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IMAGE-BASED CLASSIFICATION OF AIR POLLUTION USING DIFFERENT PRETRAINED CNN MODELS AND A SMALL DATASET

RAYAN AWNI MATLOOB and MOHAMMED AHMED SHAKIR
Dept. of Electrical and computer Engineering, College of Engineering, University of Duhok, Kurdistan Region-Iraq

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ABSTRACT

Because contaminants and particles are volatile, dynamic, and highly variable in both time and place, predicting air quality is a challenging endeavor. At the same time, the ability for modeling, predicting, and monitoring the quality of air is becoming increasingly pertinent. In this study, we demonstrate that utilizing several pretrained convolutional neural network models, such as ResNet18, ResNet50, ResNet101, Mobilenetv2 and Shufflenet is feasible to anticipate fine particulate matter (PM2.5) concentrations with minimal computation time. The results show that, it is possible to estimate the PM2.5 level through pretrained models using a small single scene dataset. The models are tested with 2500 images and trained with (50% for training, 25% for validation, and 25% for testing). Among all the models, ResNet101 has the highest accuracy prediction (Acc = 86.27% at LR = 0.0007) with an average learning time about (92 minutes) followed by ResNet50 that achieved a prediction accuracy equal to (Acc = 84.19% at LR=0.00007) with about half the needed learning time that is about (40 minutes). These followed by Shufflenet (Acc = 83.97% with about 44 minutes), and Mobilenetv2 (Acc = 82.70% with about 40 minutes). It is also noticeable that ResNet18 has a reasonable accuracy (Acc = 83.28%) with the least needed learning time about (16 minutes).

KEYWORDS: Deep Learning, Convolutional Neural Network (CNN), Air Quality, Particulate Matter, Image Classification, Pretrained Models.

I. INTRODUCTION

Environmental pollution issues, such as water, noise, and air pollution, are emerging with urban economic and technological development. The scientific community has become more interested in air pollution and its effects since it directly affects human health by exposing people to toxins and particulates [1, 2]. Due to the fast industrialization and urbanization, air pollution has emerged as a serious environmental concern worldwide. The human body is significantly harmed by airborne particulate matter (PM) with a diameter of less than 2.5 micrometers (PM2.5), which is one type of air pollution. PM2.5 is able to transmit dangerous chemicals into the human blood and lungs, which can lead to cardiovascular, respiratory, and cerebrovascular diseases as well as reduced lung function and heart attacks. One of the most frequent air pollutants is airborne particulate matter (PM), which is a complex mixture of solid (such as dust, soot, and smoke) and liquid particles floating in the air. In recent years, PM has drawn growing scientific attention for two primary reasons: (1) PM2.5, or particulate matter with a diameter of less than 2.5 micrometers, is extremely damaging to human health that is because it can carry dangerous substances into the blood and lungs of people, leading to serious illnesses. According to estimates, PM pollution kills about 3 million people worldwide [3]; additionally, PM has become a major air contaminant as a result of the world's rising urbanization and industrialization, particularly in emerging nations. PM2.5 concentration has thus been utilized as a key global indicator of air quality. The majority of regions do not have access to air quality monitoring stations, which are the current standard because of their high setup costs and pricey advanced sensors. Images are used more and more often to convey and describe information as portable smart phones and cameras become more widely accessible. Analyzing photo images to estimate PM2.5 and Air Quality Index (AQI) will offer an effective and reasonably priced technique to monitor air quality. because Videos and pictures are becoming increasingly important in the depiction and explanation of information as more and more accessible cameras, camcorders, and smart phones become available at affordable prices. Automatic information extraction with image-based has received a lot of attention in computer vision and machine learning, and it has effectively solved several cutting-edge interdisciplinary challenges. The rest of this study is divided into the following sections. We describe some earlier work on machine learning for picture classification in Section 2. We discuss the contributions of our research and the equipment utilized for the experiments in Sections 3 of this article. We discussed the architecture of the neural convolution networks employed in Section 4 of the paper. The proposed classifier is showed in section5. The experimental findings in Section 6 demonstrate how well the models performed. We conclude this paper in Section 7.

