2021 8th International Conference on Networking, Systems and Security (NSysS)

21-23 December, 2021, Cox's Bazar, Bangladesh

Machine Learning Applications

Cloud Pattern Classification for Rainfall Prediction using Convolutional Neural Network

Sourav Dey Roy
Department of Computer Science and Engineering,
Tripura University (A Central University),
Suryamaninagar-799022, Tripura (W), India
souravdeyroy49@gmail.com

Anindita Mohanta
Department of Computer Science and Engineering,
Tripura University (A Central University),
Suryamaninagar-799022, Tripura (W), India
aninditamohanta@yahoo.in

Dipak Hrishi Das
Department of Information Technology, Government Degree College, Gandacherra, Dhalai, Tripura-799284, India
dhdcse@gmail.com

Mrinal Kanti Bhowmik*
Department of Computer Science and Engineering,
Tripura University (A Central University),
Suryamaninagar-799022, Tripura (W), India
mrinalkantibhowmik@tripurauniv.ac.in

ABSTRACT

Rainfall prediction is an important research topic because of its wide range of applications in disaster and agricultural communities. It depends on several features of earth's atmosphere such as cloud information, speed and direction of wind, temperature, dew point, atmospheric pressure, etc. Most of the existing rainfall prediction models are based on time series dataset. Considering the computational complexity, and cost factors of time series dataset, in this paper we extensively explored the performance of different Convolutional Neural Networks (CNNs) architectures for rainfall prediction using cloud images in different scenarios. In our work, we have used two different stages for effective prediction of rainfalls from cloud images. Experiment results on SWIMCAT dataset reveals that usefulness and effectiveness of CNNs for rainfall prediction. This study can be a useful contribution for the research community of weather forecasting with broad range of applications i.e., flight navigation to agriculture and tourism.

CCS CONCEPTS

• **Computing methodologies**; • **Machine learning**; • **Machine learning algorithms**; • **Feature selection**;

KEYWORDS

Cloud Pattern, Rainfall Prediction, Convolutional Neural Network, Classification, Performance Evaluation

ACM Reference Format:

Sourav Dey Roy, Anindita Mohanta, Dipak Hrishi Das, and Mrinal Kanti Bhowmik. 2021. Cloud Pattern Classification for Rainfall Prediction using Convolutional Neural Network. In *8th International Conference on Networking, Systems and Security (8th NSysS 2021), December 21–23, 2021, Cox's Bazar, Bangladesh.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3491371.3491379

*Corresponding Author

8th NSysS 2021, December 21–23, 2021, Cox's Bazar, Bangladesh

ACM ISBN 978-1-4503-8737-8/21/12…$15.00
https://doi.org/10.1145/3491371.3491379

1 INTRODUCTION

Rainfall prediction and its effective forecasting has become an important topic for the last decades. It has received significant attention of many government and non-government communities in the form of risk management entities. Basically, rainfall is a climatic factor the affects several human day to day activities such as agricultural production, construction, power generation, forestry and tourism [1]. India has been suspected to natural disasters because of its distinctive Geo-climatic conditions. In the last few decades, around 30 million people in average were affected by natural/ climatic disasters every year [2]. Through the early prediction of the rainfall the causalities and the property loss can be minimized. Therefore, prediction and forecasting of rainfall is necessary because this is one having utmost link with adversarial natural calamities such as landslides, flooding, mass movements and avalanches. Among various atmospheric features, appearance of cloud patterns could have a significant impact on rainfall [3–7]. Moreover, excess rainfall, on the other hand, can be moderately hazardous by producing a flood that is an important warning to natural life and belongings [7]. Accurate prediction of heavy rainfall can allow for the warning of floods before rainfall occurs. Moreover, precipitation and rainfall information is beneficial in agriculture to increase watering observes and the efficiency of put on pesticides, and compost to harvests.

