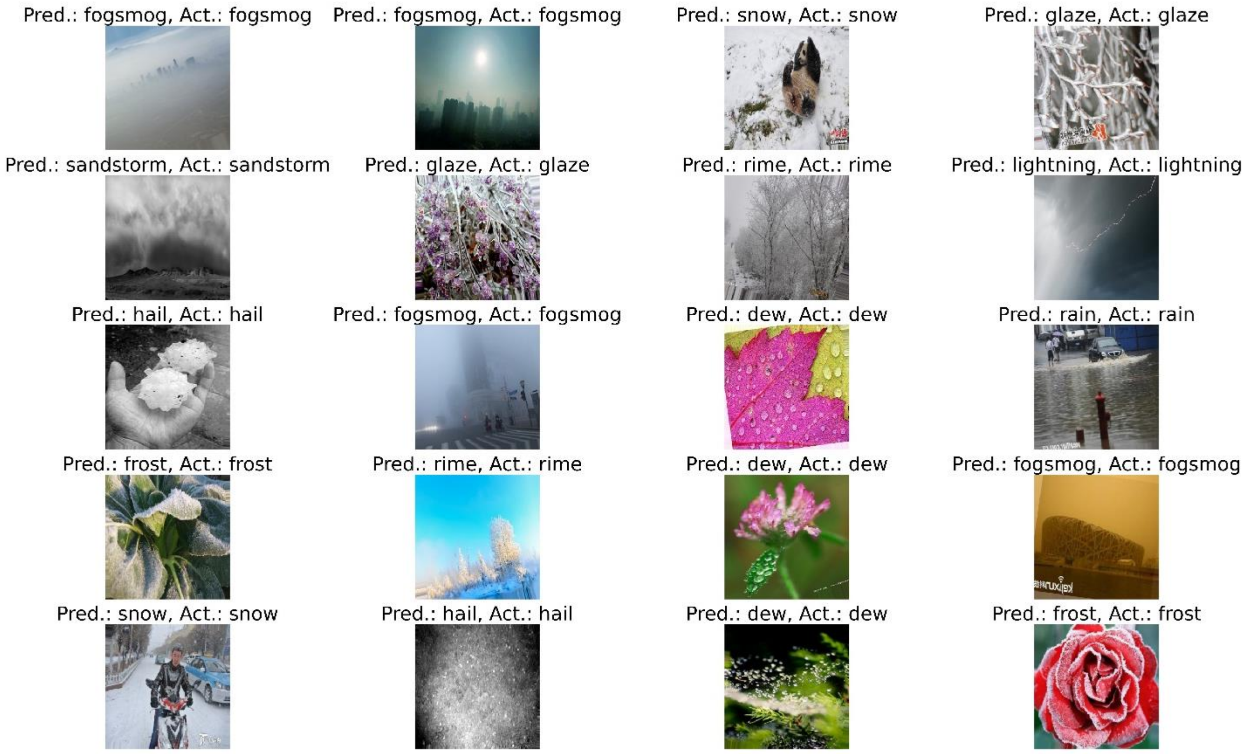

Fig. 6. Classification output results of the proposed model

Fig. 6 shows the results of the proposed model when the test images as actual and predict are given as input to the model.

V. CONCLUSION

In this study, a large dataset consisting of various weather images is classified. A new model was developed based on the ResNet152V2 architecture, which was trained using the pre-trained network ImageNet. As a result of the experimental studies, competitive results were obtained with the studies in the literature. The system, which is designed as an assistant to weather observers, will be a decision support system that helps experts. In many areas from agriculture to environmental monitoring, the classification of weather images has an important planning effect.

REFERENCES

[1] C. C. Ummenhofer and G. A. Meehl, "Extreme weather and climate events with ecological relevance: a review," *Philos. Trans. R. Soc. B Biol. Sci.*, vol. 372, no. 1723, p. 20160135, 2017.

[2] T. Hoare, "Comparative analysis of deep and transfer learning techniques for two and multi-class weather image classification." Dublin Business School, 2021.

[3] J. Xia, D. Xuan, L. Tan, and L. Xing, "ResNet15: weather recognition on traffic road with deep convolutional neural network," *Adv. Meteorol.*, vol. 2020, pp. 1–11, 2020.

[4] Y. Wang and Y. Li, "Research on Multi-class Weather Classification Algorithm Based on Multi-model Fusion," in *2020 IEEE 4th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC)*, 2020, vol. 1, pp. 2251–2255.

[5] M. R. Ibrahim, J. Haworth, and T. Cheng, "WeatherNet: Recognising weather and visual conditions from street-level images using deep residual learning," *ISPRS Int. J. Geo-Information*, vol. 8, no. 12, p. 549, 2019.

[6] B. Zhao, X. Li, X. Lu, and Z. Wang, "A CNN–RNN architecture for multi-label weather recognition," *Neurocomputing*, vol. 322, pp. 47–57, 2018.