II. RELATED WORK

Since there are two types of methods for analyzing the PM2.5 level in photos, image feature-based and deep learning neural network-based approaches, With the aid of machine learning algorithms, researchers have been attempting to resolve issues in the actual world. Numerous classification and prediction issues have been solved using neural networks [4, 5], and [6]. There are various established techniques for applying deep learning to monitor air quality, all of which share the same objective to offer information sources that are complementary to official data.

[7], In this article, the researchers suggested a method to estimate the amount of air pollution in an area by utilizing a smartphone camera to capture an image of Tehran and then processing it with (482 images). They created a seven-layer convolutional neural network (CNN) comprising three convolutional layers, two scaling layers, and two fully connected layers that can process an image of the sky as input and output the amount of air pollution. Their findings indicate that the accuracy of the suggested strategy is 59.38%.

The **[8]** researchers blend image and weather data. The approach proposed by the researchers employs first a ResNet convolutional neural network (CNN) for PM index estimation according to the information of image (based on two databases collected from the city of Shanghai in China with a total of 1885 images and the other database was from the city of Beijing with a total of 1514 images), and then combines the PM2.5 estimated by the neural network besides two other features of weather that are the wind speed and the humidity, to get the final estimation of the particulate index using a created SVR model. ResNet + Weather has a low RMSE for the Shanghai dataset. When compared to using ResNet alone, performance has been somewhat improved by the weather. For the database of the city of Beijing, the R-squared, and the Root Mean Square Error values of ResNet are 0.5577 and 59.15 respectively. Once weather features have been added to the ResNet in the proposed approach, the R-squared has been increased to 0.6046 (by increasing percentage of 8.4%), and the RMSE has been reduced to 56.03 (by decreasing percentage of 5.27%). This is an obvious performance boost due to the method's incorporation of the humidity and wind speed characteristics.

According to **[9]**, they calculated the last pollution prediction value of a 1460 images dataset taken at various locations in Beijing utilizing a suggested outfit of deep neural networks-based regression that utilize a 5-layer feed forward neural network (using the meta learner in a non-linear manner) to integrate the PM2.5 forecasts produced by ResNet50, Inception-v3 and VGG-16 neural networks. According to their findings, the approach has a low RMSE of 49.37 and a low R-squared of 0.684.

Another scientific research in **[10]** proposed a novel forecasting approach for pollution and particle levels and to estimate the quality of air in the city of California using SVR-support vector regression and a radial basis function (RBF) kernel (AQI). The results show that SVR with RBF kernel enables accurate hourly pollutant concentration predictions for the state of California, including sulfur dioxide, carbon monoxide, ground-level ozone, nitrogen dioxide, and particulate matter. With a 94.1% accuracy, unseen validation data were classified into the six categories of Air quality index as (Hazardous, very unhealthy, Unhealthy, Unhealthy for sensitive groups, Moderate and Good) set forth by the Environmental Protection Agency of the United States.

A new PM2:5 estimate technique was proposed by Kun Li et al. in **[11]** based solely on a captured image and high-level properties of a hybrid convolutional neural network. The approach uses simulation to fit the relationship between PM2:5 and atmospheric attenuation coefficient for scene depth prediction using the atmospheric scattering model with the estimated PM2.5 value using non-local sparse priors. Their experimental findings demonstrate the accuracy of our method's PM2:5 estimation and depth inference. Both good and bad weather can be handled by our approach.

