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Deep Learning Navigation & Detection for Autonomous Vehicles in Extreme Weather

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Abstract

In creating decision-making systems that work for autonomous cars regarding the weather, weather detection systems (WDS) play a salient role in adverse weather conditions. Deep learning techniques specify the modalities of allowing autonomous vehicles to understand and appreciate what happens outside under different weather scenarios. This should provide adaptive decision-making concerning various dynamics in the environment, which is very pivotal for autonomous systems. The framework for detection as deep learning-based proposed in this article improves the accuracy of recognizing weather conditions, especially under adverse conditions. This framework proposes transfer learning for using the computational potential of an Nvidia GPU to assess diverse models via three distinct deep Convolutional Neural Networks, namely SqueezeNet, ResNet-50, and EfficientNet. Further evaluation will be made with the two most recent weather imaging datasets, DAWN2020 and MCWRD2018, which together consist of six weather categories: rain, sand, cloudy, snow, sunny, and sunrise. Our experimental analysis validates the claim that high classification accuracy is ensured for all three models. Interestingly, the ResNet-50 CNN model outruns the others by a wide margin of 98.51% precision, 98.48% accuracy, and 98.41% sensitivity along with an extremely short detection time of just about 5 ms during inference on the GPU. We have provided a systematic discussion regarding the comparison of our proposed model with several other pre-trained models and the accuracy gains accrued from it. Cross weather categories, a range of improvements in classification accuracy, between 0.5% and 21%, is recorded. Altogether thus, it is a practicable and dependable solution fast execution for autonomous vehicles in object detection, which therefore is imperative for decisions in a dynamic and complex environment.

Krywords: Autonomous vehicle, Transfer learning, Deep learning, Weather condition, CNN, SqueezeNet, ResNet 50 and EfficientNet-B0.

Introduction

The Vehicle detection is an important aspect of the traffic monitoring system and intelligent surveillance. This research has traveled light-years ahead in autonomous and AI-driven self-driving technologies over the past few years, benefitting from advances in sensors, graphics processing units (GPUs), and deeper learning algorithms. Object recognition and classification of traffic items are critical to storing decisions made by the autonomous vehicle to reactively achieve safety. This is made possible by object detection in an autonomous vehicle through various sensors which are generally found in such vehicles; cameras, lasers, and light detection and ranging, usually termed LiDAR. This harsh weather conditions-thick fog, heavy rains, blizzards, dust storms, and low-light environments-influence the captured images very much [4]. Such visibility impairments within the roadways make it impossible to accurately acquire vehicular information and remain an increment factor for traffic accidents; therefore, treatment techniques are devised for such images to maintain visibility [5]. It plays a very important and direct role in image enhancement to increase the accuracy of vehicle detection for intelligent surveillance and autonomous driving applications [6]. Numerous object recognition methods for vehicle detection have received extensive attention. All types have been employed to measure their importance in the field, ranging from manual and semiautomatic detection approaches to fully automated detection [7]. Most manual and semiautomatic methods rely on human inspectors performing visual assessment on foot or moving slowly in vehicles. Due to such characteristics, these methods are highly time-intensive [8]. Fully automated detection, on the other hand, uses high-resolution cameras and sensors mounted on the vehicle that capture data and analyze it for rapid object detection [9]. The trend of increasing importance of deep learning applications in traffic object detection in autonomous vehicles is evident from this work, as it shows the potential for accurate identification of such objects, as referenced in [10]. The real-time detection paradox that remains unsolved in the area of controlling the immediate operation of vehicles under different weather conditions will remain unsolved unless comprehensively analyzed [11]. Most existing solutions do not compromise between accuracy and efficiency of detection for very degraded measurements in these harsh weather environments [12]. This research, therefore, holds the promise of this gap through the new model for vehicle detection, which promises to improve accuracy and speed detection. The model will reduce false alarms while improving visibility conditions, especially during unfavorable weather conditions as backed by the relative literatures [13]. Not really. Deep neural networks have proved their worth-for example, if a very large-scale autonomous car or intelligent surveillance system or smart-city application could be produced at a cost much lower than traditional methods of machine learning [14][15]. The deep neural network paradigm transferred using transfer learning tips through Nvidia GPU computational power and is utilized in the weather detection framework proposed to recognize six prevalent weather conditions such as raining, sandy, cloudy, snowy, sunny, and sunrise. To achieve precision and high granularity in sensitivity and precision-by-weight-light implementation-on-the-ground applications of autonomous vehicle systems, the model consists of three CNN architectures: EfficientNet-b0, ResNet-50, and SqueezeNet. On the three core system modules for any data, the preprocessing module provides the learning model and evaluation system. The system is built using many metrics that offer performance evaluation for all of the weather images classified in a multiclass nature. The simulation results showed the results of this method by showing a superiority advantage over all of the existing methods in some of the important criteria used for evaluation: precision, accuracy, F1 score, and sensitivity. Further, the time of processing is also great as compared to the inexpensive hardware used in the implementation. The suggested system can therefore be considered an excellent alternative to large scale integration with the autonomous vehicle domain as it can improve safety systems, promote quick decisions, and remain inexpensive relative to other systems. This structure of proposal is logically arranged in such a way that Section 2 contains the relevant literature review in this area. Section 3 then gives an explanation of the model architecture.

