Rainfall Prediction using Ground Based Cloud Images

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***Abstract*—Clouds are one of the most important ways to predict rainfall. The state and types of clouds in the sky also have a significant impact on rainfall predictions. Accordingly, different specialists are keen on concentrating on clouds, one of the most interesting and significant parts of meteorology. The essential target of this paper is to utilize pictures of downpour creating clouds to make forecasts about precipitation. Using an image of clouds as input, it attempts to predict the anticipated rainfall. Based on their altitude, the cloud images in the dataset are divided into three groups: clouds at middle, high, and low elevations.**

Keywords—Deep Learning, Image Classification, Cloud Images CNN, Mobile Net, L2 Regularization

I. INTRODUCTION

In recent years, ground-based cloud picture autonomous observation techniques have received more attention. The steady recognizable proof of the sort of cloud is one of the basics. items from observation because it is connected to local weather forecasting in real time. However, the vast majority of automated classification methods currently in use are unable to accurately identify the numerous cloud categories established by the World Meteorological Organization because they are unable to distinguish even the tiniest differences between classes. This method has the potential to significantly improve the backbone network's performance, as the cloud dataset in this paper demonstrates. Particularly evident is an increase in the accuracy of difficult samples. Machines can now identify and extract features from images thanks to deep learning. CNN is typically used for image classification in deep learning. A CNN comprises of an information layer, a secret layer, and a result layer. Convolution, relu, and fully connected layers make up the hidden layers, all of which are necessary for extracting image features. This method outperforms other deep learning-based cloud picture categorization algorithms without requiring additional computation. It demonstrates that this technology is better suited to the real-world classification of cloud images [9-15].

TABLE I. TYPES OF CLOUDS AND THEIR COMPOSITION

Type of clouds	Level of clouds	Composition
Cirrus(Ci)	High-Level	It is composed of tiny ice crystals
Cirrostratus (Cs)	High-Level	It mainly consists of ice crystals
Cirrocumulus(Cs)	High-Level	Mostly made up of ice crystals
Altocumulus(Ac)	Mid-Level	Mostly water droplets and at low temperatures may contain ice crystals
Altostratus(As)	Mid-Level	Made up of Liquid droplets or ice crystals
Nimbostratus(Ns)	Mid-Level/Low-Level(Multilevel)	It contains rain or snowflakes
Stratocumulus(Sc)	Low-Level	Composed of liquid droplets, if the weather becomes highly cool, ice crystals may form
Stratus(St)	Low-Level	Made up of liquid droplets
Cumulus(Cu)	Low-Level	Mainly composed of liquid water
Cumulonimbus	Low-Level	Mainly droplets and ice crystals at the top

Clouds can be categorized based on their altitude level, shape, and Precipitation

Cirrus clouds   cirrostratus clouds   cirrocumulus clouds

Fig. 1. High-level clouds

High-Level Clouds: Clouds that are arranged at a high height, typically surpassing 20,000 feet (6,000 meters), are named significant level cloud. Figure 1 shows several examples of high-level clouds, including Cirrocumulus, Cirrus, and Cirrostratus.

Mid-level clouds: Clouds that are normally found at a rise going from 6.500 to 20,000 feet (2.000 to 6,000 meters) over the ground level are known as mid-level clouds. In colder temperatures, these clouds may also contain ice crystals. The majority of these clouds are made up of water droplets. Instances of mid-level clouds are altostratus and altocumulus.

In contrast, Nimbostratus clouds typically fall under the category of low-level clouds due to the descending base they have as a result of continuous precipitation. They structure when altostratus clouds thicken and seem dim dark, and can create tireless precipitation that goes on for cut off hours. Several visual representations of mid-level clouds are shown in Figure 2.