Using the benefit of extraction features (the Low-level features and High-level features) from photos and classification of feature into levels of air quality, the researchers in **[12]** proposed an image-based CNN-RC convolution learning model which combines the RC-regression classifier and the CNN- convolutional neural network for predicting the quality of air at interested areas. To improve model dependability and estimation accuracy, the models were trained and evaluated on databases containing various combinations of the baseline image, the current image, and the hue, saturation, value (HSV) statistics. At the Linyuan air quality monitoring station in Kaohsiung City, Taiwan, a total of 3549 hourly air quality datasets were collected, and the method is divided into three steps. First off, the CNN-RC technique and results demonstrated a clear ability to estimate and categorize PM2.5, handle daytime and nighttime images, and learn from and extract relevant information from large-scale datasets. Second, because the model's weights are changed by the smoke and the image's clarity, the suggested CNN-RC technique may generate accurate estimates of pollutant concentrations for images that are less clear and have a lot of smoke. The CNN-RC technique worked better at night than during the day, which is a third intriguing conclusion. The difference in hue between an image and a notable feature, such smoke, may be the cause. In general, the smoke in the photographs appears white, gray, or black. Nighttime visuals appear to be black and white, in contrast to daytime images, which are colored and/or contain clouds (i.e., noises related to smoke).

III. CONTRIBUTIONS AND MATERIAL

3.1. Contributions

The following is a summary of our work's significant contributions:

- This work uses five pretrained models to predict the air quality (PM2.5) using single scene images dataset. Since there is no PM station in the city of Duhok /Iraq, we used a dataset of Shanghai city /China, which is available online [13] and the values is also available on the US site [14].
- This research aims to classify the quality of the air in to five classes according to the weather condition as Good, Satisfactory, Moderate, Poor, and Severe.
- At the end, the result should clarify which one of the used models is better in term of estimating accuracy of the PM2.5 levels and the prediction time.

3.2. Dataset and augmentation

A rise in air emissions can cause the air quality index (AQI) to rise. For instance, during rush hour traffic, when a forest fire is burning upwind, or when there is insufficient dispersion of air pollutants. High concentrations of pollutants, chemical interactions among air pollutants, and foggy conditions result from stagnant air, which is frequently brought on by an anticyclone, temperature inversion, or low wind speeds. This paper considered the air quality using photos taken at fix locations in Shanghai [15]. The images have been divided into five classes based on the number of micrograms (the mass or weight) per cubic meter of air as (µg/m3), The level of PM2.5 images start with good class and a concentration between (0 to 30) and end with the Severe class with concentrations start from (121 to +250) as shown in table (1)

Table (1): PM2.5 classes and concentration’s

Classes levels	PM2.5 concentration
Good	0 - 30
Satisfactory	31 - 60
Moderate	61 - 90
Poor	91 - 120
Severe	121 - +250

The Shanghai PM2.5 dataset available online through [13] and contain 1250 images with different air quality levels through different weather situation and during the day light. The images are 389 by 584-pixel resolution. In order to use the images with Resnet, and as its first layer of size [224,224,3], we resized the image to fit the input layer. besides, for image augmentation, we flipped all the images horizontally to get a total image equal to 2500 images. The number of images in each class are shown in table (2). According to [16], using a pretrained model, 20 images per class is sufficient to achieve reasonable classification accuracy (Reasonable, not the best).

Table (2): The number of images in each class

Classes	No. of images
Good	507
Satisfactory	418
Moderate	580
Poor	447
Severe	548
All classes' images	2500

IV. METHODOLOGY

Comparing neural networks to supervised machine learning techniques, we can see that they are a different breed of models. Learning from scratch is exemplified by neural networks and convolutional neural networks (CNNs). In the case of an image-related task, both of these networks collect characteristics from a given set of photos and then categorize the images into their respective classes based on these extracted features. Transfer learning and pre-trained models are very helpful in this situation. Any deep learning project currently under development benefits greatly from pre-trained models. They are models that have previously been created and trained by a single individual or team to address a particular issue. Remember that when training models like CNNs and neural networks, we gain an understanding of the weights and biases. When these weights and biases are multiplied by the pixels of the image, features are produced. Pre-trained models transfer their learning to new models by passing along their weights and biases matrices. Therefore, whenever we perform transfer learning, we start by choosing the best model that has already been trained before passing its weight and bias matrix to the new model. There are a large number of pre-trained models available online. In this research we will test five models which are (ResNet18, ResNet50, ResNet101, MobileNetV2 and ShuffleNet), to decide which will be the best-suited model for our problem in term of accuracy and time. Conceptually, the approaches are based on:

• Initial preprocessing for image resizing.