Section 4 contains all results and their important comparative analysis, and Section 5 is dedicated to the conclusions and future directions of this research.

Literature Review

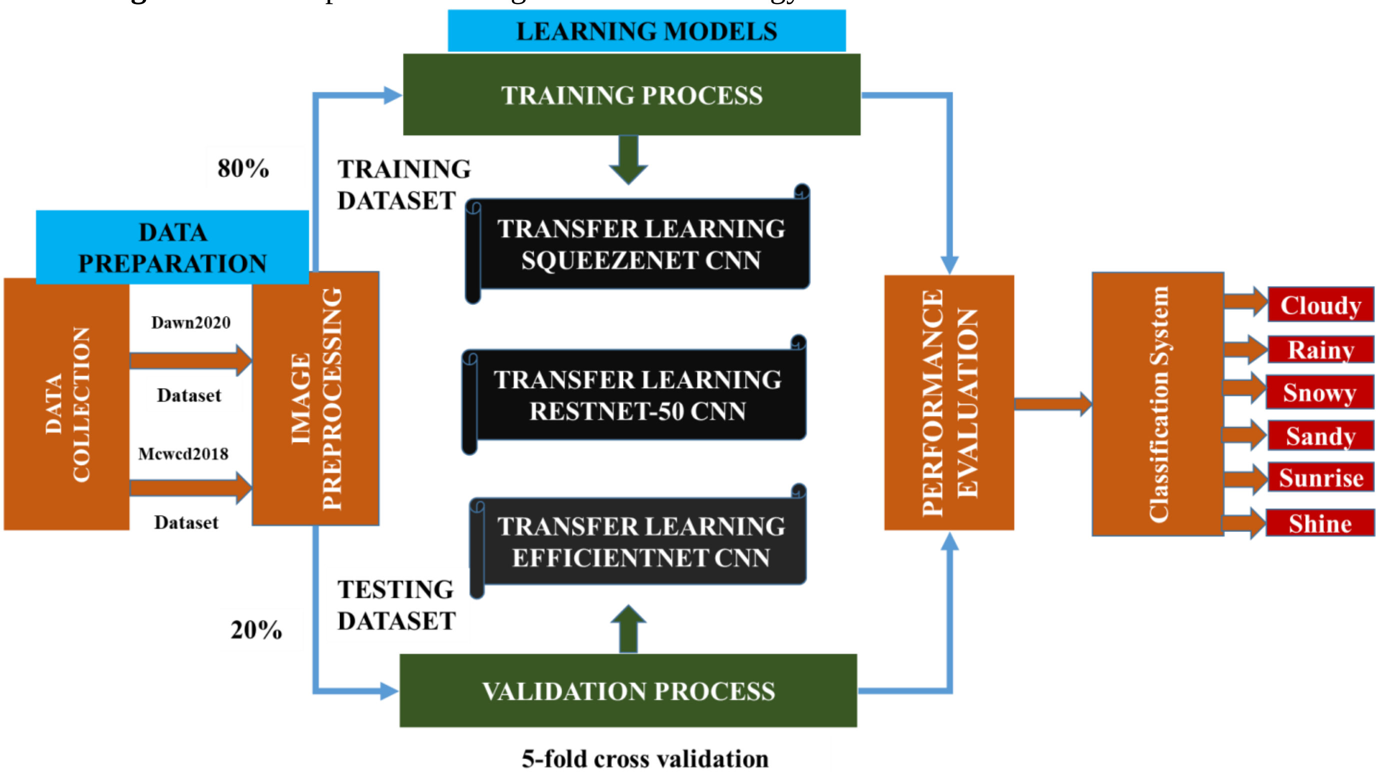
More recently, deep learning techniques and deep convolutional neural networks (Deep CNNs) have gained popularity in the weather conditions that can be automatically recognized from visual data. The present section evaluates the established attempts in the field of weather condition recognition based on image analysis. In their work, [16] studied weather classification by CNNs, comparing the feature spaces created in different layers of the CNN. This work specifically dealt with binary weather-classification problems in which it classified only sunny and cloudy types. With a fine-tuning approach, the pre-trained network was adapted to weather-classification tasks. This design included five layers: one convolution/pooling layer, two fully connected layers, and an output layer. The last layer had two nodes corresponding to the two classes: sunny and cloudy. A dataset of 10,000 images was created to represent both classes in training and testing. The implementation achieved a normalized classification accuracy of 82.2% and a standard classification accuracy of 91.1%. In a different study [17], research was initiated, proposing that cameras function as weather sensors and estimate the weather based on images acquired. The work constructed a large image dataset with more than 180,000 images in a variety of weather conditions, including foggy, sunny, cloudy, snowy, and rainy. The temperature and humidity were also taken as weather attributes. An SVM model was applied to classify the images as indoor or outdoor, rejecting the indoor ones. The classifier thus obtained an overall accuracy of 98%. Part two of the system rejected images where sky coverage was less than 10%. Toward obtaining the relevant weather data from an online weather platform, geotags and temporal metadata were used for each image. A random forest algorithm was used to draw upon weather-related information from each image using the metadata correlated with weather parameters. An average weather condition classification accuracy of 58% was noted in the study. It also suggests a system of weather-aware landmark classification, where weather data are important for classification.It is from deep learning advances and the repercussions of extreme weather on urban transportation that this model emerged. In lieu of the find, a ResNet-15 model, a simplified form of ResNet-50, has been constructed whereby the number of layers was reduced from the existing 50 to 15. This deep CNN model would then associate meteorological parameters with image features such as the sky and road, using convolutional layers within the network. It is to mention that classifying input images will make use of fully connected layers as well as a SoftMax classifier. The most satisfactory results were accomplished by the leaner model, even under the constraints posed by a standard CPU. This required creating a dataset to validate the proposition, which consists of weather-related images together with traffic roads. The four weather categories considered here, divided into approximately 5,000 images, formed the dataset. After training and testing with this dataset, recognition accuracy results for four weather conditions showed as follows: rain-97.3%, fog-96.4%, sunny-95.1%, and snow-94.7%. In their research [19], the authors suggested a new scheme which collects weather information from street level images. This system acquired features from deep learning, computer vision techniques, and there was no preposition assumed towards the images being analyzed. The model, therefore, was able to extract different weather profiles at varying times of the day, namely dawn/dusk, daytime, and night-time, with correct time classifications. One of the interesting things from the study was that they have proposed four Deep

