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ANALYZING THE PERFORMANCE OF CNN MODELS FOR WEATHER IMAGE RECOGNIZATION

NARAYANAM.R.S.LAKSHMI PRASANTHI [#1], JAYA RELLI [#2]

[#1]Assistant Professor, Department of Artificial Intelligence & Data Science,
[#2]Assistant Professor, Department of Computer Science & Engineering,
Vignan's Institute of Information Technology(Autonomous),Visakhaptnam.

ABSTRACT

Turbid media, such as haze, smoke, fog, rain, or snow, typically impair image data collected by outside visual sensors. As a result, weather conditions would typically impair or impede the proper operation of vision-assisted transportation systems, or ADAS (advanced driver assistance systems), as well as a variety of other outside surveillance-based systems. To address these issues, the removal of weather effects (or deweathering) from photographs has become more significant and has gained a lot of attention. As a result, it is critical to include a preprocessing stage that automatically determines the weather state for an input image, after which the appropriate deweathering processes (e.g., removal of haze, rain, or snow) are correctly triggered. This study proposes a deep learning-based weather image recognition framework that takes into account the three most typical weather variables in outdoor scenes: hazy, wet, and snowy. Our approach automatically classifies an input image into one of the three categories or none of them (e.g., sunny or others). Extensive experiments on well-known CNN models such as VGG-19 and Inception V3 conclude that VGG-19 provides more than 96% accuracy when compared to Inception V3, and thus Vgg-19 is declared as the best model for performing the application on jehanbhathena/weather-dataset to evaluate the proposed method and the feasibility has been verified.

KEY WORDS:

Turbidmedia, Advanced Driver Assistance System, Deweathering, Deep Learning, Inception V3.

1. INTRODUCTION

Tropical cyclones (TCs), together with gales, rainstorms, and storm surges, are considered catastrophic weather occurrences that can cause massive losses in coastal areas around the world. Numerous meteorologists and warning centres devoted themselves to this study over the last century, making advances in observational technology, intensification physics, atmospheric environment interactions, the atmospheric boundary layer and air-sea interface, ocean responses, and forecasting techniques [1]. However, significant issues with predictive abilities persist, particularly with TC genesis, intensity, and risk forecasting. In general, the most prominent tropical cyclone dynamical forecast models have low accuracy, owing to erroneous vortex initiation of TCs, insufficient description of complicated physical processes, and coarse resolution [2,3].Furthermore, there is a general consensus that upper ocean feedback has significant influence on TCs, although few operational numerical forecast models take it into account, reducing model performance [4,5]. Furthermore, other methods, such as statistical models, are incapable of dealing with the complicated and nonlinear interaction between TC-related factors; as a result, their forecast outcomes must be improved [6-10]. In recent years, scientists have begun to study utilising machine learning (ML) to explore satellite, radar, in-situ data, and other sources to improve TC forecasting skills. Machine learning algorithms, as a type of artificial intelligence (AI), are classified into three types based on their applications: feature selection, clustering, and classification.

Feature selection algorithms can reduce extraneous attributes through attribute selection to improve task effectiveness and, as a result, model correctness. A common Tucker decomposition method, for example, can tackle spatio-temporal problems that the classic tensor decomposition algorithm cannot [12]. A clustering algorithm, which can automatically partition a sample dataset into many categories, is one of the early approaches used in pattern recognition and data mining. This has numerous uses in large data analysis.

A deep neural network with numerous hidden neural layers that excels at feature learning can overcome the challenge of training through layer-by-layer initialization and achieve overall network optimization [20]. Convolutional neural networks (CNNs) [21] and recurrent neural networks (RNNs) [22] are examples of classic networks. Deep learning (DL) has advantages over typical machine learning algorithms in high-dimensional data, making it more suitable for difficult applications. As a result, selecting the right machine learning.

2. LITERATURE SURVEY

This section will mostly concentrate on the background research that has been conducted to demonstrate the effectiveness of our proposed Method. The literature review is the most important stage of the software development process. Before attempting to create the work, the programmers will first look at the pre-defined inventions that have been made utilising the same principle.

MOTIVATION

1) "Automated Weather Analysis Using Image Recognition" by Martin Isaksson.

Many sectors require the identification of present and historical weather conditions. The data assists them in planning, organising, and/or optimising their operations. Farmers, for example, may consider the present weather to determine whether to turn on or off the sprinklers. Snowmaking equipment may be enabled by ski resort operators based on various weather conditions over the mountain. Construction workers may prepare their supplies and rain gear for a remote job site.Making such decisions currently necessitates manually inspecting video feeds from remote cameras, relying on weather forecasts, or simply gazing out the window.Machine learning (ML) has the ability to automate this by acting as a digital eye. If, for example, an image recognition ML model could be built to identify conditions by simply looking at images of the weather, it could be deployed in scenarios like those described above.

