WEATHER FORECASTING USING PHYSICS AND DEEP LEARNING TECHNIQUES

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ABSTRACT: Weather forecasting, due to its enormous impact on human life worldwide, has drawn the attention of several scholars from a variety of scientific communities. Since the agricultural and industrial sectors heavily rely on accurate weather forecasting, it is imperative. Weather classification from outdoor photos aids in preventing traffic accidents, planning outdoor activities, and enhancing the dependability of outdoor video surveillance systems and driver assistance vehicles. Numerous industries, including transportation, tourism, aquaculture, and agriculture, find applications for weather classification. Weather classification was a labour-intensive and time-consuming procedure that required a large crew and expensive sensors. Automating the process of categorising weather conditions from photographs will result in significant time and resource savings. This study provides a system based on the transfer learning technique for identifying weather photos using features learned from pre-trained deep CNN models in a much shorter amount of time. Moreover, the amount of training data affects the model's efficiency. More high-quality data usually translates into more accurate findings. Therefore, in order to make the suggested framework scalable for big datasets, we implemented it using the Spark platform. We conducted tests on the weather picture dataset to demonstrate the reliability of the suggested framework. With a maximum accuracy of 97.77%, the results show that the Inception V3 model and Logistic Regression classifier yield the greatest results when employed for weather classification.

Key words: Deep learning, weather classification, Big Data, Convolution neural networks, weather forecasting, Machine and machine learning.

I INTRODUCTION

The phrase "weather forecast" describes the thorough application of contemporary science and technology to predict the temperature, humidity, wind, and other characteristics of a future place over a period of time. The weather forecast has a big influence on people's everyday lives in today's society; especially travel plans, agricultural output, and the avoidance of natural calamities Typhoons [1]. and flood catastrophes have recently impacted Shenzen, but good weather forecasting can prevent flood disasters. The extraction and quantification of these features have advanced in computer vision techniques in recent years [2]. In order to create weather forecasts, scientists now gather quantitative information about the state of the atmosphere and utilise their scientific knowledge of atmospheric processes to predict how the atmosphere will change over time. Forecasts lose accuracy as the forecast range grows due to the chaotic nature of the environment, the enormous amount of computing power needed to solve the equations that describe the atmosphere, and our poor understanding of atmospheric dynamics. It becomes clear that precise weather forecasting is necessary when taking into account the advantages. Although these forecasts can't stop a tornado, hurricane, or flood, they can help us get ready in case one occurs. Since then, meteorologists have advanced the field of meteorology tremendously by using a variety of techniques to anticipate the weather [3]. In 1922, Lewis Fry Richardson put forth the idea that numerical weather prediction might be possible. The advent of programmable electronic computers in 1955 marked the beginning of the practical application

of numerical weather prediction. Monitor the temperature, wind speed, and air pressure. Automated weather stations and trained observers measure wind direction, humidity, and precipitation near the earth's surface.

The World Meteorological Organization works globally to harmonize these observations' time, equipment, and observational procedures. The World Meteorological Organisation uses two techniques for weather prediction. The dynamical approach and the empirical approach are the two methods. Analogue forecasting serves as the foundation for the empirical method. This approach can benefit both forward simulations of the atmosphere and local-scale predictions. Computer modelling brings vitality to the process. The dynamical technique can be helpful in simulating large-scale weather occurrences, but it might not be able to accurately forecast erratic short-term weather. The majority of weather forecasting systems integrate both dynamical and empirical methods. [4] These studies motivated me to explore the accuracy of weather prediction and ascertain whether each prediction system employs back propagation neural networks, optical neural networks, radial basis function neural networks, regression neural networks, and fuzzy ARTMAP neural networks.