Convolutional Neural Network (CNN) models for detecting different Visibility parameters, namely dawn/dusk, daytime, nighttime, glare, etc., concerning different weather conditions such as rain and snow. The accuracy of recognition with regard to those different categories was above 91% and below 95.6%. The authors improved the MeteCNN deep CNN model for various weather condition classifications. They compiled a collection of more than 6,877 images uniquely tagged according to the 11 different weather phenomena: hail, rainbow, snow, and rain. The author derived the labels from shape and color features analysis from the images. Both training and test data are incorporated into the dataset to evaluate the performance of the model proposed. The architecture consists of thirteen convolutional layers, six pooling layers, and one SoftMax classifier. The accuracy of this proposed model is about 92% as reported in the tests. Of the many things noted above, Roser et al. have now taken their work-on driver assistance systems-integrating cars to new levels. The experimentalists worked on histograms of weather features for classification and then derived an SVM classifier-they trained the classifler on contrast, intensity, sharpness and color features between various weather such as clear, light, and heavy rainfall to classify images from a vehicle camera. High levels of accuracy were reported in the SVM results of the study; it was important to note that feature selection was key to this success. The recorded error rate was around 5%. They set up a weather recognition framework against the driver assistant systems adversely affecting these systems due to weather hindrances like fog and rain [21]. This framework is meant to detect particular weather states like haze, rain, and snow. This method's efficiency was first-aid checked by testing several deep neural networks including GoogLeNet and AlexNet after several changes were made to classify them over four output classes. Deep learning-based methodologies were compared to those that adopt a more traditional, handcrafted approach, using one's own features. The results indicate jams deep learning models have much higher competition than the previous ones. Moreover, authors created the first large-scale dataset for general purposes and included photographs that largely recreate states of undergone climate perturbation such as snow, rain, and fog [22]. Furthermore, a novel augmentation algorithm based on super pixel delimiting masks is given in this study. The major reason for this is testing the impact of super pixel masks over several models such as CaffeNet, PlacesCNN, ResNet-50, and VGGNet16. This is to verify if such masks would help any model in performance. Findings reported that weather conditions were classified under clear, overcast, fog, rain, and snow. Performance results showed that the models' performance was between 68% and 81%, with ResNet-50 being the best performing of these models. Transfer learning techniques along with traditional learning techniques were also applied using deep CNN methods [23,24]. The research is based on such pre-trained models trained originally on the ImageNet dataset. Many parameters of intermediate layers were frozen during training, while input and output layers were modified to ensure higher efficiency in terms of computation for deep learning models. Building a detection model using a dataset across different environment conditions was achieved in addition to using commercially available Nvidia GPUs. The model was capable of classifying images under six categories, such as rainy, cloudy, sandy, snowy, sunny, and sunrise. The three important CNN Models, ResNet-50, EfficientNet-b0, and SqueezeNet, were compared using a transfer learning-based approach. Testing and comparison of various metrics showed that the ResNet-50-based model is better than the other models: EfficientNet-b0, SqueezeNet, and several other advanced ones.