In the world of evolving technologies, digital media in the form of images and videos plays a major role in many vision based applications. Among various applications, one of the applications is the cloud pattern classification for effective rainfall prediction. In recent times, deep learning based methodologies, especially Convolutional Neural Networks (CNNs) has receive a significant attention for solving various real-time computer vision applications including face recognition, object detection, cancer abnormality detection, and scene labelling. Depending upon the huge success of CNNs in various computer vision applications, in this paper we investigated and conducted an extensive experiments to evaluate the capability

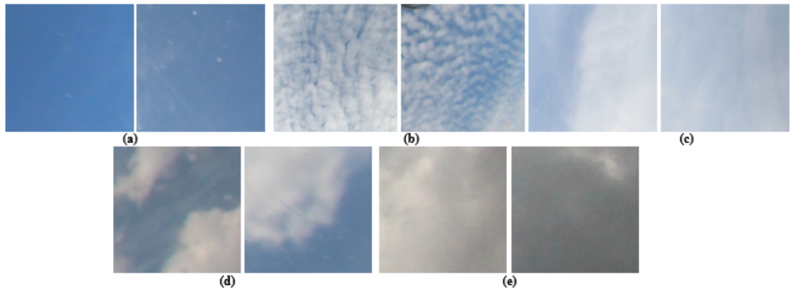

Figure 1: Sample Images of Various Cloud Types for Rainfall Prediction (a) Clear Sky; (b) Cirro-form Cloud (No/ No Rainfall will occur within 24 hours); (c) Strato-form Cloud(Yes/ Light Rain will occur); (d) Cumulo-form Cloud (No/ Never Produce Rainfall); (e) Nimbo-form Cloud (Yes/ Steady Rain or Snow) [Images are Taken From [27]]

of Convolutional Neural Network (CNN) for effective classification of cloud patterns for rainfall prediction from digital images. The investigation has been carried out by using state-of-the-art CNN models as a feature extractor followed by conventional classifier (i.e., Support vector machine) and fine-tuned classifier for effective classification of cloud patterns followed by prediction of rainfall based on the patterns of the clouds. Basically, clouds are four types based on their formation (excluding clear sky) [3]. The key characteristics of these four types of cloud patterns used in our study are shown in Figure 1.

The whole paper is outlined as: In Section 2, the literature survey on the rainfall prediction is elaborately described. Section 3 describes our methodology for cloud classification towards rainfall prediction using convolutional neural network. In Section 4, experimental results and discussions of our methodology for cloud classification has been reported. And finally, Section 5 concludes the paper.

