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An efficient weather recognition algorithm on highway roads for vehicle guidance

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***Abstract*---**Adverse weather has long been recognized as one of the major causes of motor vehicle crashes due to its negative impact on visibility and road surface. Automatic recognition of weather condition has important application value in traffic condition warning, automobile auxiliary driving, intelligent transportation system, and other aspects. Providing drivers with real- time weather information is therefore extremely important to ensure safe driving in adverse weather. Most of the Department of Transportations (DoTs) in the U.S. have installed roadside webcams mostly for operational awareness. This study leveraged these easily accessible data sources to develop affordable automatic road weather condition for vehicle guidance. The developed detection model is focused on four weather conditions; rainy, snowy, sunny and foggy. The main goal of the proposed work is to use two neural network models such as K-Nearest Neighbour and pre- trained Convolutional Neural Network (CNN) models to achieve the classified tasks. The ResNet50 issued to train and test on the

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"Weather Dataset" and desirable recognition results are obtained. AlexNet, GoogleNet, ResNet50 and SqueezeNet has been compared .The Result has been achieved with ResNet50. ResNet50 is proposed as higher accuracy as compared to AlexNet, GoogleNet ,ResNet and SqueezeNet. ResNet50 in this models works efficiently in terms of accuracy. The best performance is achieved with the help of CNN model Resnet50 overKNN.

***Keywords*---**weather condition, recognition accuracy, convolutional neural network.

Introduction

The accident on the road occurs more due to weather condition such asfine, fog, rain and snow. The weather conditions will affect the accident rate and exposureto the traffic hazards. Due to rain, a layer of water on the road surface can cause the vehicles to skid and lose contact with the surface of road. Due to fog, the crash happened because of limited visibility. The droplets of water are so small in a fog and light that they remain floating in the air. This will lead to less visibility to the drivers because the light is diffused by the fog droplets. In the last few years, road accident prediction due to bad weatherconditions has been conducted by many professional organizations to increase the road safety for drivers. Some automobile auxiliary systems can improve driving safety through weather identification, such as setting speed limits in bad weather conditions. Outdoor traffic image experiments showed that this method can effectively improve the classification accuracy of the four weather conditions (sunny, foggy, rainy and snowy) [1]. A method based on support vector machine (SVM) was proposed to classify and identify weather images by extracting features such as power spectrum slope, contrast, noise, and saturation [2]. At present, with the rapid development of ResNet50, and other traditional convolutional neural networks (CNN) have shown amazing performance in various machine vision tasks including image classificationandsemanticsegmentation.A pretrained KNN network was fine-tuned through a weather dataset, and the recognition accuracy reached 82.2%.Then, the features extracted by hand and by CNN were combined to improve the classification performance, and the recognition accuracy can reach 91.4%, achieving good results [3]. However, most of the background information in the weather images is relatively complex. Due to the complexity of weather recognition, not all weather images can be correctly recognized.)e first reason can be attributed touncertainty,asthereisnoclearboundary between the various weather categories. In addition, sometimes weather recognition is not a simple classification task because there is more than one weather element in some weather images; those may be a multilabel classification task [4, 5], which can be summarized as incompleteness. ResNet50 is used to train and test on the dataset, and desirable recognition results are obtained. At present, with the rapid development of deep learning, AlexNet, GoogLeNet, Mobile Net, ResNet, and other traditional convolutional neural networks (CNN) have shown amazing performance in various machine vision tasks including image classification, object detection, and semantic segmentation [7–11].The rest of this paper is structured as follows. Section 2 introduces the construction method. Section 3 describes the architecture of ResNet50 for weather recognition. Section 4 present the results of ResNet50 on “Weather Dataset” and compare them with other methods. Finally, the conclusion are summarized in Section 5.