Materials & Methods

It should be noted that the research aims mostly at clear enhancement in an area loosely defined as developing an intelligent system with deep-learning methods for the actual weather estimation going from extreme to normal. Special attention is given to the incorporation of this system into autonomous vehicles and its ability to perceive real-time weather. Therefore, the intelligent vehicle would be able to make decisions or adjust its operations based on dynamic environmental conditions. The proposal emphasizes the development of an intelligent system that utilizes deep learning models to identify and classify all weather conditions, ranging from extreme to normal. It is an intelligent weather system specifically developed for autonomous vehicles, which can recognize real-time environmental weather conditions. Consequently, the decision making or adjustment of operations of these intelligent vehicles depends on changing conditions.

Figure 1. Developed Block Diagram for Methodology.



The four of three interacting main subsystems running at the background level are Data Preparation (DP), which mainly takes care of acquiring and pre-processing datasets of images containing data on the weather condition; Learning Models (LM), which focuses on training, validation and testing of deep learning algorithms; and Evaluation and Deployment (ED), which works towards performance evaluation and generation of classifications using multiclass classification technique.

A. The Subsystem for Data Preparation

The two incorporated into this dataset are DAWM2020 and MCWCD2018 which yield a dataset of 1,656 images classified into six unique weather conditions: sandy (319 images), sunrise (365 images), rainy (215 images), overcast (300 images), snowy (204 images), and shine (253 images), and the figure shows those images representing each weather condition in the dataset.

All the dataset images went through preprocessing using MATLAB2021b such that in JPEG format conversion, all images are 224 × 224 × 3 RGB images by resizing them, and followed data augmentation. The procedure for photo augmentations included cropping, resizing, digital rotation or reflection, and distortions invariant to these transformations to produce some other images for increasing and training the models' operations.

Figure 2. The Dataset attributes.

The original and augmented image data comprise, in effect, forward and backward near pairs of about 5,000 JPG images, each of the dimension 224 × 224 × 3. Random shuffling of the images was applied to eliminate any bias prior to their split into two subsets, which are 80% for training and 20% for testing. The applicability of the methodology is assured through a five-fold cross-validation scheme.

B. Subsystem Model Learning

This subsystem trains and validates the model for classification of weather conditions using deep supervised convolutional neural networks (CNNs). To improve the performance of this application, transfer learning is sought, and emphasis is placed on three CNN architectures pre-trained on large datasets: EfficientNet-b0, SqueezeNet, and ResNet-50. Fine-tuning is done in which the specific task is trained using a learned representation and features obtained in pre-training using large datasets to increase accuracy and speed.