2 PREVIOUS WORK

During the last few decades, researcher communities have been working to advance the performance of rainfall prediction by mostly using the time series dataset with optimizing and data mining techniques. Some of the chosen studies are mentioned in this section. The brief summary of the previous works for rainfall prediction are shown in Table 1. In [8], P.R. Larraondo et al. illustrated the use of encoder-decoder Convolutional Neural Networks (CNN) to measure the total precipitation using geo-potential height. In their work, several well renowned CNN architectures are compared with the machine learning algorithms. Also, the method to recognize the levels of geo-potential height was proposed that have a higher impact on precipitation. For instance, S. Aswin et al. [6] predict the rainfall using the time series dataset of precipitation obtained from NCEP center. They predicted the rainfall by using their designed deep learning architectures LSTM and CNN, which consist of multiple hidden layers. In [9], X. Shi et al. discussed the problem of deep learning based now-casting precipitation, and they proposed a new model for precipitation now-casting. Moreover, P.R. Larraondo et al. [10] proposed the utilization of CNN architectures for understanding the numerical weather model data from the spatial and temporal relationships of the input variables. In their work, many CNN architectures are compared and a methodology to cope up with the existing models is presented. In [11], M. Qui et al. proposed a multitask convolutional neural network to extract the weather related features from the time series data acquired at various locations and influence the correlation between the multiple locations for weather prediction. E. Hernández et al. [12] proposed a deep learning based architecture for prediction of the accumulated daily precipitation for the next day. For this, they incorporated auto encoder in their architecture to decrease and acquire non-linear relations between attributes. Finally a multilayer perceptron is used for the prediction task. In [13], S.H.I. Xingjian et al. predict rainfall forecast intensity in a local for a short period using MNIST and Radar Echo Dataset. For that, they proposed ConvLSTM architecture, which is used for rainfall now-casting. A.G. Salman et al. [14] utilized deep learning techniques for weather forecasting. Their work comprises of the performance comparison of Recurrence Neural Network (RNN), Conditional Restricted Boltzmann Machine (CRBM), and Convolutional Network (CN) models using weather dataset for weather forecasting. In [15], B. Klein et al. presented a novel deep network layer entitled as "Dynamic Convolutional Layer" for generalization of the conventional convolutional layer in short range weather prediction. F. Cui et al. [16] presents a unique GHI (Global Horizontal Irradiance) prediction approach that mixes ground-based sky photos using that they extracted cloud map forecast (CMF) and cloud base height numerable pattern. To accomplish the correct CMF, a metamorphosis of original sky pictures proceeds. In [17], S.M. Sumi et al. performed modeling of the rainfall using a proposed novel hybrid multi-model method to develop an optimal input technique. The proposed model incorporates artificial neural network, multivariate adaptive regression splines, the k-nearest neighbour, and radial basis support vector regression for rainfall forecasting. Considering these existing methods daily and monthly rainfall are modelled. K. Kaviarasu et al. [7] discussed the difficulty of working with time series dataset. Their proposed work is based on digital cloud images to predict the rainfall. They used the K-means clustering technique to identify the type of cloud first. In their work, they only classified two types of rainfall clouds i.e., Nimbostratus and Cumulonimbus for rainfall prediction. In [18], S. Lee et al. proposed a divide and conquer methodology for rainfall prediction where the entire region is sub divided into four sub-areas and each of these sub areas is modeled with a different method. In their work, depending on the location oriented information, RBF networks are incorporated for predictions of two larger areas and

Table 1: *Methodological Review of Rainfall Prediction*

Author/ Year	Algorithm Used	Dataset Used	Performance Evaluation
P.R. Larraondo et al./ 2019 [8]	Convolutional Encoder-Decoder Neural Network	NWP ERA-Interim global climate reanalysis dataset	Mean Absolute Error (MAE) [mm]= 0.3417 (No precipitation); MAE [mm]= 0.4845 (0.45 mean precipitation)
S. Aswin et al./ 2018 [6]	Convolutional Neural Network	The Global Precipitation Climatology Project (GPCP) dataset	Root Mean Square Error (RMSE)= 2.44; MAPE= 1.7281
X. Shi et al./ 2017 [9]	Convolutional LSTM and Trajectory GRU models	HKO-7 (Hong Kong Observatory) Dataset	Not provided
P.R. Larraondo et al./ 2017 [10]	Convolutional Neural Networks	Numerical Weather Predictions (NWP) dataset	71% accuracy
M. Qui et al./ 2017 [11]	Multi-Task Convolutional Neural Network	Guangdong province (GD-data) dataset; Manizales city (MC-data) dataset	RMSE = 11.253
E. Hernández et al./ 2016 [12]	Auto-encoder network and a multilayer perceptron network	Meteorological station dataset	Mean Square Error (MSE)= 40.11; RMSE= 6.33
S.H.I. Xingjian et al./ 2015 [13]	Convolutional LSTM Network	MNIST dataset; Radar Echo dataset	Rainfall-MSE=1.420; Correlation= 0.908
A.G. Salman et al./ 2015 [14]	Conditional Restricted Boltzmann Machine (CRBM) and Convolutional Neural Network	EI-Nino Southern Oscillation (ENSO) dataset; BMKG dataset	84% accuracy
B. Klein et al./ 2015 [15]	Convolutional Neural Network	Tel Aviv dataset (TAD); Israel dataset	Running time is faster than the Patch Based CNN
F. Cui et al./ 2015 [16]	Global Horizontal Irradiance (GHI)	Ground-Based Sky Images Dataset	RMSE=1.8% (clear sky condition); RMSE=13.6% (cloudy sky condition)
S.M. Sumi et al./ 2012 [17]	Artificial neural network; Multi-variant adaptive regression splines and radial basis support vector regression	Fukuoka and Saga rainfall dataset	95% accuracy
K. Kaviarasu et al./ 2010 [7]	K-Means Clustering technique	Private dataset	Average accuracy 51.58%
S. Lee et al./ 1998 [18]	Artificial Neural Network	Private dataset	Relative Error = 0.46; Absolute Error = 55.9