Exisiting System

While comparing to AlexNet, GoogLeNet,SqueezeNetandResNet50can be trained easily and minimize the percentage of error. ResNet50 gives better accuracy while comparing to AlexNet, GoogLeNet, and SqueezeNet. A pretrained AlexNet was fine turned withfour categories of weather dataset, providingthe accuracy of 71.8%. A pretrained GoogLeNet network was fine turned weather dataset has been collected and improved accuracy up to 74.3%. The fine turned SqueezeNet providing the accuracy of 67.8% comparing these methods ResNet50 model can efficiently providethe accuracy of 91.3% also reduces the testing and training time speed. These methods of weather recognition based on deeplearning are generally superior to traditional methods, but they require large-scale datasets as a support and can only be efficiently trained on high-end GPU,making them very expensive to recognize weather conditions. Therefore, it isdifficult to apply these methods to the terminal equipment in the field of traffic widely at present.

Proposed system

The proposed study has the potential to provide more accurate and consistent weather information in real-time that can be made readily available to be used by road users and other transportation agencies. In weather conditions such as rain, sunny, foggy and snow. The developed detection models are focused on four weather conditions; foggy, sunny, snow and rainy. The proposed method has training and classification phases. In training phase, from a given set of training images the texture features are extracted and used to train the system using the K-nearest neighbour classifier. In classification phase a given test image is segmented and then the above mentioned texture feature are extracted for classification. Several pre-trained Convolutional Neural Network (CNN) models, including, we will be doing with proper modification via transfer learning to achieve the better classification tasks.

Block Diagram

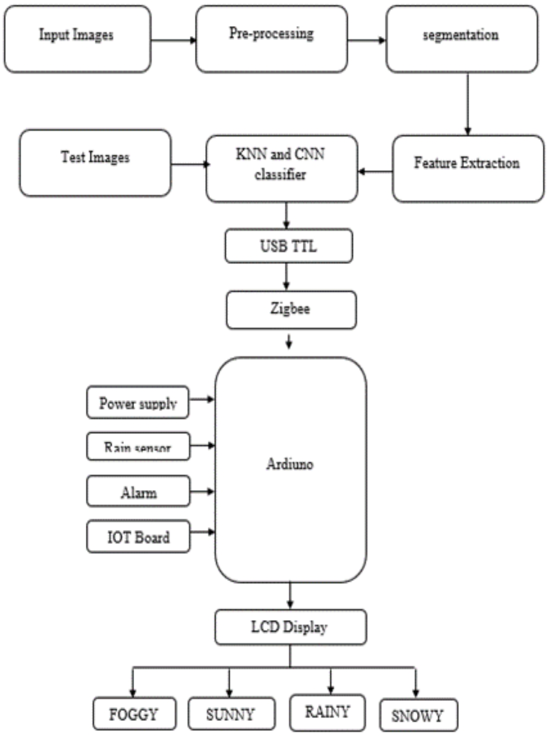


Figure 1: The general work-flow diagram of the proposed system

The training procedure of the K- nearest neighbour (KNN) and Convoluted Neural Network (CNN) and model are implemented in the project. The testing procedure that is followed to obtain our results. By using Software Serial Library here, we have allowed serial communication on pin 10 and 11, and made them Rx and TX respectively and left the Rx pin of IOT Module open. By default Pin 0 and 1 of Arduino are used for serial communication but by using the Software Serial library, we can allow serial communication on other digital pins of the Arduino. 12 Volt supply is used to power the iot Module. Here in this project, they are going to build an Arduino based traffic sign. Stop sign detects the sudden change in the IOT module sends the alert message on your Mobile Phone with the location of the sign recognize place is sent in the form of Google Map link, derived from the latitude and longitude from android app.

Description modules

- Data set acquisition
- Pre-processing
- Data augmentation
- Segmentation
- Feature Extraction
- Classification using KNN and CNN
- Ardiuno

- Rain sensor
- LCD Display
- Buzzer
- Wifi module
- Zigbee

Data set acquisition

Most of these images are collected from the internet and selected according to the specific requirements. The images are rescaled to the size 200×200. This dataset contains a total of 400 weather images covering most of severe weather, which are divided into four categories: foggy, rainy, snowy, and sunny.

