International Journal for Multidisciplinary Research (IJFMR)

E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Weather Classification Using Deep Convolutional Neural Network

G. Lakshmi

MCA, Assistant Professor, Department of Computer Applications, Mohan Babu University, Andhra Pradesh, India

ABSTRACT

When making various decisions , the weather is a highly significant factor that is considered. The classification of the weather appears to be particularly crucial in the industrial sector, including the development of modern transfer systems, self-driving cars, and outside visual patterns in the environment. Physical weather recognition is unclear and time-consuming by humans. The information gathered from online sources is not always available. The atmosphere is clearly visible in the photographs. Since one weather pattern can mimic another, we describe a special system for automatically extracting this information from roadside photographs. We then employ a combined approach of deep learning & artificial intelligence, with essentially no well before bounds in the pre-processing step.

The Batch Normalization is one of four deep convolutional neural network (CNN) designs that are created and use dense structure and residual learning to get the most out of weather and visual conditions like rainy, snowy, rainbow, dew, and foggy, among others, of weather conditions.

The proposed system CCN model is excellent at extracting this information from viewer images, which could be used for a variety of purposes, such as behavioural tracking, security research, driverless cars and driver assistance systems, and sometimes even helping policy makers quickly identify towns through images.

I INTRODUCTION:

Weather is an essential component of human experience, and it has influenced human communities throughout history, according to anthropologists. Weather has influenced people’s lives, livelihoods, and well-being in a variety of cultural and scientific ways. Impact on Culture and Society: Weather has a profound impact on cultural behaviours, customs, and even language. Weather-related proverbs, folklore, and rituals have evolved in many cultures to represent their understanding and beliefs about weather patterns. Festivals and festivities are frequently centred on seasonal changes and weather-dependent activities such as agriculture. Agriculture and business.

Weather has a direct impact on agriculture, which is a vital factor in the economies of many nations. It is a critical aspect in the economies of many nations. Favorable weather conditions, such as adequate rainfall and mild temperatures, are critical for crop output success. Extreme weather occurrences, on the other hand, such as droughts, floods, or storms, can cause crop failures, food shortages, and economic losses. Weather has the potential to dramatically impact transportation and communication networks. Extreme weather can affect travel and logistics, causing delays, accidents, and economic consequences. Furthermore, extreme weather can disrupt communication networks, affecting both individuals and businesses. Health and happiness.

Removing weather effects from photographs has become increasingly crucial and has gained a lot of attention. By taking into account the most typical weather conditions in outdoor sceneries, this project proposes a deep learning-based weather image classification framework. My technique automatically classifies an input image into one of the weather categories or none (e.g., sunny or others). Weather recognition is frequently required in various fields, and it is also a difficult and novel subject. Unpleasant visual effects in photographs can be caused by meteorological conditions such as haze, fog, smoke, rain, or snow. Such effects have the potential to significantly reduce the performance of several outdoor vision systems, including object detection, tracking, and recognition, as well as scene analysis and classification, for outdoor surveillance, vision-assisted transportation systems, and ADAS (advanced driver assistance systems) applications.

II OBJECTIVE

I initially propose a specific approach for automatically obtaining this data from roadside photos, as there are essentially no well before bounds in the pre-processing stage. Then used a collaborative strategy based on deep learning and artificial intelligence. The BatchNormalization is one of four deep convolutional neural network (CNN) designs that employ dense structure and residual learning to make the most of weather and visual circumstances such as rainy, snowy, rainbow, dew, and foggy, among others. The proposed CCN model excels at extracting this information from viewer images, which could be used for a variety of purposes, including behavioral tracking, security research, driverless cars and driver assistance systems, and even assisting decision-makers in quickly identifying towns.

III RELATED WORK

I utilized a training set of 12,000 clean photos, each 30 30 in size, to build a Convolutional Neural Network (CNN) model for weather identification. Based on known climate conditions with differing standard deviations, then classified the photos into eleven different weather groups. The model was trained in a CNN environment, taking into account the depth of the organization and the appropriate field size.