two smaller areas. Finally, the predictions in these two areas were done using existing regression model depending on the information of elevation.

3 METHODOLOGY

In this section, our methodology for multi-class cloud classification followed by rainfall prediction is described. The classification of cloud images for rainfall prediction from all types of cloud images is performed using two-stage classification modules. In first stage classification (Stage-I Classification module), the cloud images are classified for clear sky and non-clear sky. After Stage-I Classification module, if it is classified as the "sky is clear", then the model gives the prediction result based on "clear sky" information. And if the cloud images are detected as non-clear sky, then the cloud patterns are further classified into four major categories i.e., Cirro-form Cloud; Strato-form Cloud; Cumulo-form Cloud; Nimbo-form Cloud in Stage-II Classification module and then the model gives the prediction result based on cloud information.

In our proposed work, we have used state-of-the art Convolutional Neural Network (CNN) architectures in both Stage-I and Stage-II classification module. CNN is a highly efficient identification method comprising of Artificial Neural network (ANN) which has been attracted wide attention in recent years. It typically consist of four building blocks/ layers [19]: Convolution layer; Activation layer; Pooling layer; and Fully Connected layers. The first three layers i.e. convolution, activation and pooling layers are also in combination known as feature extraction layer whereas the fourth layer i.e., fully connected layer is termed as classification layer. Many pre-trained models of CNN are available publicly for the research community. These models are generally pre-trained on ImageNet challenge dataset [20]. From literature, we implemented six well-known pre-trained CNN models for cloud classification and rainfall prediction. These CNN architectures are: VGG16 [21], VGG19 [21], AlexNet [22], Inception-V3 [23], GoogleNet [24], and ResNet-101 [25]. For effective classification, we have used the aforementioned CNN architectures as binary classification task in Stage-I Classification module and multi-label classification task in Stage-II Classification module. The pre-trained models of CNN are used in two major categories in both Stage-I and Stage-II module. In first section, we extracted the discriminative features of the cloud images using CNNs and classified with conventional Support Vector machine (SVM) classifier [26] with linear kernel and k-fold cross validation. In second section, we have fine-tuned the pre-trained CNN architectures there by replacing the last fully connected layer with two neurons for Stage-I classification module and four neurons for Stage-II classification module.

Dataset and Augmentation. In our work, we have used the cloud images from SWIMCAT [27] dataset. The SWIMCAT dataset contains 784 images of sky /cloud images in five major categories so as described in Fig. 1. Each of the images are in .PNG format with a resolution 125×125 pixels. To increase the size of the dataset, we have performed the flipping (horizontal and vertical flipping), translations (±5, ±10, ±15, ±20, ±25, and ±30), and rotations (45°, 90°, 135°, 180°, 225°, 270°, and 315°) to create the different views of the cloud images. Therefore applying the following augmentation techniques, the original dataset is increased with 16,464 augmented cloud images.