Fig. 2. Mid-level clouds

Low-level clouds: Low-level clouds are those that are close to the surface and below 6,500 feet (2.000 meters). These clouds are normally made out of water beads and re bountiful in dampness, which brings about precipitation and snowfall in colder environments. The stratocumulus, stratus, cumulus, and cumulonimbus clouds are all examples of low-level clouds. Figure 3 shows several visual representations of low-level clouds.

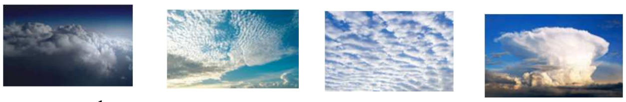

Fig. 3. Low-level clouds

Ten particular clouds were noticed, as the former table (Table 1) illustrates: The constellations that make up the constellations are Cirrus (Ci), Cirrostratus (Cs), Cirrocumulus (Cc), Altocumulus (Ac), Altostratus (As), Nimbostratus (Ns), Stratocumulus (Sc), Stratus (St), Cumulus (Cu), and Cumulonimbus (Cb). The table also includes the cloud level. There are three types of these clouds: clouds in the centre, high, and low levels. Due to their altitude, Cirrus (Ci), Cirrostratus (Cs), and Cirrocumulus (Cc) are high-level clouds. Due to their elevation, the mountains Altostratus (As) and Altocumulus (Ac) are in the middle level. Due to their altitude, the Nimbostratus (Ns), Stratocumulus (Sc), Stratus (St), Cumulus (Cu), and Cumulonimbus (Cb) are all classified as low-level. The other clouds in this area are very different from the Nimbostratus. Because it typically causes prolonged rains and is at a low level, this data places Nimbostratus in the category of a low-level cloud. However, it is sometimes referred to as a multilevel cloud because it alternates between low and middle levels in response to the precipitation that is associated with it. Based on the rainfall associated with each type of cloud study, it is possible to draw the conclusion that high-level clouds do not in any way contribute to rainfall. Clouds with a moderate drizzle are those that occasionally don't rain much or at all. This paper examines these three categories of rainfall prediction using ground-based cloud images, despite the fact that low-level clouds are largely to blame for rain. Let's now talk about the dataset. For every one of the ten cloud picture envelopes, there are three organizers in the dataset: The middle, high, and low Cirrus (Ci), Cirrostratus (Cs), and Cirrocumulus (Cc) have been added as high-resolution images. Altostratus (As) and Altocumulus (Ac) are depicted in the middle of the folder. Nimbostratus (Ns), Stratocumulus (Sc), Stratus (St), Cumulus (Cu), and Cumulonimbus (Cb) are now in the low folder. The model's testing costs 20 percent, while its training costs 80 percent.

II. Literature Survey

[1] Y. Liang, Research on cloud recognition technology of ground-based cloud image, Huazhong University of Science and Technology, pp. 1, 2019.

Ground-based cloud image categorization accuracy is an important but difficult subject that has not received sufficient attention. The extraction of representative visual features is one of the most important factors that influence performance. Local binary patterns, the Census Transform histogram, and the scale-invariant feature transform are just a few examples of the hand-crafted descriptors that are utilized in virtually every method that is currently in use. For sure, their feeble discriminative capacities are at fault for their disappointing presentation. We propose "Deep Cloud," a novel method for extracting cloud image features from deep convolutional visual features, as a solution to this problem. Numerous areas of computer vision and image interpretation have recently seen promising results from the deep convolutional neural network (CNN). It has not yet been applied to cloud image data classification. As a result, we end up paying for the initial effort to close this gap. Since cloud picture order is a multi-occurrence learning issue, utilizing just CNN's convolutional elements won't deliver the ideal outcomes. Fisher vector encoding is used to collect spatial components, and high-layered include planning based on fundamental profound convolutional highlights is used to overcome this issue. Additionally, the hierarchical convolutional layers simultaneously capture high-level semantic information and fine textural properties. Additionally, a cloud design mining and decision-making strategy is suggested to support the presentation. It seeks to identify distinguishing local patterns in order to better differentiate between the various cloud types. The experiments conducted on a challenging ground-based cloud image data set demonstrate that the proposed approach is superior to existing ones.