[7] C. Dannheim, C. Icking, M. Mäder, and P. Sallis, "Weather detection in vehicles by means of camera and LIDAR systems," in *2014 Sixth International Conference on Computational Intelligence, Communication Systems and Networks*, 2014, pp. 186–191.

[8] S. Metlek and H. Çetiner, *Matlab Ortamında Derin Öğrenme Uygulamaları*. Ankara: iksad publishing house, 2021.

[9] M. Toğaçar, B. Ergen, and Z. Cömert, "Detection of weather images by using spiking neural networks of deep learning models," *Neural Comput. Appl.*, vol. 33, no. 11, pp. 6147–6159, 2021, doi: 10.1007/s00521-020-05388-3.

[10] M. Elhoseiny, S. Huang, and A. Elgammal, "Weather classification with deep convolutional neural networks," in *2015 IEEE International Conference on Image Processing (ICIP)*, 2015, pp. 3349–3353. doi: 10.1109/ICIP.2015.7351424.

[11] J. An, Y. Chen, and H. Shin, "Weather Classification using Convolutional Neural Networks," in *2018 International SoC Design Conference (ISOCC)*, 2018, pp. 245–246. doi: 10.1109/ISOCC.2018.8649921.

[12] J. C. V. Guerra, Z. Khanam, S. Ehsan, R. Stolkin, and K. McDonald-Maier, "Weather Classification: A new multi-class dataset, data augmentation approach and comprehensive evaluations of Convolutional Neural Networks," in *2018 NASA/ESA Conference on Adaptive Hardware and Systems (AHS)*, 2018, pp. 305–310. doi: 10.1109/AHS.2018.8541482.

[13] M. Kalkan *et al.*, "Cloudy/clear weather classification using deep learning techniques with cloud images," *Comput. Electr. Eng.*, vol. 102, p. 108271, 2022, doi: https://doi.org/10.1016/j.compeleceng.2022.108271.

[14] J. A. Weyn, D. R. Durran, and R. Caruana, "Improving Data-Driven Global Weather Prediction Using Deep Convolutional Neural Networks on a Cubed Sphere," *J. Adv. Model. Earth Syst.*, vol. 12, no. 9, p. e2020MS002109, 2020, doi: https://doi.org/10.1029/2020MS002109.

[15] M. G. Schultz *et al.*, "Can deep learning beat numerical weather prediction?," *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.*, vol. 379, no. 2194, p. 20200097, Feb. 2021, doi: 10.1098/rsta.2020.0097.

[16] J. Zhang, P. Liu, F. Zhang, and Q. Song, "CloudNet: Ground-Based Cloud Classification With Deep Convolutional Neural Network," *Geophys. Res. Lett.*, vol. 45, no. 16, pp. 8665–8672, 2018, doi: https://doi.org/10.1029/2018GL077787.

[17] A. Sharma and Z. S. Ismail, "Weather Classification Model Performance: Using CNN, Keras-Tensor Flow," *ITM Web of Conferences*, vol. 42. EDP Sciences PP - Les Ulis, Les Ulis, 2022. doi: https://doi.org/10.1051/itmconf/20224201006.

[18] Q. A. Al-Haija, M. A. Smadi, and S. Zein-Sabatto, "Multi-Class Weather Classification Using ResNet-18 CNN for Autonomous IoT and CPS Applications," in *2020 International Conference on Computational Science and Computational Intelligence (CSCI)*, 2020, pp. 1586–1591. doi: 10.1109/CSCI51800.2020.00293.

[19] M. S. Ghaleb, H. Moushier, H. Shedeed, and M. Tolba, "Weather Classification using Fusion Of Convolutional Neural Networks and Traditional Classification Methods," *Int. J. Intell. Comput. Inf. Sci.*, vol. 22, no. 2, pp. 84–96, 2022.

[20] M. Yildirim, A. Çinar, and E. Cengİl, "Classification of the weather images with the proposed hybrid model using deep learning, SVM classifier, and mRMR feature selection methods," *Geocarto Int.*, vol. 37, no. 9, pp. 2735–2745, May 2022, doi: 10.1080/10106049.2022.2034989.

[21] J. Lu *et al.*, "P_SegNet and NP_SegNet: New neural network architectures for cloud recognition of remote sensing images," *IEEE Access*, vol. 7, pp. 87323–87333,

2019.
[22] H. Xiao, F. Zhang, Z. Shen, K. Wu, and J. Zhang, “Classification of Weather Phenomenon From Images by Using Deep Convolutional Neural Network,” *Earth Sp. Sci.*, vol. 8, no. 5, p. e2020EA001604, May 2021, doi: https://doi.org/10.1029/2020EA001604.
[23] M. Abadi *et al.*, “{TensorFlow}: a system for {Large-Scale} machine learning,” in *12th USENIX symposium on operating systems design and implementation (OSDI 16)*, 2016, pp. 265–283.
[24] A. Gulli and S. Pal, *Deep learning with Keras*. Packt Publishing Ltd, 2017.
[25] D. Kingma and J. Ba, “Adam: A Method for Stochastic Optimization,” *Int. Conf. Learn. Represent.*, Dec. 2014.