Parameter Configuration. Each of the pre-trained CNN models are implemented and tested on GPU platform of workstation with 64 GB installed memory (RAM). For training purpose, we used 80% augmented cloud images from each cloud category, and for testing purpose, we used 20% images of augmented images from each cloud categories. Further, the training set along with its ground truth labels (class labels) are randomly shuffled and splitted into training and validation set in 80:20 ratio. The training and validation accuracy/ loss are measured using stochastic gradient descent optimizer [28] and binary cross entropy [29] for Stage-I classification module. Similarly, training and validation accuracy/ loss are measured using stochastic gradient descent optimizer [28] and categorical cross entropy [29] for Stage-II classification module. In general, the training performance are measured with varying epochs (i.e., 50 to 150 epochs) and a batch size of 10 images for each of the considered epochs and are described in the next section.

4 EXPERIMENT RESULTS AND DISCUSSIONS

In this section, the prediction performance of both the Stage-I and Stage-II classification modules are described.

First, for measuring the performance of pre-trained CNN models as a feature extractor followed by conventional SVM classification, the prediction performance for cloud classification and rainfall prediction are shown in Table 2 and Table 3 respectively. The prediction performance of the pre-trained CNN models are evaluated by the comparison of Accuracy, Recall, Precision, and F1-Measure. The best performed CNN model is represented by bold texts. From Table 2 and Table 3, it has been observed that Resnet-101+SVM outer performed the other CNN models for both the modules i.e., with an accuracy, recall, precision, and F-Measure of 0.8122, 0.6762, 0.7142, and 0.6946 respectively for Stage-I classification module and with an accuracy, recall, precision, and F-Measure of 0.7809, 0.6410, 0.5833, and 0.6108 respectively for Stage-II classification module.

Second, for measuring the performance of the pre-trained CNN models thereafter fine tuning (as described in Section 3), the training performance is measured in terms of training accuracy and validation accuracy and the testing performance of the trained models on cloud dataset are measured in terms of Accuracy, Recall, Precision, and F1-Measure. The performance evaluation of the fine-tuned CNN models for both the Stage-I and Stage-II classification module are reported in Table 4 and Table 5 respectively. Here also the best performed CNN model is represented by bold texts. From Table 4 and 5, it can be observed that number of epochs also plays a significant role in the cloud classification based on CNN models for rainfall prediction. Most of the CNN models showed best prediction performance with the increase in number of epochs. Moreover, it can be observed that for Stage-I module, VGG-16 model (i.e., for 150 epochs) has shown best prediction performance with training and validation accuracy of 91.10% and 87.50% respectively. And the testing performance in terms of accuracy, recall, precision, and F1-Measure is of 0.8037, 0.6821, 0.7293, and 0.7049 respectively. Conversely for Stage-II module, ResNet-101 model (i.e., for 150 epochs) has shown best prediction performance with training and validation accuracy of 89.89% and 81.81% respectively. Also, the testing performance in terms of accuracy, recall, precision, and F1-Measure is of 0.7481, 0.5832, 0.6268, and 0.6042 respectively.

5 CONCLUSION

In this paper, the effectiveness of CNNs has been evaluated for rainfall prediction using cloud images. The performance of the CNN models for rainfall prediction has been explored in two stage modules. In Stage-I, the cloud images are classified using CNNs as clear-sky and non-clear sky images. In Stage-II, the non-clear sky images are further classified using CNNs in four major categories including Cirro-form Cloud; Strato-form Cloud; Cumulo-form Cloud; Nimbo-form Cloud and then gives the rainfall prediction result based on the cloud information. Experimental results shows that CNN architectures as a feature extraction method obtained highest accuracy.

ACKNOWLEDGMENTS

The work presented here is being conducted in the Computer Vision Laboratory of Computer Science and Engineering Department, Tripura University (A Central University), Suryamaninagar-799022, Tripura (W).