[2] C Shi, C Wang, Y Wang et al., "Deep Convolutional Activations-Based Features for Ground-Based Cloud Classification", IEEE Geoscience & Remote Sensing Letters, vol. 14, no. 6, pp. 816-820, 2017.

Ecological structure and the water cycle. Nevertheless, the connections between ground-based cloud images are ignored by current methods. The graph convolutional network (TGCN) for ground-based cloud classification, which takes into account image relations, is the original approach we propose in this letter. Task-based clouds are used most often in weather forecasts. In order to accomplish this, we incorporate graph computation into TGCN and construct the graph by employing supervised learning of convolutional neural networks to construct ground-based cloud picture attributes. Since existing ground-based cloud data sets include limited named preparation photographs and are organized using different grouping techniques (GRSCD), we present the largest ground-based remote detecting cloud data collection to provide a comparative report to various strategies and to also work on the investigation of provincial sky conditions. The results of the GRSCD experiment show that TGCN works well for classifying clouds at ground level.

[3] J Y Ma, T J Zhang, G D Jing, W J Yan and B Yang, "Ground-Based Cloud Image Recognition System Based on

Multi-CNN and Feature Screening and Fusion", IEEE Access, vol. 8, pp. 173949-173960, 2020.

Multi-view ground-based cloud detection is extremely challenging due to the large variations in cloud photographs taken from various angles. A perspective shift study in this field is presented in this report. Our primary advantages are creating appropriate component portrayals and gaining distance measures from test matches. As a result, we propose weighted metric learning (WML) and deep local binary patterns (TDLBP). On the one hand, we begin by developing a convolutional neural network (CNN) that makes use of cloud images to control view shift in the same way that different kinds of illuminations, areas, objectives, and obstacles are managed. Next, we remove neighbourhood highlights from part-adding maps (PSMs) in light of component maps. At long last, we incorporate events from those locales to the depiction of the last part. However, there are unbalanced comparable pairs because each category contains a large number of unique cloud photos. Consequently, we advocate using a weighted approach to measure learning. The experimental results, which we validate using three cloud datasets (the MOC e, IAP e, and CAMS e) gathered by various Chinese meteorological institutions, demonstrate the effectiveness of the suggested method.

[4] Z Zhang, D Li and S Liu, "Salient Dual Activations Aggregation for Ground-based Cloud Classification in Weather Station Networks", IEEE Access, pp. 1-1, 2018.

In recent years, ground-based cloud categorization in weather station networks has included multimodal data; however, the fundamental connections between multimodal and visual data have not been adequately exploited. For ground-based cloud classification in meteorological station networks, we propose a novel strategy known as Hierarchical Multimodal Fusion (HMF). Deep multimodal and deep visual data are combined using this strategy's two distinct levels of fusion: low-level fusion and high-level fusion. The modality-specific fusion is the primary focus of the low-level fusion, which directly combines the various aspects. Significant level combination can learn perplexing connections between the result of low-level combination, profound visual highlights, and profound multimodal attributes thanks to the profound combination structure. In order to get the entire system of the HMF ready to function on the separation of cloud representations, we make use of one unfortunate capability. Our superior performance in tests on the MGCD dataset demonstrates the usefulness of HMF for ground-based cloud classification.

[5] Z Jing, L Pu, Z Feng et al., "CloudNet: Ground-based Cloud Classification with Deep Convolutional Neural Network", Geophysical Research Letters, 2018.