• Image augmentation with one horizontal flip to the right.

V. THE PROPOSED CLASSIFIER

The flowchart of the proposed classifier in this work is shown in figure (1). As the input image dataset should first divided into five levels according to the PM2.5 concentration. That is followed by two important steps which are data augmentation and resizing. After importing the data, a special part of the data should be preserved for the training and validation. Another part (the test images) of the data should not go through the system for later evaluation. Using matlab, one of the five proposed models should be imported with a specific training option for classifying the images.

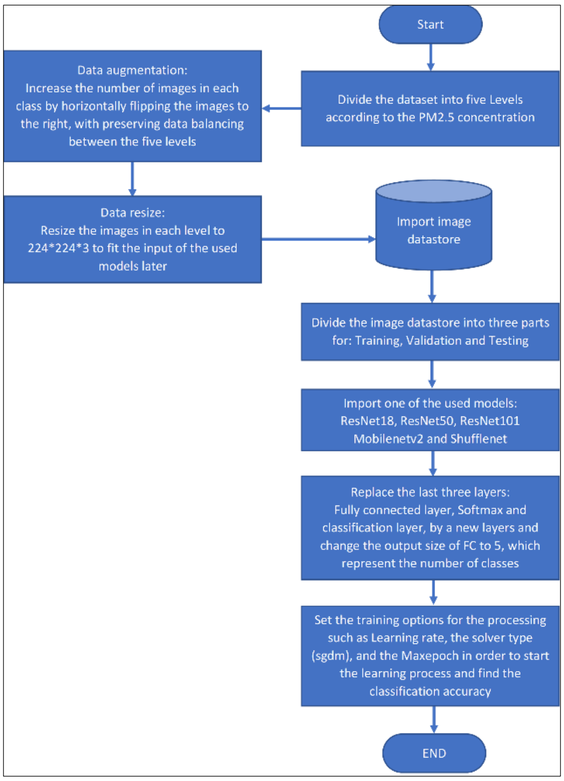

Fig. (1): flowchart of the proposed classifier

The structure of each model is described next:

5.1 Resnet18 Architecture

ResNet18 has 18 layers with a 7x7 kernel as 1st layer. It has four layers of ConvNets that are identical. Each layer consists of two residual blocks. Each block consists of two weight layers with a skip connection connected to the output of the second weight layer with a ReLU. If the result is equal to the input of the ConvNet layer, then the identity connection is used. But, if the input is not similar to the output, then a convolutional pooling is done on the skip connection. Resnet18 also used two pooling layers throughout the network one at the beginning and the other at the end of the network. The input size taken by it is (224, 224, 3), where 224 is the width and height. 3 is the RBG channel. The output is an FC layer that gives input to the sequential layer [17,18].

5.2 Resnet50 Architecture

ResNet-50 is a pretrained model that won the 2015 ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) competition. It was trained on a portion of the ImageNet database. The model can categorize photos into 1000 object categories, is trained on more than a million photographs, and has 177 layers in total, or a 50-layer residual network [19] and the input size taken by it is (224, 224, 3). The ResNet architecture (figure 2) is considered to be among the most popular Convolutional Neural Network architectures around. Introduced by Microsoft Research in 2015, Residual Networks (ResNet in short) broke several records when it was first introduced by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in their 2015 computer vision research paper titled 'Deep Residual Learning for Image Recognition'. [19]. Convolutional Neural Networks have a major disadvantage — 'Vanishing Gradient Problem'. During backpropagation, the value of radiant decreases significantly, thus hardly any change comes to weights. To overcome this, ResNet is used. It makes use of skip connection which Adding the original input to the output of the convolutional block as shown in figure (3) [18].