REFERENCES

[1] Z. Zhao, Z. Jia, Z. Guan, and C. Xu, "The Effect of Climatic and Non-climatic Factors on Groundwater Levels in the Jinghuiqu Irrigation District of the Shaanxi Province, China," Water, MDPI, Vol. 11, No. 5, pp. 956, 2019.
[2] D.A. Lavers, G. Villarini, R.P. Allan, E.F. Wood, and A.J. Wade, "The detection of atmospheric rivers in atmospheric reanalyses and their links to British winter floods and the large-scale climatic circulation," Journal of Geophysical Research: Atmospheres, Wiley Online library, Vol. 117, No. D20, 2012.
[3] The Four Core Types of Clouds. Available. [Online]. https://www.weather.gov/jetstream/corefour
[4] M.A. Shabib Aftab, N. Hameed, M.S. Bashir, I. Ali, and Z. Nawaz, "Rainfall Prediction using Data Mining Techniques: A Systematic Literature Review," International Journal of Advanced Computer Science and Applications, Vol. 9, No. 5, pp. 143-150, 2018.

Table 2: ***Performance Evaluation of Stage-I Classification Module Using Pre-Trained CNN Architectures and SVM Classifier***

CNN Models	Accuracy	Recall	Precision	F1-Measure
VGG-16 + SVM	0.7395	0.6470	0.6007	0.6267
VGG-19 + SVM	0.7032	0.5753	0.5189	0.5456
AlexNet + SVM	0.6891	0.5547	0.4830	0.5164
GoogleNet + SVM	0.6654	0.5103	0.4487	0.4775
Inception-V3 + SVM	0.7197	0.6200	0.5342	0.5739
Resnet-101 + SVM	**0.8122**	**0.6762**	**0.7142**	**0.6946**

Table 3: ***Performance Evaluation of Stage-II Classification Module Using Pre-Trained CNN Architectures and SVM Classifier***

CNN Models	Accuracy	Recall	Precision	F1-Measure
VGG-16 + SVM	0.7003	0.6194	0.5491	0.5821
VGG-19 + SVM	0.7025	0.6107	0.5038	0.5521
AlexNet + SVM	0.6529	0.5321	0.4531	0.4894
GoogleNet + SVM	0.6628	0.5022	0.4409	0.4696
Inception-V3 + SVM	0.6976	0.5399	0.4498	0.4907
Resnet-101 + SVM	**0.7809**	**0.6410**	**0.5833**	**0.6108**

Table 4: ***Performance Evaluation of Stage-I Classification Module Using Fine-Tuned Pre-Trained CNN Architectures***

CNN Models	Epochs	Training Performance		Testing Performance			
		Training Accuracy	Validation Accuracy	Accuracy	Recall	Precision	F1-Measure
VGG-16	50	85.57%	82.34%	0.7672	0.6027	0.6788	0.6384
	100	89.93%	84.78%	0.7891	0.6461	0.6869	0.6658
	150	**91.10%**	**87.50%**	**0.8037**	**0.6821**	**0.7293**	**0.7049**
VGG-19	50	85.90%	80.63%	0.7470	0.6001	0.5430	0.5701
	100	88.77%	81.72%	0.7887	0.6103	0.5732	0.5912
	150	**91.06%**	**85.39%**	**0.7993**	**0.6663**	**0.6904**	**0.6766**
AlexNet	50	88.07%	82.96%	0.7551	0.6532	0.5410	0.5918
	100	**89.34%**	**85.78%**	**0.7905**	**0.6778**	0.5984	**0.6356**
	150	88.99%	84.01%	0.7670	0.6502	**0.6003**	0.6243
GoogleNet	50	89.48%	84.89%	0.7459	0.5965	0.5351	0.5641
	100	90.04%	**85.67%**	**0.7803**	0.6872	0.6043	0.6431
	150	**90.33%**	**85.67%**	0.7630	**0.6900**	**0.6068**	**0.6496**
Inception-V3	50	90.87%	80.02%	0.7705	0.6493	0.5310	0.5842
	100	**90.96%**	**80.47%**	**0.7796**	**0.6509**	**0.5553**	**0.5993**
	150	90.91%	82.34%	0.7894	0.6449	0.5480	0.5930
Resnet-101	50	89.43%	81.29%	0.7729	0.5754	0.4979	0.5339
	100	89.58%	84.01%	0.7831	0.5974	0.5069	0.5484
	150	**89.99%**	**84.32%**	**0.8024**	**0.6231**	**0.5753**	**0.5982**