Clouds have a tremendous impact on the energy balance, temperature, and weather of the planet. The cloud radiative effect, which varies depending on the type of cloud, is a key sign of the cloud's impact on radiation. Therefore, determining the type of cloud is crucial in meteorology. In this letter, we introduce CloudNet, a novel convolutional neural network model that enables accurate classification of meteorological clouds at the ground level. We develop an 11-category ground-based cloud data set called Cirrus Cumulus Stratus Nimbus based on meteorological standards. Compared to the prior database, there are three times as many cloud images. Because it includes contrails, the Cirrus Cumulus Stratus Nimbus data set is more thorough and discriminating than earlier ground-based cloud databases. this is the first time

[6] S Liu and M Li, "Deep multimodal fusion for ground-based cloud classification in weather station networks", EURASIP Journal on Wireless Communications and Networking, vol. 2018, no. 1, pp. 48, 2018.

Most existing ground-based cloud categorization techniques rely primarily on optical sensors and ignore other essential cloud properties. This paper focuses on deep multimodal fusion (DMF), a novel method for ground-based cloud identification using multimodal data from meteorological station networks. We train a CNN model to get the sum convolutional d map (SCM) for learning the visual features by pooling all of the feature maps in deep layers. The weighted technique is then used to combine the visual and multimodal features. The experimental results show that the suggested DMF outperforms the most recent techniques when used on the multimodal ground-based cloud (MGC) dataset, proving its usefulness.

[7] Ambildhuke, Geeta Mahadeo; Banik, Barnali Gupta, "Transfer Learning Approach - An Efficient Method to Predict Rainfall Based on Ground-Based Cloud Images." , Ingénierie des Systèmes d'Information . Aug2021, Vol. 26 Issue 4, p345-356. 12p.

In order to predict the climate, clouds are essential. Prediction of rainfall is also greatly influenced by the quantity and nature of clouds in the sky. As a result, the most fascinating and important topic in meteorology is cloud detection, which also draws the most scholars from other fields. The transfer learning method used in this paper to forecast rainfall using ground-based cloud pictures is presented. Convective systems, fronts, and tropical cyclones will all be present. Global climatologies of the primary cloud types are provided by observations from space.

[8]. Gogoi, M., Devi, G. (2015). Cloud Image Analysis for Rainfall Prediction: A Survey. Advanced Research in Electrical and Electronic Engineering, 2(13): 13-17.

Detecting the rotten fruits become significant in the agricultural industry. Usually, the classification of fresh and rotten fruits carried by humans is not effectual for the fruit farmers. Human beings will become tired after doing the same task multiple times, but machines do not.

III. Objective

1. Performance on a large scale may suffer if rains cannot be predicted at smaller locations.
2. The paper's main goal is to find a solution to that particular problem. Other applications use algorithms like logistic regression and artificial neural networks (ANN) to solve this problem, but they do so with less precision.
3. In this study, CNN, Mobile Net, and L2 Regularization are used in place of ANN and Logistic Regression, and their outcomes are superior to those of the previous two.
4. It is easy to utilize and get to this application. accomplishing further developed execution and more prominent steadfastness.

IV. PROPOSED SYSTEM

1. The prediction of weather is the primary application of forecasting. Despite the fact that it is powerful all alone with regards to enormous scope weather conditions estimating, it has a couple of restrictions, the most huge of which is its failure to foresee precipitation in more modest regions.

2. Despite the fact that they might be minor setbacks, they might have a big effect on productivity as a whole. Activities that are heavily weather-dependent, such as farming, could be hindered or even prevented by rainstorms in that smaller area.

Keeping in mind that the proposed system aims to address the shortcomings of the current one. The smaller-area lands are the primary focus of this proposed system. As the name suggests, "Ground based cloud Images" allows users to take pictures of clouds and have the app categorize them based on their levels