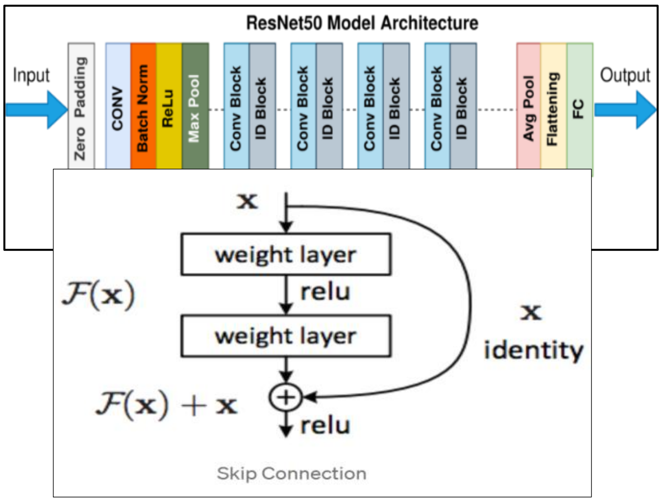

Fig. (3): Resnet skip connection

5.3 Resnet101 Architecture

ResNet-101 is a convolutional neural network that is 101 layers deep. It has the same concept of the other ResNet models 18 and 50, but with higher number of layers. It also trained on the ImageNet data set. It constructed by using more 3-layer blocks. And even at increased network depth, the 152-layer ResNet has much lower complexity (at 11.3bn FLOPS) than VGG-16 or VGG-19 nets (15.3/19.6bn FLOPS) [20].

5.4 Mobilenetv2 Architecture

It is an architecture for a convolutional neural network that aims to function well on mobile devices. It is built on an inverted residual structure where the bottleneck layers are connected by residual connections. In MobileNetV2, there are two types of blocks. One is residual block with stride of 1. Another one is block with stride of 2 for downsizing. For both varieties of blocks, there are three levels. This time, 1x1 convolution with ReLU6 makes up the first layer. The depthwise convolution is the second layer. The third layer is an x11 convolution once more, but this time there is no non-linearity. According to this argument, deep networks only have the capability of a linear classifier on the non-zero volume portion of the output domain if ReLU is applied once more [21].

5.5 ShuffleNet architecture

ShuffleNet is a straightforward but incredibly efficient CNN design that was created specifically for hardware with minimal memory and processing power, i.e., 10-150 MFLOPs

(Mega Floating-point Operations Per Second). It gained enormous popularity as a result of its excellent experimental outcomes. The ShuffleNet uses channel shuffle and pointwise group convolution to minimize computing costs while preserving accuracy.

EXPERIMENTATION SETTINGS

The five classes are presented with number of images as in table (2). The images are of (.jpg) format and have a size of 389 by 584 pixels. Figure (4) highlights the variability of the five classes. Prior to learning and classification steps, the input images are used directly after resizing them to 224x224x3, with no other previous filtering or preprocessing. Images data augmentation used to expand the dataset is obtained using Python and achieved by flipping the images horizontally to one side only (left or right). We specified No special parameters in matlab for image data augmentation. The experiments were set with the following parameters (option of training): Solver for training network = sgdm (use the stochastic gradient descent with momentum optimizer), This work, tried different learning rates (0.007, 0.0007, and 0.00007), with tested batch sizes equal to 10. The number of iterations per epoch was (125) and a total of 7500. The loss function computes the cross-entropy loss between the labels and predictions for the training set and the validation set. The proposed model is trained first on 50% of the training set while 25% of the data are used for validation step and 25% for testing. The statistics about the training, test and validation for the sub-images datasets is detailed in Table (3).

Table (3): Datasets statistics for training, validation, and testing.

Set	Percentage	No. of images
Training	50 %	1250
Validation	25 %	650
Test	25 %	650

Fig. (4): a variability of the five classes starting by Good, Satisfactory, Moderate, Poor, and Severe

The environment for the experiment used along with MATLAB R2022a is as follow:
System Manufacturer: LENOVO LEGION5
OS Name: Microsoft Windows 11 Home
System Type:x64-based PC
Processor: Intel(R) Core (TM) i7-10750H CPU @ 2.60GHz, 2592 Mhz, 6 Core(s), 12 Logical Processor(s)
Installed Physical Memory (RAM): 16.0 GB