[5] The 10 Basic Types of Clouds. Available. [Online]. The 10 Basic Types of Clouds and How to Recognize Them (thoughtco.com)

[6] S. Aswin, P. Geetha, and R. Vinayakumar, "Deep learning models for the prediction of rainfall," in Proceedings of 2018 International Conference on Communication and Signal Processing (ICCSP), IEEE, pp. 0657-0661, 2018.

[7] K. Kaviarasu, P. Sujith, and G. Ayaappan, "Prediction of rainfall using image processing," in Proceedings of the IEEE International Conference on Computational Intelligence and Computing Research, IEEE, 2010.

[8] P.R. Larraondo, L.J. Renzullo, I. Inza, and J.A. Lozano, "A data-driven approach to precipitation parameterizations using convolutional encoder-decoder neural network," arXiv preprint arXiv: 1903.10274, 2019.

[9] X. Shi, Z. Gao, L. Lausen, H. Wang, D.Y. Yeung, W.K. Wong, and W.C. Woo, "Deep learning for precipitation nowcasting: A benchmark and a new model," arXiv preprint arXiv:1706.03458, 2017.

[10] P.R. Larraondo, I. Inza, and J.A. Lozano, "Automating weather forecasts based on convolutional networks," in Proceedings of the ICML Workshop on Deep Structured Prediction, PMLR, Vol. 70, 2017.

[11] M. Qiu, P. Zhao, K. Zhang, J. Huang, X. Shi, X.Wang, and W. Chu, "A short-term rainfall prediction model using multi-task convolutional neural networks," In 2017 IEEE international conference on data mining (ICDM), IEEE, pp. 395-404, 2017.

[12] E. Hernández, V. Sanchez-Anguix, V. Julian, J. Palanca, and N. Duque, "Rainfall prediction: A deep learning approach. In International Conference on Hybrid Artificial Intelligence Systems," Springer, Cham, pp. 151-162, 2016.

Table 5: ***Performance Evaluation of Stage-II Classification Module Using Fine-Tuned Pre-Trained CNN Architectures***

CNN Models	Epochs	Training Performance		Testing Performance			
		Training Accuracy	Validation Accuracy	Accuracy	Recall	Precision	F1-Measure
VGG-16	50	84.50%	74.51%	0.7071	0.5174	0.4671	0.4909
	100	89.35%	80.28%	0.7274	0.5438	0.5024	0.5223
	150	**89.65%**	**81.32%**	**0.7333**	**0.5741**	**0.5323**	**0.5524**
VGG-19	50	85.57%	76.00%	0.7193	0.5502	0.4700	0.5069
	100	86.66%	76.68%	0.7200	0.5537	0.4863	0.5178
	150	**89.07%**	**79.77%**	**0.7201**	**0.5609**	**0.5109**	**0.5347**
AlexNet	50	89.05%	76.27%	0.6579	0.4473	0.4828	0.4643
	100	89.49%	78.35%	0.7182	0.5096	0.4864	0.4977
	150	**89.57%**	**80.44%**	**0.7285**	**0.5563**	**0.4991**	**0.5261**
GoogleNet	50	86.59%	74.30%	0.7298	0.5102	0.4393	0.4721
	100	**89.20%**	**77.98%**	**0.7478**	**0.5693**	**0.4899**	**0.5266**
	150	88.99%	76.78%	0.7356	0.5600	0.4873	0.5211
Inception-V3	50	89.38%	78.92%	0.7000	0.5213	0.4432	0.4791
	100	**89.87%**	**79.76%**	0.7043	0.5392	0.4651	0.4994
	150	89.45%	80.58%	**0.7186**	**0.5588**	**0.4983**	**0.5268**
Resnet-101	50	88.68%	79.11%	0.7203	0.5009	0.4784	0.4893
	100	88.79%	79.31%	0.7221	0.5553	0.5089	0.5311
	150	**89.89%**	**81.81%**	**0.7481**	**0.5832**	**0.6268**	**0.6042**