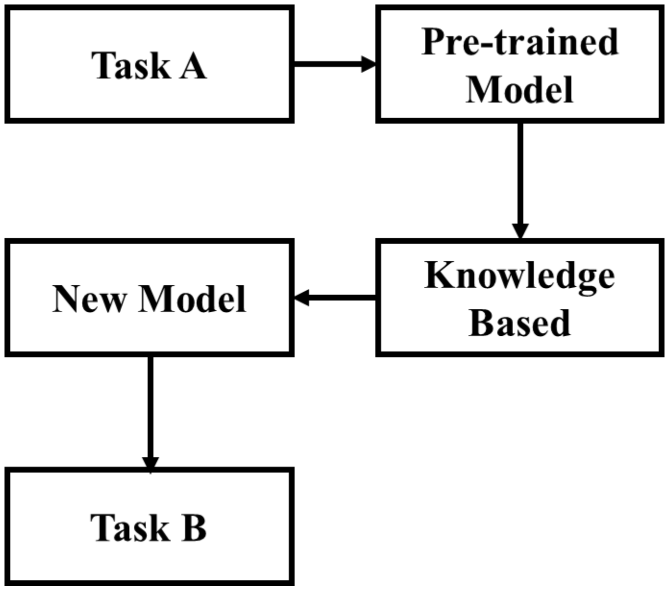


Figure 3. The Dataset attributes.

Input supplies pre-processed RGB images of size 224 by 224 by 3. The images after they enter Input Layer then go to Processing Layer, which actually performs feature extraction and true classification with them. Lastly, the Output Layer comprises trainable parameters of already trained CNNs working with SoftMax probabilistic functions to deliver final classification results.

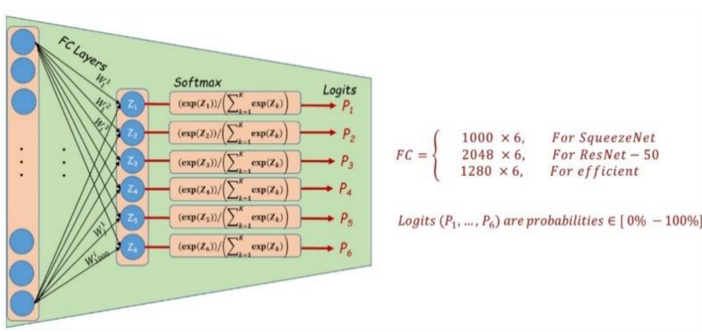


Figure 4. The Learning output model development layer.

C. Assessment and Implementation Module

The effectiveness of these proposed deep learning models was usually assessed by the use of these standard proposed evaluation metrics along with some confusion matrix analysis at the test stage. This study focuses on these major metrics: true positive (TP); true negative (TN); false positive (FP); and false negative (FN). Some derivations of these values are used to determine accuracy, sensitivity (recall), precision, and F1-score. The last realtime model is selected in the light of being the best model from these performance measures. When the system is deployed, it uses the softmax probabilities to discriminate all the different weather cases. Whenever the output of any SoftMax probability of an image lends itself to high(prior) probabilities corresponding to the ill weather conditions defined in Table 1, then it automatically changes the controls of an autonomous vehicle for the sake of safety and environment optimization.

Table 1. The Soft-Max classifier output samples.

P_{Cloudy}	P_{Sandy}	P_{Snowy}	P_{Rainy}	$P_{Sunrise}$	P_{Shine}
1.25%	1.00%	1.75%	93%	1.20%	1.80%

Results and Discussion

The Inquiry examines the development of a cognitive computing model by means of deep learning algorithms to forecast poor weather conditions, as well as one that conforms to the principles governing the use of autonomous cars. Soon, we will present the empirical results that demonstrate how the system performed on the evaluation metrics stated earlier.

A. Performance Trajectories

The graphs provided in Figure 5, Figure 6, and Figure 7 represent the performance trajectories seen with the classification of the proposed weather detection system. Three CNNs were utilized for this purpose: EfficientNet-b0 C, SqueezeNet, and ResNet-50. All the accuracy curves for the CNNs initially kept some steady order of increasing improvement; however, as the number of learning epochs increased, it was seen that those of the models whose accuracy had followed that trend were saturating around the 100% mark, where next epochs' divergence in accuracy only decreased until nearly 60 learning epochs. It has been observed that all models trained by the higher-scoring accuracy datasets present their training accuracies slightly above 100%. The testing datasets were also providing high accuracy with SqueezeNet 98.48%, ResNet-50 97.78%, and EfficientNet-b0 96.05%. This gives a valid support for the efficiency and reliability of the model in classifying the considered dataset. The margin of difference is workable, thus ensuring avoidance of either underfitting or overfitting [26].