II RELATED WORK

To address the problem of weather classification, researchers have been working hard over the last few years. Researchers have used big data technologies like Hadoop and Spark to process the weather dataset due to its considerable size. Alam and Ajmad designed an architecture that utilized the Hadoop and Map Reduce platforms for the distributed and parallel processing of large weather datasets [5]. Yang et al. implemented a regression model using big data technologies to forecast weather conditions with a large amount of weather data [6]. With the Map Reduce approach, Ismail et al. developed a big data system that could predict weather temperature they Enhanced its scalability and efficient[7] .With Keras and the Tensorflow library, Sharma and Ismail developed a 19-layer deep CNN that classified weather photos into four categories: rain, shine, sunshine, and cloud. The model yielded 94% accuracy [8]. Wang and Li used the combination of DenseNet and ResNet CNN to sort weather photos into nine groups and found that the output of the suggested integrated model was better than that of the basic models alone [9]. Compared to the VGG19, VGG16, ResNet18, ResNet34, and MobileNet models, the suggested model performed better and yielded an accuracy rate of 92%.

When Elhoseiny et al. looked at how well the CNN layer worked for two pre-trained models—ImageNet-CNN and Weather-Trained CNN—to classify weather photos [10], the suggested method did better than cutting-edge methods. Ibrahim et al. proposed WeatherNet, a weather and visual condition-combining architecture with four parallel deep CNN models. (a) Precipitation Net detects clear, rain, and snow; (b) Glare Net classifies glare and no glare; (c) Night Net detects dawn, night, day, and dusk; and (d) Fog Net detects fog and no fog [11].

III LIMITATTIONS OF EXISTING APPROACHES

Many existing weather classification techniques rely on expensive sensors and a large amount of manpower to classify weather images. These methods rely on human observations, are thus more prone to errors, and are very time-consuming. We also widely use numerical weather prediction (NWP) models to forecast weather conditions, but these techniques are quite expensive and rely on the power of supercomputers for data processing.

Recent work on weather classification includes the classification of weather conditions from images. CNN has the advantage of automatically detecting important features in images without any human intervention. For optimal results, CNN models require a huge amount of processing power and large datasets for training. Further, training weather images using CNN models also requires tuning a number of hyper-parameters, such as the number of convolutional and max-pooling layers, kernel size, regularisation techniques, etc.

We use transfer learning techniques to transfer knowledge from pre-trained deep CNN models to our weather image dataset, thereby resolving the aforementioned issues. By utilizing features extracted from pre-trained CNN models, transfer learning significantly reduces training time. It also eliminates the need for tuning the number of hyper parameters. Transfer learning has proven its potential in a number of applications, such as natural language processing, sentiment classification, text classification, spam email detection, video classification, drug efficacy classification, etc. [12].

Further, the size of the weather images generated is also huge. Existing weather classification techniques that rely on transfer learning do not use big data technologies and lack scalability.

IV METHODOLOGY

To bridge the existing knowledge gap, we offer the so-called WeatherNet, a framework of parallel deep CNN models for urban scene weather and visual condition recognition from street-level photos. ThisWeatherNet employs four deep CNN models to identify fog, rain, snow, glare, daylight, and dusk/dusk, in that order. (Fig.1) displays these models. 1) NightNet recognises the distinctions between day and night and sunrise and dusk. It aims to understand the nuances of photos taken at street level while considering the weather and urban layout dynamics.

2) Glare Net can identify glaring images in a variety of weather circumstances, at dawn and dusk, and from any source of light—man-made or artificial. Glare is a direct light source that, without any correction, produces rings or a star effect on the camera's length.

