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CLASSIFYING WEATHER BASED VISUAL DATA USING NOVEL HYBRID APPROACH

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ABSTRACT

Aspects such as the climate play a significant part in the expansion of businesses in the current period, in which companies from a variety of sectors are collaborating to fulfil the objectives of commercial enterprises. The climate not only has an impact on our day-to-day lives, but it also plays a significant role in a wide range of businesses, including retail, construction, and supply chain management, among others. Aside from that, it also has an effect on the functionality of a great deal of visual systems, such as those used in vehicles to assist drivers, outdoor video observation system, and so on. The presence of fog in the weather poses a significant risk for automobile accidents. The impact of the severe weather that has been affecting the region can also be observed in India. Although there is a significant amount of study that is now being conducted in the topic of "Weather Analytics," there is still a significant amount of research that needs to follow the role of A.I. in this particular field. This research work presents a specific study that has been done to fill the void. The aim of this research is to investigate potential applications of combining various deep learning models known as convolutional neural networks for solving weather detection issues. Expensive sensors are required for the more conventional methods of determining the current state of the weather. This article provides a strategy using computer vision to detect real weather conditions with precise accuracy in order to keep the costs to a minimum.

KEYWORDS—*Computer Vision, Weather Classification, Image processing, Deep Learning, Ensemble Learning, Accuracy*

I. INTRODUCTION

Computer vision has only recently begun to explore the concept of weather recognition. In contrast to other challenges involving object or scene recognition, the recognition of weather requires an understanding of the intricate phenomena of refraction and reflection as well as the overlap of various particles in the air on the surface of things and the overall picture. The weather has a significant role in each of our lives. The topic of instantaneously collecting information on the weather is an empirical one that has a significant impact on society. Images provide a wealth of information that can be used to better comprehend the weather. Images also have other distinct advantages, such as high acquisition with advent of big data at a relatively low cost.

The methods that are now used to monitor weather rely on sensors, which are really rather pricey. There is a chance that artificial intelligence can be related to the identification of weather conditions. This is because the world is shifting toward the implementation of AI systems in every industry. A computer vision solution that makes use of deep learning technology has been presented as part of this body of work as a method for determining the weather condition from an input image. By making use of the CCTV surveillance cameras that are already in place, it could be able to identify weather using a computer vision system in a cost-effective manner.

It is still not easy to classify the weather using only one picture, despite the fact that it is useful. Because of the one-of-a-kind qualities of the weather, the challenge arises from the fact that many of the global and local invariant traits that are useful for object detection and classification are rendered ineffective. Methods for weather recognition are also noticeably distinct from object recognition since the variation of object in various meteorological situations, rather than the structure of object themselves, needs to be examined. This requires a significantly different set of computational resources.

In this research paper we are attempting to combine various state-of-the-art convolution neural network architectures using weighted average as an ensemble method to accurately analyze the image and classify in into 11 distinct categories as listed in the table 1.1. The ensemble learning can be extended to wider extensive deep learning methodologies to help the trained model avoid overfitting and generalize better to complex real-world data.

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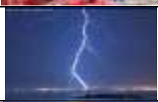
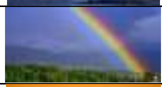
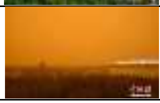
Table 1.1 Different classes in the data

DEW	
FROST	
HAIL	
RAIN	
RIME	
SNOW	
FOG SMOG	
GLAZE	
LIGHTNING	
RAINBOW	
SANDSTORM	

II. LITERATURE SURVEY

Nayar [1] presented the earliest works about the observable manifestations of various weather situations. “Lu”. [2] was the first to attempt to classify picture weather data into two classes (cloudy and sunny). They concentrated on characteristics such as clear sky, hazy shadows, refraction of light rays, and contrast. Using Support vector machines on their experiment, they attained 53% normalized accuracy. Their model failed to interpret certain scenarios, such as extremely cloudy or sunny day or a low-intensity, sunny day. “Elhoseiny”.[3] also experimented with the categorization of two-class weather images and obtained superior results using a deep convolutional neural network. They attained a normalized classification accuracy of 82.2%.

“Chaabani ”.[4] suggested a artificial neural network model for estimating range of visibility in dense, foggy or hazy conditions,. Providing a device capable of detecting the fog's density and visibility range. The most recent publication [5] conducted experiments with their own Multiple Class Weather Image dataset. They suggested a method free of external factors for identifying the weather in a single photograph. Their image data contains 20,000 photographs that are primarily focused on the entire weather state, as opposed to any particular object in the image. To extract features, HOG similarity, color space, the intensity histogram, and other methods have been utilized. After obtaining the features, the work applied the Multiple Kernel Learning technique, discovering the ideal combination of kernels which is linear in nature and achieving a score of 71% for the resulting technique. “Guerra”. [6] also studied weather identification, primarily focusing on employing new data augmentation technique, and then experimenting with various neural layers using the enhanced dataset.