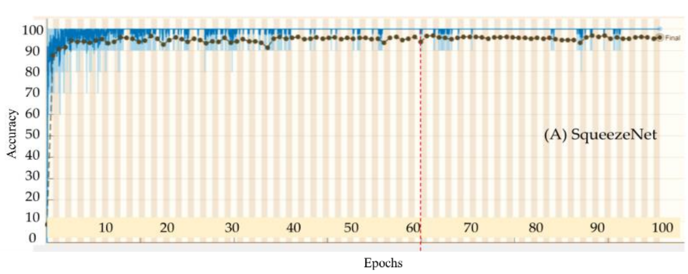


Figure 5. The Squeeze-Net performance net trajectories.

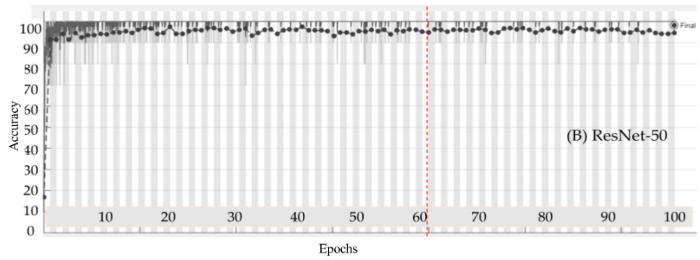


Figure 6. ResNet-50 performance trajectories.

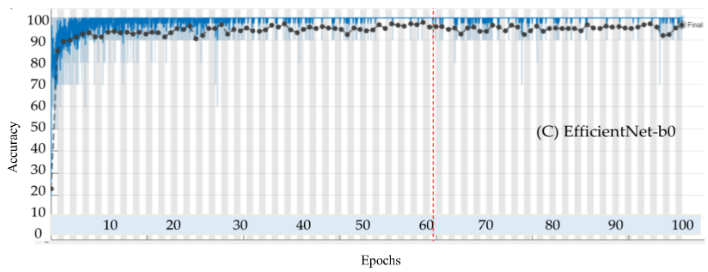


Figure 7. The EfficientNetb0 performance net trajectories.

B. Confusion Matrix Analysis

Afterward, all developed models were validated and tested using the samples indicated above for the six classes, respectively, in the confusion matrix representation, as depicted in Fig. 8. There is a good concentration of correctly predicted samples along the diagonal of the confusion matrix, implying that many models can be trusted since there were cases of true positives and true negatives. Among all tested models, the ResNet-50 has been shown to outperform them. ResNet-50 performed very well in classifying samples, where 326 true positives and true negatives were correctly identified, four others were misidentified out of a total of 330 samples, yielding an excellent report card. Testing of all models against performance produced results wherein some were preferred over ResNet-50.

True Classes \ Predicted Classes	Cloudy	Rainy	Snowy	Sandy	Shine	Sunrise
Cloudy	62	1	0	1	0	0
Rainy	2	39	0	0	0	0
Snowy	0	0	60	1	0	0
Sandy	0	2	2	39	0	0
Shine	0	0	3	0	46	1
Sunrise	0	0	0	0	0	71

(A) Confusion Matrix of SqueezeNet Model

True Classes \ Predicted Classes	Cloudy	Rainy	Snowy	Sandy	Shine	Sunrise
Cloudy	62	1	0	1	0	0
Rainy	0	41	0	0	0	0
Snowy	0	0	61	0	0	0
Sandy	0	1	0	42	0	0
Shine	0	0	1	0	49	0
Sunrise	0	0	1	0	0	70

(B) Confusion Matrix of ResNet50 Model

True Classes \ Predicted Classes	Cloudy	Rainy	Snowy	Sandy	Shine	Sunrise
Cloudy	64	0	0	0	0	0
Rainy	0	41	0	0	0	0
Snowy	2	0	58	1	0	0
Sandy	0	0	1	41	1	0
Shine	1	0	1	0	48	0
Sunrise	0	0	0	0	0	71