3) PreciptationNet is capable of detecting clear, snowy, or wet weather during the day or night. 4) FogNet, as depicted in (Fig. 2), is capable of detecting fog at dawn or dusk, day or night, and whether it occurs in the presence of clear, snowy, or rainy weather.
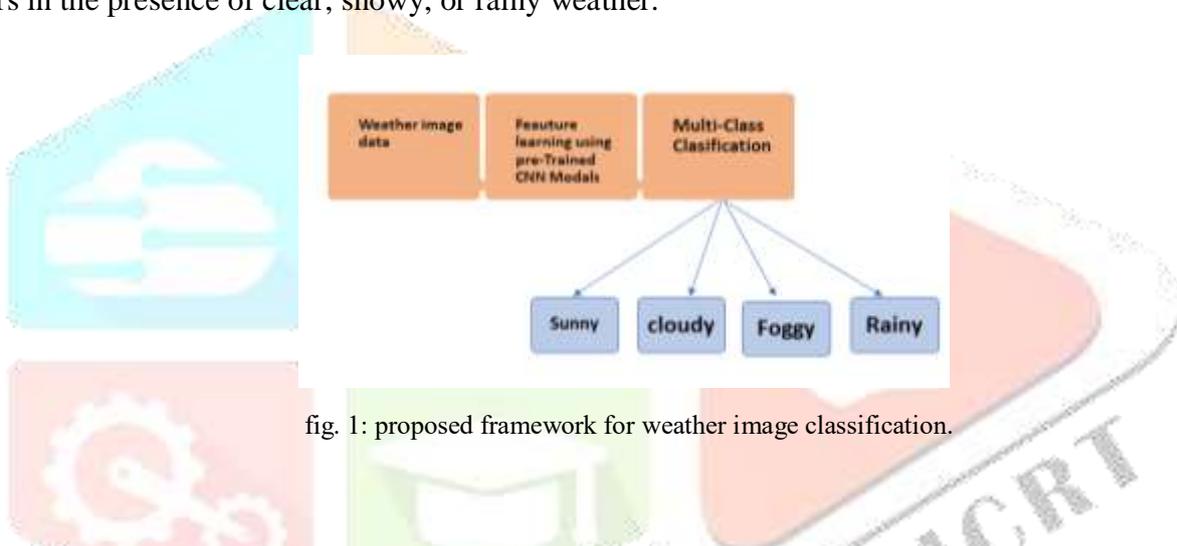

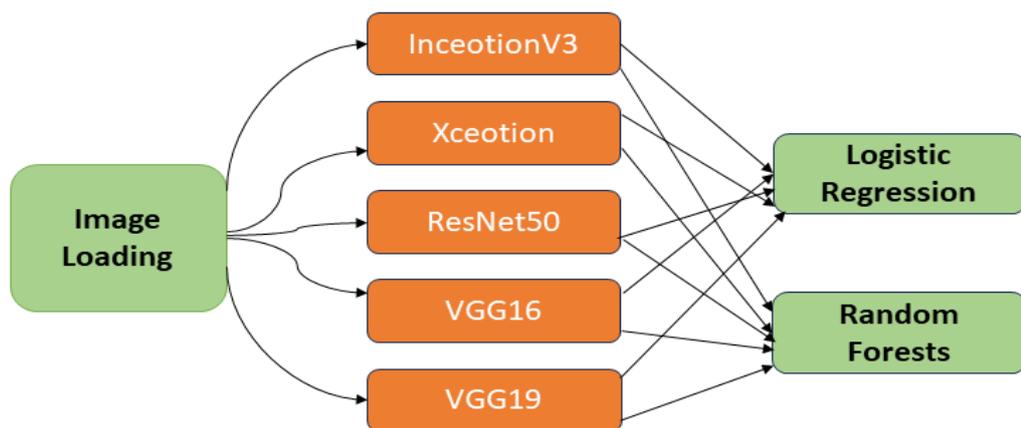fig. 1: proposed framework for weather image classification.