Figure 4 is the block diagram which depicts the proposed system

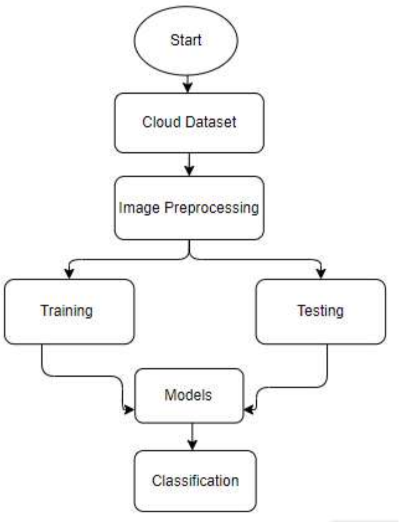

Fig. 4. Block Diagram

Keeping in mind that the proposed system aims to address the shortcomings of the current one. The smaller-area lands are the primary focus of this proposed system. As the name suggests, "Ground based cloud Images" allows users to take pictures of clouds and have the app categorize them based on their levels

V. METHODS AND METHODOLOGIES

1. CNN : The primary deep learning algorithm for categorizing cloud images into three groups based on their altitude—high, middle, and low—and forecasting rainfall into three groups—no precipitation, little to no precipitation, and moderate to heavy precipitation—is CNN.

2. MOBILE NET: When compared to a network with regular convolutions and the same depth in nets, its primary objective is to reduce the number of parameters. In the end, this results in lightweight deep neural networks.

3. REGULARIZATION OF L2: The enthusiastic researchers who worked on this problem statement encountered issues with overfitting models when using well-known neural networks. They inspired us to use L2R to address the overfitting problem because they learned that L2Regularization is used to solve it. Table 2 depicts the accuracy of all three models CNN, L2 Regularization and Mobile Net

Levels are used by the application to classify clouds. The dataset contains ten distinct types of clouds, each with a distinct level. The CNN, L2 Regularization, and Mobile Net algorithms were used to classify them. The first user must first take a picture of an object before entering it into this algorithm with an image. If the clouds are high, there is very little to no chance of rain; If the cloud level is medium, there is little to no chance of rain; Additionally, if the cloud level is low, there is a good chance of training there.

TABLE II. MODELS ACCURACY

Algorithms	*Training Accuracy*	*Validation Accuracy*	*Epochs*	*Time taken per epoch(average)*
CNN	98.16	83.74	50.0	44 seconds
L2 Regularization	92.1	77.7	50.0	14 seconds
Mobile Net	98.4	85.3	50.0	140 seconds

VI. RESULTS

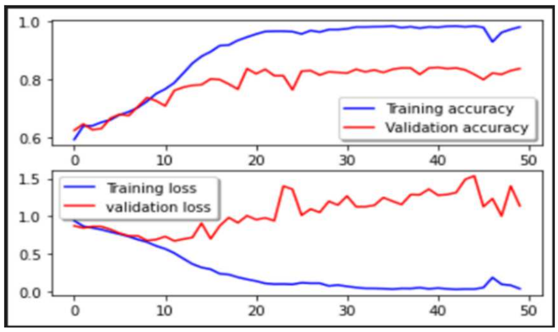

Fig. 5. Accuracy and loss plots of CNN

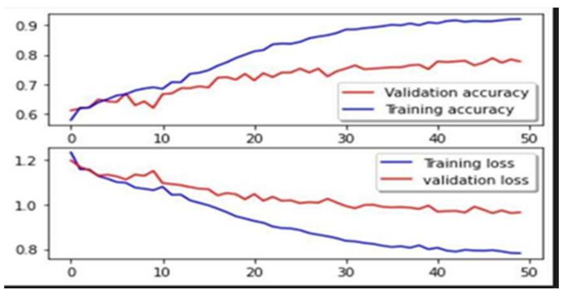

Fig. 6. Accuracy and loss plots L2regularization

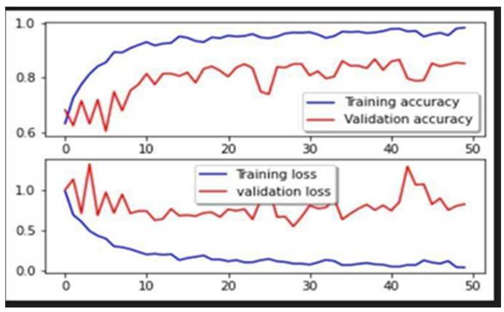

Fig. 7. Accuracy and loss plots of Mobile Net

Fig 5, Fig 6 and Fig 7 depicts the Accuracy and loss plots of CNN, L2regularization and Mobile Net.