All these previous works came a long way into effective classification of images for weather applications. However these researches yet not utilized the prospects of convolution neural nets which are adept at handling advanced computer vision problems. These architectures along with ensemble shows remarkable promise for accurate future weather classification tasks.

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III. DATASET AND METHODOLOGY

1) Dataset

The model is built using multiclass weather image dataset, which consists of 6,856 images having 11 distinct categories of dew , frost , hail, rain, rime , snow , fog smog, glaze, lightning, rainbow, sandstorm. Further the distribution of the categories is highly uneven as demonstrated in the figure 3.1. The dataset is a subset of Weather Phenomenon database (WEAPD) [7], published in the Harvard Dataverse by Xiao and Haixia. The data is collected from geographical ranges throughout the Europe and United States. For the purposes of this research, 225 representative and random samples are collected from each class for precise weather classification task.

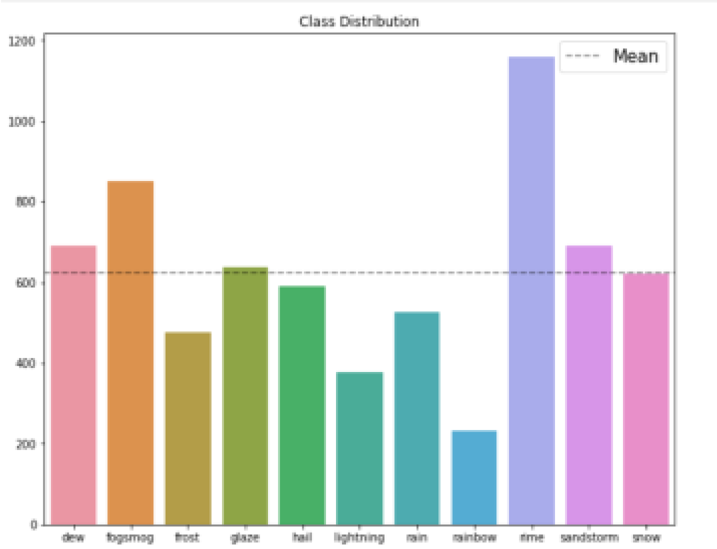

Figure 3.1. Class Distribution in the dataset subset

2) Methodology

The architectural diagram in the figure 3.2 illustrates the working of the entire process which can be divided into 2 particular phases namely – preprocessing stage and training stage. The models used are ResNet150V and Xception and they are combined using weighted average method to provide a higher accuracy.

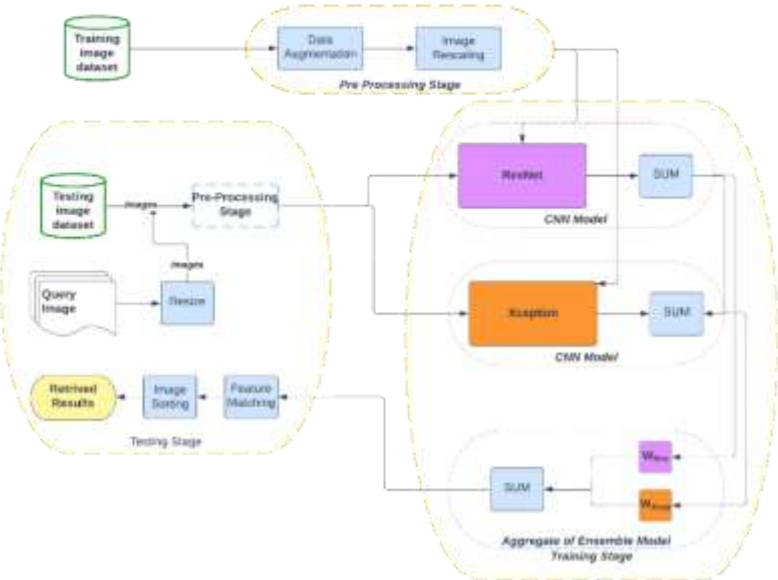

Figure 3.2 Architectural Diagram illustrating the methodology

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Pre-Processing Stage

The dataset acquired is imbalanced and contains images with varying sizes in RGB format. The first step is to resize the images to a specified size (256 x 256) and rescale the pixels to a value between 0 and 1 which are accepted by the convolution neural networks used in this literature. The next step is to split the data in 80-20 ratio for training and testing purposes and perform data augmentation on the training data. Data augmentation helps overcome the challenges posed by the small size of the dataset by generating artificial images which are representative of the current domain. The size of the training set can be increased by a factor of ten or more using this strategy and make the model much more resilient (overcome overfitting) and practical for real- life scenario. The optimal parameters for data augmentation can be derived using hyperparameter tuning as well as studying the variance of different images to understand the measures of central tendency.