(C) Confusion Matrix of EfficientNetB0 Model

Figure 8. The Matrix (Confusion) for the deep-learning Model

B. Performance Indicators

This showed in-depth comparative results between the different SqueezeNet, ResNet-50, and EfficientNet-b0 models, running for major performance indicator values such as detection sensitivity, accuracy, F1 score, and precision for a weather detection system. ResNet-50 surpassed the other models in terms of precision, accuracy, F1 score, and sensitivity by margins of 0.72%-2.45%, 0.77%-3.00%, 0.45%-2.45%, and 0.60%-2.76%, respectively. Therefore, ResNet-50 is the optimal model for deploying onboard safe autonomous vehicles for the real-time atmosphere detection of weather.

Table 2. Developed KPIs (methodology).

Model	Accuracy	F1-Score	Precision	Sensitivity
EfficientNet-b0	97.78%	97.84%	97.74%	97.96%
ResNet-50	98.48%	98.44%	98.51%	98.41%
SqueezeNet	96.05%	95.68%	95.51%	95.96%

C. Comparative Analysis

This table shows a total comparative analysis of our ResNet-50 weather detection model with the others coming up recently in the last five years and includes important state-of-the-art developments. The model is primarily known for being the most superior in getting the highest accuracy rate for the six-class weather detection scheme, 0.5% more, and even sometimes higher up to 21% in comparison with latest advanced classifiers. It is further able to maximize the classification accuracy obtained from all the six weather-theory classifiers. The ResNet-50 Convolutional Neural Network (CNN) model is also capable of detecting the objects with a great convenience with an average inference time of only 5 milliseconds at the Graphics Processing Unit (GPU). Thus, this very clearly demonstrates the promising future of the proposed framework in real-time applications where autonomous vehicles are likely to make speedy yet accurate decisions in variable weather conditions.

Table 3. Comparison of the results with the Literature (existing).

Reference Number	Classification Model	Intersection with the Used Dataset	Classes	Accuracy
[**25**]	Discriminative dictionary learning	Partial	Sunny Cloudy overcast	94.00%
[**26**]	ResNet-15	Partial	Sunny	96.03%

	CNN		Snowy Rainy Foggy	
[**27**]	GoogLeNet CNN	Partial	Sunny Snowy Blizzed Foggy	95.46%
[**28**]	ResNet-50 CNN	Partial	Clear Foggy Snowy	97.69%
[**29**]	GoogLeNet and AlexNet CNNs	Partial	Hazy Rainy Snowy	92.00%
[30]	Deep MeteCNN	Total + Additional classes	11 classes	92.00%
Developed Methodology	ResNet-50 CNN	Combined Dataset	Cloudy Rainy Snowy Sandy Shine Sunrise	98.50%,

Conclusion

The automatic intelligent weather detection system forms a crucial reservation for decision making enhanced intelligence over autonomous vehicle systems. Weather sensing is facilitated by models Resnet-50, SqueezeNet, and EfficientNet-b0, which are three deep CNNs. This work investigates a merged dataset belonging to six weather classes: cloudy, rainy, snowy, sandy, bright sunshine, and sunrise comprising the MCWDS2018 and DAWN2020 datasets. It is seen from the results that the system works efficiently and perform adaptively with various weather conditions. The experimental results showed that all of the models gave their best output, with ResNet-50 rated at 98.48%. On the other hand, ExcellentNet-b0 and SqueezeNet were rated 97.78% and 96.05% respectively. Great metric performance and inference time on the GPU testify to the real-time applicability of this model. A significant contribution of this work is that it provides the first integration of the DAWN2020 dataset with MCWDS2018 to develop a weather classification mechanism for deep learning purposes. This combination justifies the six-weather class representation in the database while enhancing the reflection of extremes related to weather phenomena. Actually, it has been noted that there is no one-stop dataset supporting various weather detection systems, even though the popular and established criteria for judging performance are accuracy. This study presents a synopsis of many models for weather detection with a strong focus on those unusual combinations of datasets and classification schemes. In future works, the application will also be expanded to evaluate performance of the proposed lightweight design on various hardware considering the processing time and accuracy as performance indicators. The other areas of improvement could involve inclusion of more types of urban street items, including signs, mailboxes as well as streetlights, which should be categorized by this system. The use of diverse datasets about autonomous driving in intricate environments with many objects is the final goal of this research to increase the applicability and efficiency of the system in real-life settings.

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