2) "Weather image classification using convolutional neural network with transfer learning" by Mohammad Farid Naufal.

The weather is an important component that is taken into account when making various decisions. Weather classification is particularly important in the industrial sector, such as in the creation of self-driving automobiles, smart transportation systems, and outside vision systems. Manual weather classification by humans is inefficient and time-consuming. Weather forecast data collected from the internet is not accurate in real time for a given place. Because one sort of weather can be similar to another, weather images have distinct qualities. Computer vision is a discipline of computer science that uses picture recognition and classification to help identify weather photographs that do not rely on weather forecast information from the internet. The goal of this research is to categorise weather photos using a Convolutional Neural Network (CNN) and Transfer Learning. There are four CNN architectures such as MobileNetV2, VGG16, DenseNet201, and Xception were used to perform weather image classification.

3) "Recognising weather and visual conditions from street-level images using deep residual learning" by Mohamed R. Ibrahim.

Extraction of information relating to weather and visual conditions at a specific time and area is critical for scene awareness, which has a substantial impact on human behaviors ranging from walking in a metropolis to riding a bike, driving a car, or autonomous drive assistance. Despite its importance, machine intelligence has yet to fully address it by relying on deep learning and computer vision to detect multi-labels of meteorological and visual conditions with a unified way that can be simply utilised for practise.To date, rather sectorial models that handle a restricted number of labels and do not cover the full range of meteorological and visual circumstances have been developed. Nonetheless, weather and optical circumstances are frequently treated separately. We introduce ourselves in this document.

3. EXISTING METHODOLOGY

In the existing system there was no proper method to classify the images and identify the name of that image category very efficiently and accurately, hence following are the main limitations in the existing system.

LIMITATION OF EXISTING SYSTEM

1. More Time Delay in finding the image and its category.
2. There is no technique which can classifu all the images accurately.
3. There is no technique which can classify all the images as per dimensions.
4. All the existing methods try to classify inages using ML algorithms.

4. PROPOSED SYSTEM

Deep learning, in particular Convolutional Neural Network (CNN), is achieving significant results in image classification. In this paper a deep neural network model is been implemented which takes the images and it is then classified into the respective classes as per the dataset. Deep learning is one of the accurate and most reliable methods compared to the other methods. This paper presents a new technique to intensify the performance of image classification.

ADVANTAGES OF PROPOSED SYSTEM

The following are the advantages of proposed system. They are as follows:

1) By using CNN model it takes less time for the classification of weather images with more accuracy.

2) In this paper we survey different papers in which one or more algorithms of data mining used for the classification of weather images.

3) Result from using neural networks is nearly 100 % in this paper which can classify weather images accurately.

5. PROPOSED MODEL ARCHITECTURE

The proposed system uses two models such as : VGG-19 and Resnet 50 and now we discuss about those two models in this paper.

VGG-19

VGG-19 is a 19-layer deep convolutional neural network. A pretrained version of the network trained on over a million photos from the ImageNet database can be loaded [1]. The pretrained network can categorise photos into 1000 different object categories, including keyboards, mice, pencils, and various animals. VGG-19 is a 19-layer deep convolutional neural network. A pretrained version of the network trained on over a million photos from the ImageNet database can be loaded [1]. The pretrained network can categorise photos into 1000 different object categories, including keyboards, mice, pencils, and various animals.

As a result, the network has learned detailed feature representations for a diverse set of images. The network accepts 224-by-224 image input.For more pretrained networks in MATLAB®, see Pretrained Deep Neural Networks.You can use classify to classify new images using the VGG-19 network. Follow the steps of Classify Image Using GoogLeNet and replace GoogLeNet with VGG-19.To retrain the network on a new classification task, follow the steps of Train Deep Learning Network to Classify New Images and load VGG-19 instead of GoogLeNet.