Then enhanced the initial 220 clean photographs to get 12,000 training image patches of varying sizes for the training dataset. I used identical test photographs from a widely used informative index called the Weather Image Recognition dataset to evaluate the model's performance. This test set contains 220 regular photos and was not used in the training's development. To gather enough weather space information, the network model was constructed with four layers of depth. I employed active convolution with an initial shape setting of 3*3 for each convolutional layer.

Batch Normalization, a technique for increasing efficiency during training, was applied to the 64-node network. The process was halted during iterative training when the training error was lowered to a certain amount during a number of successive training epochs. I can train the model for 50 epochs after extensive testing, getting the expected outcome in weather classification.

IV METHODOLOGY

Weather classification using Convolutional Neural Networks (CNNs) involves leveraging the power of deep learning to identify and categorize weather conditions from input images or data. Below is a step-by-step methodology for weather classification using CNNs:

Data collection is the process of Gathering a large and diverse dataset of weather-related images or data samples. The dataset should cover various weather conditions, such as sunny, cloudy, rainy, snowy, foggy, etc. Make sure the dataset is well-labeled with the corresponding weather categories.

In data preprocessing we prepare the dataset for training by performing necessary preprocessing steps such as resizing images to a consistent size, normalization, and data augmentation to increase the diversity of the dataset and avoid overfitting.

Now we split the dataset ie: Divide the dataset into training, validation, and test sets. The training set is used for training the CNN, the validation set is used for hyperparameter tuning, and the test set is used for final evaluation.

As a next step we design the CNN architecture for weather classification. A typical CNN architecture consists of convolutional layers, activation functions (e.g., ReLU), pooling layers (e.g., max pooling), and fully connected layers. The exact architecture and the number of layers depend on the complexity of the problem and the size of the dataset.Specify the loss function (e.g., categorical cross-entropy) and an optimizer (e.g., Adam) to train the CNN. The optimizer will update the model's weights based on the loss function's gradients during the training process. Train the CNN on the training data. Feed the preprocessed weather images into the CNN and adjust the model's weights through backpropagation during training.

Use the validation set to fine-tune hyperparameters like learning rate, batch size, and the number of epochs. This process helps to optimize the model's performance and prevent overfitting. After training the CNN, evaluate its performance on the test set to assess its accuracy and generalization capabilities. The test accuracy will indicate how well the model can classify unseen weather images.

Utilize the trained CNN to predict the weather conditions of new and unseen images. The trained model can take an input image and output the predicted weather category.Once satisfied with the model's performance, deploy it to make real-time predictions or integrate it into applications where weather classification is required.

Weather patterns and conditions can change over time, so it is essential to monitor the model's performance and retrain it periodically with updated data to maintain its accuracy.

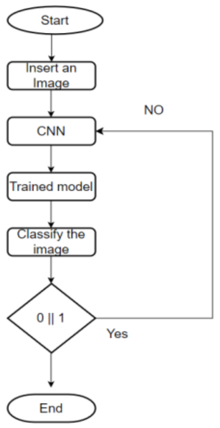

Figure 1 : Block Diagram

V RESULTS & DISCUSSION

In the process of weather classification using Convolutional Neural Network we have obtained the following results:

- I have successfully classified the weather images into different categories like fog, rain , rainbow, shiny….etc;
- I have also obtained a graph that shows the accuracy of the model.
- Moreover we also have got a confusion matrix.