Pre-processing

The input images are converted into Gray scale images. Raw data may contain noisy, incomplete and inconsistent values which may lead to error while implementing. In order to avoid these errors, we first pre-process the data.

(a) (b) (c) (d)

Figure 2: Four kinds of sample weather images. (a) Foggy. (b) Rainy. (c) Snowy. (d) Sunny

Data augmentation

For augmentation the following operations were applied: rotation range, Range of horizontal shear, Range of vertical shear and Random reflection.

Segmentation

Segmentation subdivides an image into its constituent parts or objects. A given image is transformed to HSV plane and intensity histogram corresponding to each channel is extracted.

Feature extraction

A method based on both CNN and KNN was proposed to classify and identify weather images by extracting features such as power spectrum slope, contrast, noise, and saturation.

Classification using KNN

A total of 19 training samples for each character image are used to model the KNN classifier. Training sample are character images which are resized to 200x200 pixels. The gray scale value of the training sample images are extracted as feature vector for the classifier. After the feature extraction, the KNN classifier is moded. Once the KNN classifier is trained, it can be used to classify the query character image. The query image will first go through size normalization step in which it will be resized to 200x200 pixels. Then feature extraction is applied to extract feature vector of the queryimage.

Classification using CNN

Data collection was done with four classification such as rainy, fog, sunny, snowy. CNN is to extract features from the input image. After collecting data, the next CNN structure design will be carried out. CNN has two stages namely feature learning and classification. The training process is a stage for obtaining CNN models with high accuracy. The data used for the training process are training data and validation data. The training data amounted to 80 images . The designed CNN structure consists of two times the convolution layer and the two pooling layers.

Methods

Architecture ofResNet50

The retrained architecture of ResNet50 shown in Figure 3. The convolution layer of ResNet50 are utilized to extract weather characteristics, and then the characteristics extracted at the previous layer are shortcut to the next layer through four groups of residual modules. Finally, the weather images are classified and recongnized through the fully connected layer and softmax classifier.

Results and Discussion

Recognition Performance

Then the images of test set are input into the trained model for weather recognition and the classification results are output (one of the four weather conditions: foggy, rainy, snowy, and sunny). Finally, according to the classification results of 400 test images, the recognition accuracy is calculated and the confusion matrix of weather recognition is drawn, as shown in Figure3(a).Then values on the diagonal of the confusion matrix represent the recognition accuracy of each category, respectively. Among them, the recognition accuracy of foggy is

87%, that of rainy is 93%, that of snowy is 96%, and that of sunny is 89%. The average accuracy of weather recognition is 91.3%. Therefore, ResNet50 has achieved great performance for the task of weather recognition on traffic road.

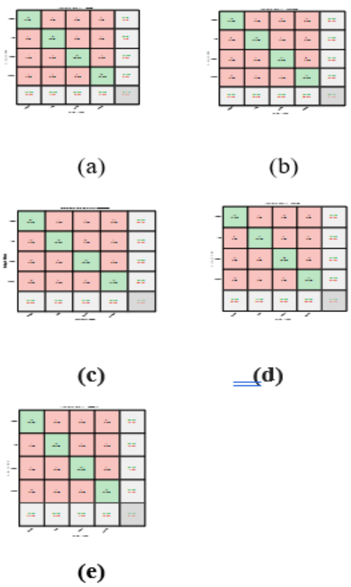


Fig. 3. Confusion matrices of different methods. (a) ResNet50. (b) GoogLe Net.(c) SqueezeNet. (d) AlexNet. (e) ResNet18.