6.1 Images Classification Results

Image classification is performed with sub-images classifier). As the number of images is limited and too low. Five pretrained models are used. Learning transfer, dataset augmentation will allow to avoid the overfitting problem by increasing the dataset and enrich the learning process. The sub-images are obtained by subdividing the original whole image (389 by 584) into five classes sub-images of size 224 by 224. The sub-images classification prediction for the test dataset is obtained using the five presented deep model. Testing all the models with the dataset using the three learning rates (LR= 0.007, 0.0007, and 0.00007) and the output chosen upon the best-validation-loss. Also, the accuracy of each model is tested three to avoid biasing to one of the models, and this is called the “training accuracy” or the “average validation accuracy”. For each model, as there is a partition of the data specified for the testing (which the model doesn’t include in the training or validation), it is calculated also three time and called the “test accuracy”. As each model take a time to finish its epochs for training, the duration called “Total time”. Next tables (4,5,6,7,8) are the result for each model respectively.

In this study, we measure the performance of the proposed method using the evaluation metric "accuracy", which is defined as the number of correctly classified images divided by the number of all images. We can see that the result of each model when using different learning rates is a bit close. All achieved reasonable performance.

Table (4): ResNet18 training results

ResNet18				
Learning rate	**Training acc.**	**Test acc.**	**Total time (min)**	**Avg. time per epoch (min)**
0.007	**83.28**	**82.13**	**16.17**	**0.27**
0.0007	82.48	82.88	15.60	0.27
0.00007	81.39	83.25	16.30	0.27

Table (5): ResNet50 training results

ResNet50				
Learning rate	**Training acc.**	**Test acc.**	**Total time (min)**	**Avg. time per epoch (min)**
0.007	84.34	83.87	45.02	0.75
0.0007	84.19	84.14	40.61	0.68
0.00007	**84.89**	**81.14**	**41.41**	**0.69**

Table (6): ResNet101 training results

ResNet101				
Learning rate	**Training acc.**	**Test acc.**	**Total time (min)**	**Avg. time per epoch (min)**
0.007	83.41	80.43	90.71	1.51
0.0007	**86.27**	**85.18**	**92.61**	**1.54**
0.00007	81.33	82.64	94.01	1.57

Table (7): MobilenetV2 training results

MobileNetV2				
Learning rate	**Training acc.**	**Test acc.**	**Total time (min)**	**Avg. time per epoch (min)**
0.007	82.10	84.00	41.68	0.69
0.0007	**82.70**	**82.37**	**40.17**	**0.67**
0.00007	80.06	80.54	38.86	0.65

Table (8): ShuffleNet training results

ShuffleNet				
Learning rate	**Training acc.**	**Test acc.**	**Total time (min)**	**Avg. time per epoch (min)**
0.007	83.26	83.22	42.01	0.70
0.0007	**83.97**	**83.03**	**44.29**	**0.74**
0.00007	79.40	79.86	46.16	0.77

VI. CONCLUSION AND FUTURE WORK

In this work, a deep learning for the classification of air quality based on PM2.5 concentration levels images is proposed. From the results with dataset divided into (50%, 25% and 25% as training, validation and testing respectively), because all the used models have large number of layers relatively, it could extract the features for the data with the previous accuracies. ResNet101 model has the highest accuracy (86.27% at LR=0.0007) which is because the high number of layers it has (101 layers). As the performance of any model drops down with the increase in depth of the architecture. It is on the contrary in ResNet. Due to its designing architecture that has the skip connection. Besides, increasing the number of layers, the extracted features by the model will increase too as increasing the layers will led to dive deeper into the details of the image. The second model that achieve high accuracy after ResNet101 is ResNet50 (84.89 at LR=0.00007). ResNet50 has high accuracy also for the same reason of the Resnet101, and it has lower accuracy than ResNet101 because it extracts less features due to its smaller number of layers than ResNet101. As a result of having a large number of layers, the ResNet101 model takes longer time (about double the time of the rest models and four times the ResNet18. For the future work, we will try to propose a model that could achieve higher accuracy with the same small dataset, and with less time.

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