fig. 2: proposed architecture for weather classification.
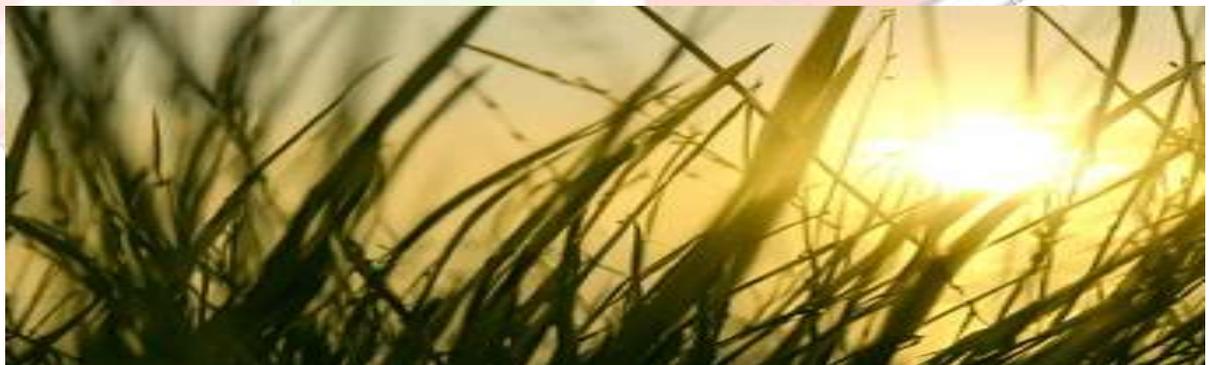
V EXPERIMENTAL SETUP

We have used multi-class weather image classification datasets from Kaggle.com to evaluate the effectiveness of the proposed framework [13]. 1125 photos from four categories—cloudy, rainy, shiny, and sunrise—make up the dataset. Figure 3.4 displays sample photos from each target class.

(a)

(b)

(c)

(d)

fig. 3 outdoor weather images (a) Cloudy (b) Rainy (c) Shine (d) Sunrise

In the experimental setup, 16 GB of RAM (12 GB of RAM is dedicated to Spark) and a 1 TB hard drive are installed on a local PC running Spark version 2.3.0 (i.e., the executor and driver are installed on the same computer). Table 1 shows the installation of Java version 1.8 and Python version 3.7. Furthermore, you must adjust more than 150 parameters for any Spark application to produce optimal results. These parameters' values vary depending on the workload and type of application; there is no default setting that works for all applications.
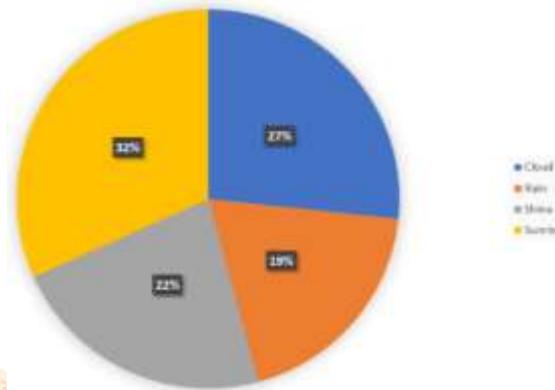

fig. 4: categorization of target class.

Table.1: Local PC configuration

Parameter	Value
RAM	16GB
Hard Disk	1TB
OS	64-Bit Windows 10
Spark Version	2.3.0
Java	1.8
Python	3.7

Optimising parameters such as driver memory, executor cores, executor memory, and number of partitions can greatly enhance the performance of a Spark application [14]. Given the small amount of data, 4 GB of memory is more than enough to store the data and run CNN models that use logistic regression as a classifier. The Random Forest classifier requires a minimum of 8 GB of driver RAM. The number of cores allotted to the executor or driver also affects how well an application performs. In a cluster with n cores, the number of partitions for input data should not be less than n, as this could result in underutilization of resources. The cluster won't have many idle cores and won't effectively use its resources. As a result, the number of input partitions ought to match or exceed the number of cores. The number of partitions and cores used in this research project is two and four, respectively.

To evaluate the efficiency of proposed framework, following metrics have been used:

- Accuracy is the percentage of samples for which every forecast is accurate.
- Precision can be defined as the ratio of all positive forecasts to actual positive values.
- To refresh your memory, the definition of this metric is the percentage of true positives in all positive samples.
- Precision and recall-harmonic means were used to calculate the F1 score.
- Training Time: The amount of time needed to achieve performanceout of the model.

VI RESULTS AND DISCUSSION

We examined the impact of parameters, lambda, logistic regression classifier, and regularisation on the y-intercept. Table 2 displays the accuracy values for various observed alpha values. The training of the logistic regression model using the ResNet50 model yields the best results.