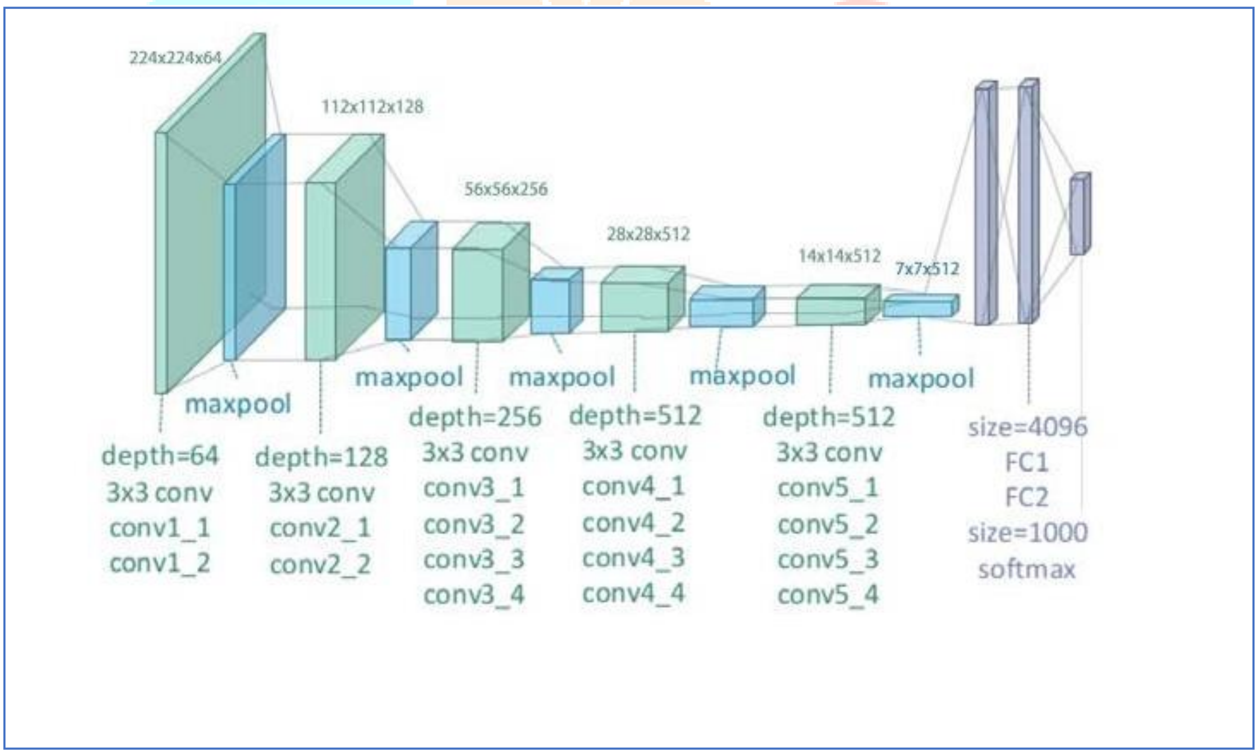


Figure 1. Represent the VGG-19 Model for Weather Image Classification

From the figure 1, Convolutional Neural Networks and regular Neural Networks are quite similar. They are composed of neurons with learnable weights and biases. Each neuron gets input, executes a dot product, and optionally follows it with non-linearity. The entire network accepts input in the form of raw image pixels on one end and class scores on the other. On the final (fully-connected) layer, they still have a loss function (e.g., Softmax).

2) Resnet 50 Model

The various parameters such as the number of convolution layers, activation functions and other important parameters required for the CNN architecture say Alex-Net are set. And in this way the model of this architecture is set. More the number of convolution layer more the training accuracy will be present in order to extract more features. The model architecture is shown in the figure 4.The convolution layer thereby has a problem that it can be conceived very easily and so the output of one layer gets transferred to another layer as input. In order to avoid such issues of curse of dimensionality the convolution layers are interlaced with the pooling layer. The main purpose of the pooling layer is to reduce the spatial size by reducing the amount of parameters and computation in the networks. Also to control the over fitting pooling layer plays an important role. Mostly the max pooling is done. A non-saturating activation function ReLU- Rectified Linear Unit function given by f(x) = max(0,x) is generally used.

6. PROPOSED METHODOLOGY

Here in this section we try to discuss about the several models which are used to detect the pedestrian who is crossing the road which is collected from live video sequence.The proposed application is mainly divided into 4 modules. They are as follows:

1) DATA GATHERING

Here we try to load the data set from kaggle and once dataset is downloaded we try to load the dataset to the system for performing the operations. Here we try to download the data

```
! kaggle datasets download -d jehanbhathena/weather-dataset
```

.

2) PRE PROCESSING

Data pre- processing is a technique that is used to convert raw data into a clean dataset. The data is gathered from different sources is in raw format which is not feasible for the analysis. Pre-processing for this approach takes 4 simple yet effective steps.

- **Attribute selection**: Some of the attributes in the initial dataset that was not pertinent (relevant) to the experiment goal were ignored.
- **Cleaning missing values:** In some cases the dataset contain missing values. We need to be equipped to handle the problem when we come across them. Obviously you could remove the entire line of data but what if you're inadvertently removing crucial information? after all we might not need to try to do that. one in every of the foremost common plan to handle the matter is to require a mean of all the values of the same column and have it to replace the missing data. The library used for the task is called Scikit Learn preprocessing. It contains a class called Imputer which will help us take care of the missing data.
- **Training and Test data:** Splitting the Dataset into Training set and Test Set Now the next step is to split our dataset into two. Training set and a Test set. We will train our machine learning models on our training set, i.e our machine learning models will try to understand any correlations in our training set and then we will test the

models on our test set to examine how accurately it will predict. A general rule of the thumb is to assign 80% of the dataset to training set and therefore the remaining 20% to test set.