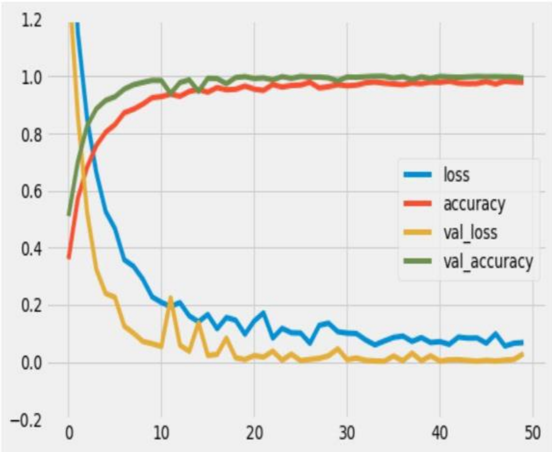

Figure 2 : Loss & Accuracy graph

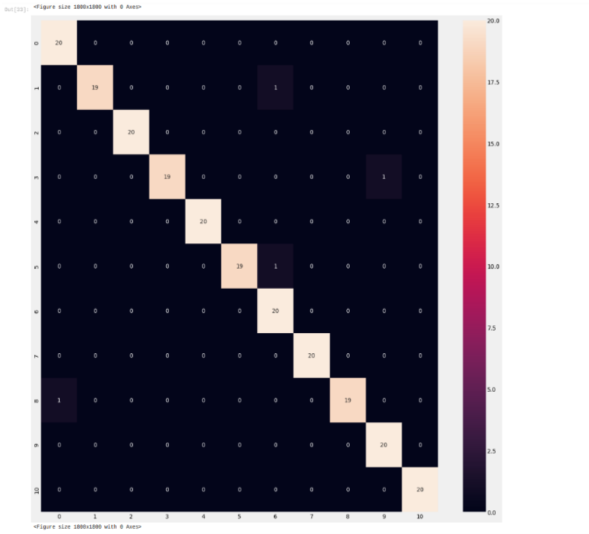

Figure 3 : Confusion Matrix

Figure 4 : Output

VI CONCLUSION

Finally, my suggested Convolutional Neural Network (CNN) model performed admirably in processing and classifying weather pictures. The CNN has shown to be a significant tool in picture categorization and weather prediction due to its capacity to reliably anticipate the weather for 11 different classes. The CNN is usually regarded as one of the most successful neural network architectures, and it certainly lived up to its billing in our research. It outperformed previous techniques and generated much better weather classification results. I got remarkable results throughout our research, with a training model accuracy rate of 98% and a testing accuracy rate of 97.06%. These high accuracy levels demonstrate CNN's robustness in extracting useful information from weather photos. My CNN model's uses go beyond weather prediction.

VII REFERENCES

1. Komal Bajaja , Dushyant Kumar Singhb,∗ , Mohd. Aquib Ansaric “Autoencoders Based Deep Learner for Image Denoising”, Third International Conference on Computing and Network Communications.
2. Buades, Antoni, Bartomeu Coll, and Jean-Michel Morel. ”Nonlocal image and movie denoising.” International journal of computer vision 76.2 (2008): 123-139.
3. Generative Adversarial Networks: Introduction and Outlook. EEE/CAA J Autom Sin 2017;4:588–98.
4. R. Donida Labati, A. Genovese, V. Piuri, F. Scotti and G. Sforza, "A Decision Support System for Wind Power Production," in IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 50, no. 1, pp. 290-304, Jan. 2020, doi: 10.1109/TSMC.2017.2783681.
5. M. Q. Raza, N. Mithulananthan, J. Li, K. Y. Lee and H. B. Gooi, "An Ensemble Framework for Day-Ahead Forecast of PV Output Power in Smart Grids," in IEEE Transactions on Industrial Informatics, vol. 15, no. 8, pp. 4624-4634, Aug. 2019, doi: 10.1109/TII.2018.2882598.
6. Y. Li and B. Jones, "The Application of Extreme Value Theory to Long-Term Substation Maximum Electricity Demand Forecasting,' in IEEE Transactions on Power Systems, vol. 35, no. 1, pp. 128-139, Jan 2020, doi: 10.1109/TPWRS.2019.2930113.
7. Cewu Lu, Chi-Keung Tang, Jiaya Jia, and Di Lin.Weather classification into two categories," in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2014, pp. 3718–3725.
8. Frank Moosmann and Martin Roser, "Classification of weather situations on single color images," IEEE Intelligent Vehicles Symposium, 2008, pp. 798–803.
9. "Imagenet classification with deep convolutional neural networks," in Advances in neural information processing systems (NIPS), 2012, pp. 1097–1105; Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton.
10. "Decaf: A deep convolutional activation feature for generic visual recognition," ACM International Conference on Machine Learning (ICML), 2014, by Jeff Donahue, Yangqing Jia, Oriol Vinyals, Judy Hoffman, Ning Zhang, Eric Tzeng, and Trevor Darrell.