Table.2: Impact of Alpha on Model's Accuracy

Alpha	Accuracy
0.1	94.27
0.2	94.27
0.4	94.27
0.6	95.70
0.8	96.80
0.9	97.28

Additionally, by employing the 5-fold cross-validation method, we have determined the optimal logistic regression lambda value. The model works best at a value of 0.01 after looking at a range of values for A, including 0.02, 0.04, 0.1,0.6, 0.8, and 0.9. Consequently, we decided to set the Logistic Regression classifier's a and an at 0.4 and0.01.

The random forest classifier's performance is highly dependent on the number of trees in the forest. Therefore, we investigated the impact of varying tree values on the accuracy and run time of the algorithm, as presented in Table 3. It makes sense that as the number of trees in the woods rises, the accuracy value of the model grows up to a certain point, or 100. The accuracy value then decreases. With 100 trees in the forest, the Random Forest classifier had a maximum accuracy of 95.73%. Furthermore, an increase in the number of trees does not significantly impact the algorithm's training time.

We divided the data 80:20 between training and testing. Table 4 lists each of the ten possible designs depicted in Fig. 2 along with its accuracy, F1 score, precision, recall, and training time. Interpretation Using the Logistic Regression classifier with the pre-trained Inception V3 model yields the highest accuracy of 97.77%. An extra set of classifiers, smaller grid sizes, factorised convolutions, and asymmetric convolutions are some of the main reasons why the Inception V3 model is more accurate. Rather than going deeper, Inception V3 takes features and extracts them in more detail.

Table.3: Impact of Number of Trees on the Performance of Proposed Network

No.of tress	Accuracy	F1 score	Precision	Recall	Time
10	93.28	93.55	93.68	93.57	13 min24 sec
25	94.39	94.38	94.4	94.38	15 min 3 sec
50	95.28	95.29	95.41	95.28	13 min 35 sec
75	95.29	95.29	95.32	95.28	13 min 58 sec
100	95.73	95.73	95.82	95.73	12 min 1 sec
125	94.38	94.4	94.49	94.38	14 min 5 sec

Table.4: Output of Proposed Framework for Numerous Pre-Trained Deep CNN Models

SI.NO		Accuracy	F1 score	Precision	Recall	Time
1.	ResNet50+R	97.28	97.29	97.33	97.28	7 min 35sec
2.	VGG16+LR	94.57	94.61	94.83	95.57	10 min 12 sec
3.	VGG19+LR	94.12	94.13	94.31	94.12	6 min 35 sec
4.	InceptionV3+LR	97.77	97.74	97.75	97.74	6 min 42 sec
5.	Xception+LR	95.02	95	95.11	95.02	8 min 2 sec
6.	ResNet50+RF	97.73	97.73	97.82	97.73	13 min 1 sec
7.	VGG16+RF	96.38	96.35	96.46	96.38	28 min 1 sec
8.	VGG16+RF	93.66	93.64	93.62	93.66	26 min 45 sec
9.	InceptionV3+RF	91.4	91.5	91.7	91.4	24 min 14 sec
10.	Xception+RF	90.04	89.98	90.32	90.04	50 min 50 sec

Further, the second highest accuracy value, i.e., 97.77%, has been achieved with the ResNet50 pre-trained model and Random Forests classifier. The ResNet50 pre-trained model, along with the Logistic Regression classifier, showed promising results. The Xception model trained using the Random Forests classifier provided the least accurate value of 90.04%. It can also be concluded that the time taken by the framework for training the dataset with the logistic regression classifier is quite low compared to the random forest.

The confusion matrix for weather image classification for dataset 1 is shown in Table 5. The rows show the actual labels, and the columns show the predicted labels. The table uses the Inception V3 pre-trained CNN model and the Logistic Regression classifier. As shown in Table 3, the total number of test images is 217. The number of test images for the classes cloudy, foggy, rain, shine, and sunshine is 44, 63, 46, and 64, respectively. The classifier predicts 211 out of 217, or 211, to be true.