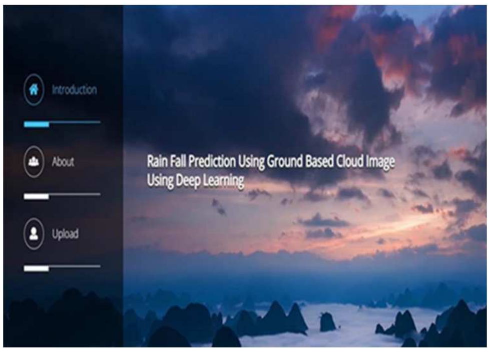

Fig. 8. Home

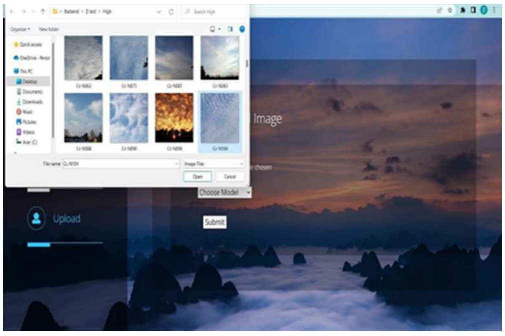

Fig. 9. Uploading Test Images

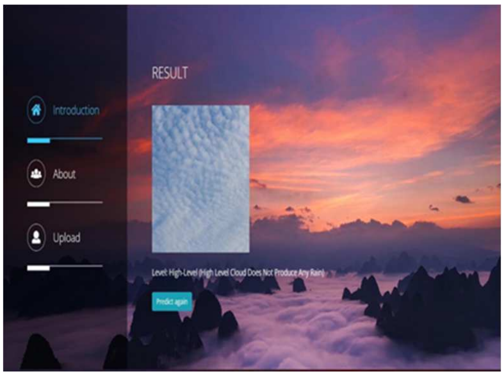

Fig. 10. Results

Figure 8 to 10 shows the functionality of this model. Figure 8 shows the home page of the website where as figure 9 and 10 shows the implementation of the model.

VII. Conclusion

CNN was the first algorithm used by the paper to classify these cloud images. This was primarily due to the fact that it minimizes information loss and reduces image dimensions. In order to guarantee that the model understands the underlying data patterns, the training process iterates over multiple epochs. CNN takes 44 seconds to complete each 50 epochs. While going through CNN, we noticed overfitting, so we used L2 regularization as a solution. By adding penalties to the parameters and making them weigh less, L2 regularization helps solve the problem of overfitting. L2 regularization takes 14 seconds per 50 epochs, which is significantly less time than CNN, but the overall accuracy suffers greatly. Last but not least, we chose MobileNet because it is a lightweight deep neural network that uses depth wise convolutions to significantly reduce the number of parameters compared to other networks. This algorithm takes 144 seconds on average per 50 epochs. Even though MobileNet outperforms CNN and L2 regularization in terms of accuracy, it takes a long time for each epoch. In conclusion, we can say that the CNN model is the best one presented in this paper because it requires less time to complete and is fairly accurate. Consequently, by utilizing information, for example, the ongoing sky picture whenever, this model will be profoundly advantageous for individuals to expect the situation with precipitation at any area, permitting individuals and ranchers to settle on urgent choices in light of the sky's overcast cover. Consolidating a few climatic factors, for example, temperature, mugginess, dew point, and wind speed which are pivotal meteorological factors that should be routinely observed to foresee momentary precipitation can reinforce the model's soundness. Future rainfall can be predicted with greater precision by combining the cloud photo method and the many atmospheric factors that cause it.

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