3) APPLY MODELS

Classification of data is a two phase process. In phase one which is called training phase a classifier is built using training set of tuples. The second phase is the classification phase, where the testing set of tuples is used for validating the model and the performance of the model is analyzed.

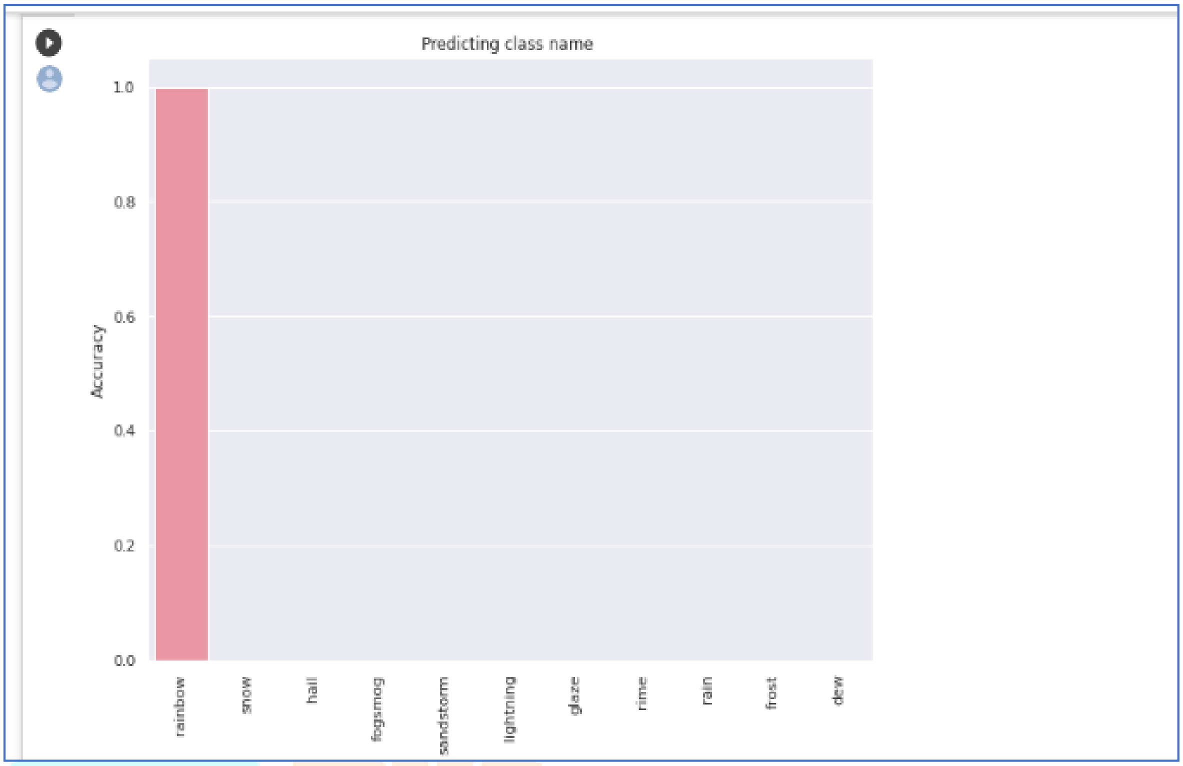
4) INTERPRETATION

The data set used for is further spitted into two sets consisting of two third as training set and one third as testing set. Here we apply VGG-19 and Inception V3 as CNN model to classify the images and display the name of that image based on its dimensions.

7. EXPERIMENTAL RESULTS

Here we developed the proposed application using Python Programming language by using Google Collab as working platform.

The above screen clearly represent the user has chosen one weather image and based on the image features, application will predict the climate.



The above graph represents several weather properties on x-axis and accuracy of prediction on Y-axis. Now we can see the input image clearly indicates it is matched with rainbow.

8. CONCLUSION

Tropical cyclones have been a source of concern for meteorologists for over a century. Numerous experts have undertaken extensive research on critical problems such as structure, dynamics, and forecasting methodologies. Machine learning is based on statistical approaches that may automatically identify useful rules from vast amounts of data for detection, analysis, prediction, and other purposes. The use of machine learning to solve critical TC problems opens up a new way of thinking about how to handle various bottlenecks in this industry. A vast number of studies have shown that techniques based on a pure data-driven approach and employing machine learning to improve numerical models can both make significant contributions to improving TC predictions. Although prior research on genesis forecasts, path prediction, intensity prediction, and TC weather prediction has made some progress and improving numerical forecast models by integrating machine learning, there are still many aspects that remain to be studied, which we regard as both an opportunity and a challenge.

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