Table.5: Confusion matrix for inseption V3 logistic regression model

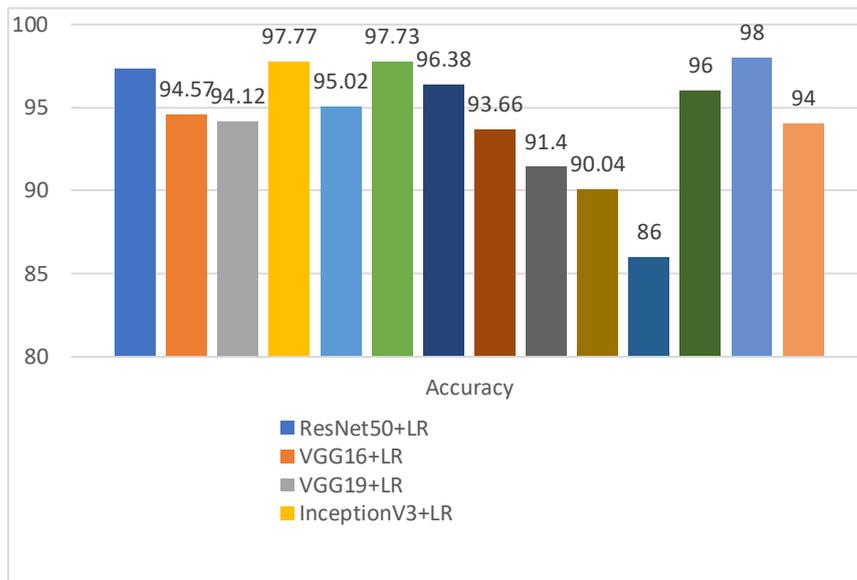| Sl.No		Cloudy	Rainy	Shine	Sunrise	Total
1.	Cloudy	43	0	1	0	44
2.	Rainy	1	62	0	0	63
3.	Shine	0	0	44	2	46
4.	Sunrise	0	0	1	63	64
5.	Total	44	63	46	64	217

Fig 5: Comparision of the proposed frame work with the existing techniques.m

We evaluated the performance of the suggested framework against state-of-the-art methods using the same dataset of weather photos for categorization. Fig. 5 contrasts the accuracy values of the suggested framework with the four current methods. Applying our suggested framework to the Inception V3 model and Logistic Regression classifier (InceptionV3+LR) yields the highest accuracy value of 97.77%. With accuracy ratings of 86%, 95.85%, and 94%, respectively, the models put forth by Oluwafemi and Zenghui (2019), Togacar et al. (2020), and Sharma and Ismail (2022) were less accurate [15]. Al-Haija et al. (2020) outperformed the suggested Inception V3+LR model with an accuracy score of 98.22% [16]. Furthermore, the suggested Inception V3+LR model has greater accuracy and sensitivity values—97.75% and 97.74%, respectively—than the Al-Haija et al. model, which had precision and sensitivity values of 96.5% and 96.4%, respectively. Therefore, compared to other methods, the Inception V3+LR model is more adept at capturing true positives and false negatives. The suggested training framework also requires relatively little time—6 minutes, 42 seconds.

VII CONCLUSION

Forecasting the weather is one important chore that comes before many daily activities. Deep CNN is a popular deep learning method for categorizing picture datasets, but for the best results, it needs huge datasets and powerful computers. We looked into how different CNN algorithm topologies handled statistical text features. We hope that the findings of this study will be useful as a guide for predicting weather change parameters in the future under different climatic circumstances.

This study checks the correctness, precision, recall, FL score, and training time of various CNN models and suggests a transfer learning-based system for identifying weather conditions from pictures taken outside. The findings indicate that the logistic regression he pre-trained Inception V3 model attains the greatest accuracy value of 97.77%. Furthermore, the framework's training time for the dataset with the logistic regression classifier is significantly shorter than that of random forests. A comparison with current methods has also verified the efficacy of the suggested framework. In addition, the suggested system supports big data sets and is scalable. In the future, we can better understand hierarchical representation by unfreezing and finetuningcertainlayers inpre-trained CNNmodels.

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