Training Stage

CNN [8] has been successfully used to a variety of real-world issues, including object identification, classification, and feature extraction, among others. Recent developments in CNN have proved significant in resolving numerous difficult classification and identification issues. CNN usually has the following four features which makes them effective for computer vision applications:

1.) Convolution : CNN use a kernel or a filter which when applied on the matrix of pixel, in which images are represented can convolve the image to extract various feature. The key aspect of kernel is its ability to understand the correlated pixels as well as tolerate the slight shifts in the augmented image data.
2.) Non- Linearity : We use rectified linear unit (ReLu) to introduce non linearity in the neurons which helps the model fit to complex image data.
3.) Pooling : The pooling layer aggregates the feature map obtained after convolution to retain the most significant features. This in turn help reducing the number of inputs to the neural network and optimizing the training time for faster computations. We utilize Global Average Pooling in our architectures for reducing the feature map.
4.) Classification Layer : After Pooling operation is performed the resulted feature map is flattened to a single array of values which are then fed to a densely connected neural network. At Last the full connected layers is attached the classification layer which uses a softmax function to output the probability based on the given input and is ideal for multi-classification tasks.

The two CNN architectures used in our research are described below:

1.) ResNet150V2[9] : Residual Nets are one of the most powerful convolution neural nets which can overcome the problem of vanishing/exploding gradients by using skip connections. Activations on one layer can be connected to those on subsequent layers via the skip connection, which bypasses those layers in between. This results in a residual block being formed. The formation of resnets involves the successive stacking of these residual blocks. The 150V2 architecture is the variant which uses a stack of 6 layers to decrease the training time and model complexity at larger depths. In addition to the base model we add two densely connected layers with drop-out to increase accuracy and decrease the validation error.
2.) Xception[10] : Extreme Inception (Xception) uses depth wise separable convolution layers. The exception is based on decoupling of cross-channel and spatial correlations in the feature map. It consist of 36 convolution layers having residual linear connections. By separating the channel and image region xception basically performs training on 2D and then 1D , instead of entire 3D images which makes learning much faster. Hence it is an optimal pick for ensemble learning which requires computationally less models as its base models. Similar to ResNet we add dropouts and densely connected layers to increase the validation accuracy and avoid overfitting.

Ensemble Learning[11] : Ensemble Learning is advanced machine learning methodology which is used to combine various different models in an effort to create an entirely new model which can outperform all the base models used in its architecture. The idea of using ensemble learning for convolution neural networks stems from the idea that weather images have intricate features each of which have significant characteristics and are difficult to be captured by a single CNN architecture. Hence it is much more efficient to train separate networks which can recognize specific regions and combine them to produce a more effective output. To aggregate the two models we use weighted average as represented by the formulae below:

$$S_i^{mix} = W_{ResNet} S_i^{ResNet} + W_{Xception} S_i^{Xception}$$

Where S_i^{mix} is the feature vectors of the aggregated model , W_{ResNet} is the weight associated with ResNet and $W_{Xception}$ is the weight given to xception model.

IV. EXPERIMENTAL RESULTS

The CNN classifier was employed to solve this problem. Accuracy score and was used to evaluate the experiments. The effectiveness of each model has been compared and aggregated in one final models. The models displayed in this experiment were trained with 10 epochs, and validation was performed using a validation sample created from the train data. The validation data is also resized and rescaled and a batch size of 32 is used for each epoch iteration.

This experiment was implemented in Python [version 3.8]. The tools utilized for this project are listed below. NumPy, Keras [version 3.7.2] utilizing TensorFlow [2.10.1] , sickit-learn, OpenCV, Operating System, Pandas and plotting libraries such as Matplotlib and Seaborn

Result Analysis: Table 4.1 shows the accuracy of different CNN architectures on the train and test set of weather image data. ResNet 150V2 outperform Xception Net on the validation data and by combining both of them a 3% increase in accuracy is achieved.

Table 4.1 Accuracy and Loss Scores of different experiment

CNN Model	Accuracy Score(Validation Data)	Loss Function Score
ResNet150V2	87.07%	0.403
Xception	83.47%	0.465
Aggregated CNN Model	90.03%	0.372

V. DISCUSSION AND SCOPE

In this study, we investigate how the classification accuracy is affected by a variety of convolutional neural network topologies as well as possible application of integrating various networks together. The work being done here is distinct from other deep learning problems such as object recognition, categorization and tracking etc. In stark contrast to these problems, which rely mostly on low-level features of an image, this latest challenge is concerned with higher-level aspects within a picture. Using different architectures we were able to capture different high level aspects of the image and then combine them together to help analyze the whole image resulting in higher accuracy. On the basis of contrast, frost, hail, rime and snowy weather are essentially identical to one another. The model is very good at identifying photographs that are exhibiting dew , rain or sandstorm , but it has a tendency to misclassify images that are rime and fog smog. Sometimes photographs depicting rime are mistakenly categorized as being frost The model suffers from all of these flaws. The efficiency of the neural networks can have their performance improved by making the data set more extensive, increasing the number of epochs or ensemble a higher number of less complex convolution neural network. However each of these will have a significant increase in the computation time.

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