Identify the Headings

Over the years, classical convolutional neural networks such as AlexNet, SqueezeNet, GoogLeNet, and ResNet have achieved the best results in the ILSVRC competitions every year. Many advanced network structures are proposed in these four classic networks, which greatly promoted the development of deep learning. Among these classic net works, the improvement of performance is almost accompanied by the deepening of convolutional neural network. However, it is not certain in all aspects due to the limitations of available datasets for weather recognition in scale and quantity. In order to evaluate the weather recognition performance of ResNet50, the recognition performance of ResNet50 on "Weather Dataset" is compared with that of other deep learning methods such as AlexNet, SqueezeNet, GoogLeNet and KNN. As can be seen from the graph, ResNet50 proposed is superior to other methods in recognition accuracy, while the gap between other classical networks is not obvious. The accuracy of four categories of weather condition and average recognition accuracy are shown inTable1.According to the average recognition accuracy of various methods, the histogram is drawn as shown in Figure 4(a), in which ResNet50 proposed in this paper has the highest recognition accuracy, followed by GoogLeNet, AlexNet, SqueezeNet, and KNN successively. Figure 1 shows the confusion matrices of different network models.

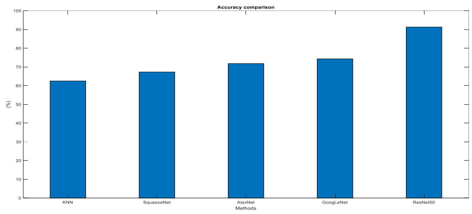


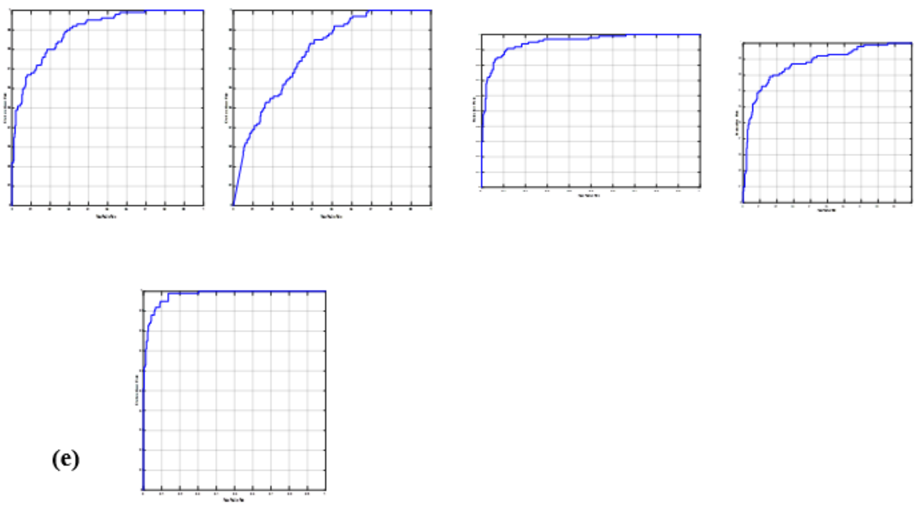
Fig. 4. Histogram Comparison of different methods. (a) Comparison of average recognition accuracy

Table 1: Recognition accuracy of different methods

Methods	Foggy (%)	Rainy (%)	Snowy (%)	Sunny (%)	Average accuracy (%)
AlexNet	70	77	74	66	71.8
GoogLeNet	69	86	76	66	74.3
SqueezeNet	51	79	81	68	67.3
ResNet50	87	93	96	89	91.3
ResNet18	79	96	93	87	88.8
KNN	62.500	75	50	87.500	68.75

Fig. 5 presents the multiclass ROC curve obtained based on the performance of the ResNet50, AlexNet, GoogleNet, ResNet18 and SqueezeNet model with an AUC value of 96.50%, 87.36%, 89.56%,95.21 and 78.35%.

(a) (b) (c) (d)



(e)

Fig. 5. ROC Curve for each class.
ResNet50. (b) AlexNet. (c) GoogLeNet. (d) SqueezeNet. (e) ResNet18.