[13] S.H.I. Xingjian, Z. Chen, H. Wang, D.Y. Yeung, W.K. Wong, and W.C. Woo, "Convolutional LSTM network: A machine learning approach for precipitation nowcasting," In Advances in neural information processing systems, pp. 802-810, 2015.

[14] A.G. Salman, B. Kanigoro, and Y. Heryadi, "Weather forecasting using deep learning techniques," in Proc. 2015 international conference on advanced computer science and information systems (ICACSIS), IEEE, pp. 281-285, 2015.

[15] B. Klein, L. Wolf, and Y. Afek, "A dynamic convolutional layer for short range weather prediction," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, IEEE, pp. 4840-4848, 2015.

[16] F. Cui, R.R. Ju, Y.Y. Ding, H. Ding, and X. Cheng, "Prediction of regional global horizontal irradiance combining ground-based cloud observation and numerical weather prediction," In Advanced Materials Research, Trans Tech Publications Ltd, Vol. 1073, pp. 388-394, 2015.

[17] S.M. Sumi, M.F. Zaman, and H. Hirose, "A rainfall forecasting method using machine learning models and its application to the Fukuoka city case," International Journal of Applied Mathematics and Computer Science, Vol. 22, pp. 841-854, 2012.

[18] S. Lee, S. Cho, and P.M. Wong, "Rainfall prediction using artificial neural networks," Journal of geographic information and Decision Analysis, Vol. 2, No. 2, pp. 233-242, 1998.

[19] A. Veit and S. Belongie, "Convolutional networks with adaptive inference graphs," In Proceedings of the European Conference on Computer Vision (ECCV), pp. 3-18, 2018.

[20] J. Deng, W. Dong, R. Socher, L. Li, K. Li and L. Fei-Fei, "Imagenet: A large-scale hierarchical image database," In 2009 IEEE Conference on Computer Vision and Pattern Recognition, IEEE, pp. 248-255, 2009.

[21] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein and A.C. Berg, "Imagenet large scale visual recognition challenge," International journal of computer vision, Vol. 115, No. 3, pp. 211-252, 2015.

[22] A. Krizhevsky, I. Sutskever and G.E. Hinton, "Imagenet classification with deep convolutional neural networks," in Advances in Neural Information Processing Systems, pp. 1097-1105, 2012.

[23] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens and Z. Wojna, "Rethinking the inception architecture for computer vision," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, IEEE, pp. 2818-2826, 2016.

[24] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V.Vanhoucke and A. Rabinovich, "Going deeper with convolutions," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, IEEE, pp. 1-9, 2015.

[25] K. He, X. Zhang, S. Ren and J. Sun, "Deep residual learning for image recognition," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, IEEE, pp. 770-778, 2016.

[26] N. Cristianini and J. Shawe-Taylor, "An introduction to support vector machines and other kernel-based learning methods," Cambridge University Press, 2000.

[27] Singapore Whole sky IMaging CATegories Database. Available. [Online]. http://www.vintage.winklerbros.net/swimcat.html

[28] I. Sutskever, J. Martens, G. Dahl and G. Hinton, "On the importance of initialization and momentum in deep learning," in Proc. International Conference on Machine Learning, ACM, pp. 1139-1147, 2013.

[29] A. Rusiecki, "Trimmed categorical cross-entropy for deep learning with label noise," Electronics Letters, IEEE, vol. 55, no. 6, pp. 319-320, 2019.