Output

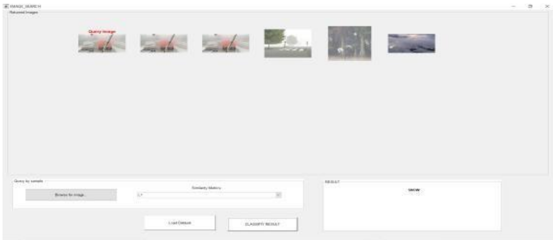


Figure 6: The classification of the query image for KNN

The figure 6 shows for searching images user provides the query image and the system returns the image similar to that of query image

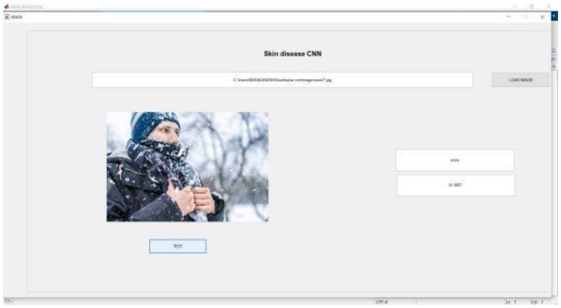


Figure 7: The classification of the images

Figure 7 represents the classification of the query image. It can be done by the following

- The four categories of output are such as foggy, rainy, sunny and snowy.
- The image shows the accuracy and category of output.

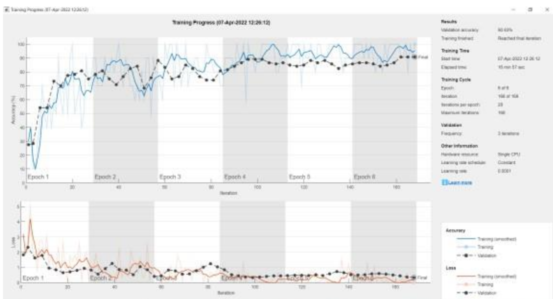


Figure 8: Training Progress

Figure 8 represents the classification of training data. It shows the validation accuracy is90.83%

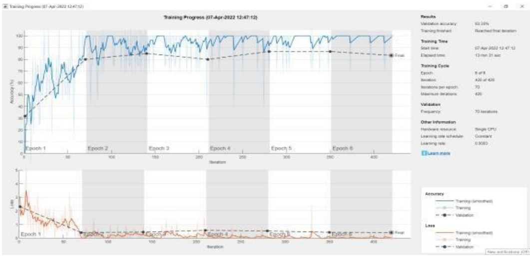


Figure 9: Testing Progress

Figure 9 represents the classification of the training data .It shows the validation accuracy is 83.33%.

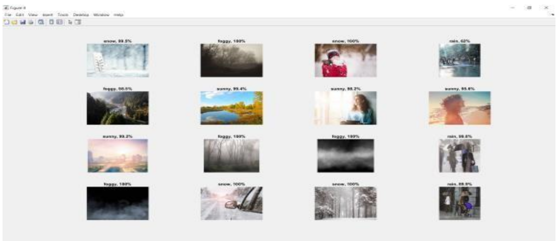


Figure 10: Testing Images

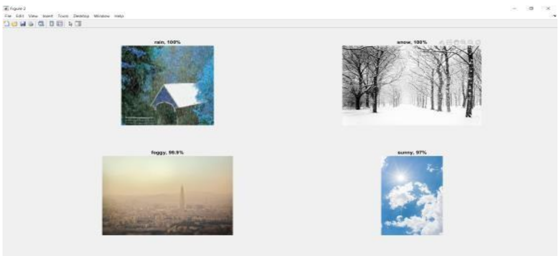


Figure 11: Testing Images

Figure 10 & 11 represents the classification of the validation images for above categories of foggy, rainy, snow and sunny.

Figure 12: final Output

Figure 12 represents It Specifies the Four categories of images such as sunny, foggy, rainy and snowy

Conclusion

The detection model is developed under four categories such as foggy, rainy, sunny and snowy of traffic images for vehicle guidance and the work is achieved with the help of KNN algorithm. The stages of this study began with the collection of data used for input training, validation, and testing. The next step is to check the accuarcy of KNN network structure for the classification task of images. The CNN is applied to and compare with KNN for analysing the classification task in terms of accuracy.TheaccuracyofKNNis62.5000. The better accuracy is achieved by CNN that as91.667.

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