Autonomous Vehicles in Extreme Weather: A Deep Learning Approach for Detection and Navigation

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Abstract- Weather Detection Systems (WDS) are of utmost importance in providing vital information for the decision-making processes of autonomous vehicles, especially when faced with adverse weather conditions. Deep learning techniques provide a reliable and effective solution for enabling autonomous vehicles to accurately perceive and interpret outdoor weather conditions. This capability plays a crucial role in facilitating adaptive decision-making in diverse and dynamic environments. This research paper introduces an innovative detection framework leveraging Deep Learning (DL) techniques, tailored to accurately classify weather conditions encountered by autonomous vehicles in both regular and challenging scenarios. The developed framework utilizes transfer learning methodologies and capitalizes on the computational capabilities of the Nvidia GPU to assess the effectiveness of three specific deep Convolutional Neural Networks (CNNs), namely SqueezeNet, ResNet-50, and EfficientNet. The evaluation process entails the utilization of two modern weather imaging datasets, specifically DAWN2020 and MCWRD2018. These datasets encompass a total of six distinct weather classes, namely rainy, sandy, cloudy, snowy, sunny, and sunrise. The experimental findings provide evidence of the exceptional classification capabilities of all the models under consideration. Notably, the ResNet-50 Convolutional Neural Network (CNN) model showcases outstanding performance metrics, attaining precision, accuracy, and sensitivity rates of 98.51%, 98.48% and 98.41%, respectively. Moreover, it is worth noting that the ResNet-50 Convolutional Neural Network (CNN) model demonstrates an exceptionally brief duration for detection, with an average inference time of 5 milliseconds when leveraging the Graphics Processing Unit (GPU) component. The results of our comparative analysis, when compared pre-trained models, demonstrate the superior accuracy of our proposed model. We observed significant improvements in classification accuracy across the six weather conditions classifiers, ranging from 0.5% to 21%. Therefore, the aforementioned framework presents itself as a viable and efficient solution for the timely execution of tasks, offering autonomous vehicles the ability to detect objects accurately and promptly. This, in turn, improves the vehicles' decision-making process in complex and ever-changing surroundings.

Index Terms- Autonomous vehicle, weather condition, Transfer learning, Deep learning, SqueezNet, CNN, ResNet 50, and Efficient-b0.

I. Introduction

The domain of traffic monitoring and general intelligent visual surveillance places significant emphasis on the crucial aspect of efficient vehicle detection. The creation of AI-based autonomous or self-driving applications has seen a dramatic uptick in research activity in the last several years. This surge could be attributed to significant advancements in sensors, graphics processing units (GPUs), and deep learning algorithms [1,2]. The real-time identification and classification of traffic objects play a crucial role in enabling autonomous vehicles to make informed control decisions and maintain a high level of safety. Autonomous vehicles frequently utilize a range of sensors, such as cameras and light detection and ranging (LiDAR), to facilitate the crucial task of object detection [3].

Adverse meteorological phenomena, including but not limited to dense fog, freezing rain, blizzards, dust storms, and reduced ambient lighting, exert a notable influence on the captured image quality as detected by the aforementioned sensors [4]. The limited visibility conditions present on roads pose a significant obstacle to the accurate detection of vehicles, thereby increasing the risk of potential traffic accidents. Hence, it is imperative to prioritize the advancement of efficacious methodologies for enhancing images in order to guarantee optimal visibility [5]. The enhancement of image quality is a critical factor in the achievement of enhanced capabilities for vehicle detection and tracking in intelligent visual surveillance systems and applications involving autonomous vehicles [6].

Numerous strategies pertaining to the recognition of objects in in-vehicle scenarios have been extensively investigated. These strategies encompass a range of methodologies, including manual, semiautomatic, and fully autonomous detection approaches, which have emerged as the most prominent ones in this domain [7]. Manual and semiautomated surveys encompass the utilization of visual inspections carried out by inspectors either on foot or in slow-moving vehicles. These methods often result in subjective evaluations and protracted procedures [8]. In contrast, the utilization of fully automated object detection involves the utilization of high-resolution cameras and sensors that are strategically positioned on vehicles. These devices are responsible for capturing and subsequently processing data, thereby facilitating the efficient detection of objects [9].

This paper highlights the increasing significance of deep learning-based traffic object identification, specifically in the context of autonomous vehicles, owing to its exceptional detection accuracy as evidenced by reference [10]. In the absence of comprehensive research, the examination of issues associated with real-time detection, which is important for active vehicle management, and the achievement of high detection accuracy in a variety of weather situations have not been performed [11].

The current solutions face challenges in achieving a satisfactory trade-off between detection accuracy and time efficiency, particularly in adverse weather conditions [12]. This study aims to bridge the existing research gap by presenting a novel vehicle detection model that emphasizes the attainment of high accuracy, while also taking into account the crucial aspect of detection speed. The primary objective is to mitigate the occurrence of false alarms and enhance visibility, particularly in challenging weather conditions. This proposed model is supported by previous research findings [13].

In contrast to conventional machine learning methodologies [14], deep neural networks, which are founded on sophisticated machine learning principles, have exhibited substantial improvements in the efficacy of autonomous vehicles, smart surveillance systems, and smart city applications [15]. This research paper introduces a weather detection framework that utilizes deep neural networks in conjunction with transfer learning techniques and leverages the capabilities of Nvidia GPUs. The framework focuses on identifying six distinct weather conditions, namely rainy, sandy, cloudy, snowy, sunny, and sunrise. The model under consideration incorporates three distinct CNNs, namely EfficientNet-b0, ResNet-50, and SqueezeNet. Its primary objective is to achieve high accuracy, sensitivity, precision, and lightweight characteristics to facilitate its effective implementation in autonomous vehicles, particularly in challenging weather conditions.

The developed model consists of three primary components: data preparation, learning model, and evaluation subsystems. The evaluation of system performance encompasses the utilization of various metrics, while the categorization of each weather image is accomplished through the implementation of a multiclass classifier. The simulation results demonstrate superior performance when compared to previous models, as evidenced by evaluation measures including precision, accuracy, F1-score and sensitivity. Moreover, the aforementioned model exhibits exceptional efficiency in terms of processing time when deployed on moderately priced hardware. This characteristic renders it a feasible and practical solution for the widespread integration into autonomous vehicle systems. Consequently, it holds the potential to safeguard human lives and facilitate prompt decision-making, all while maintaining a cost advantage over alternative systems.

The remaining of this research paper are organized in the following manner: Section 2 of this study undertakes a comprehensive review of pertinent research endeavors in the field. Section 3 proceeds to furnish a meticulous exposition of the model architecture that has been developed. Section 4 presents extensive results and comparisons. Lastly, Section 5 concludes the paper by summarizing the findings and proposing potential directions for future research.

II. Literature Review

The utilization of rapidly advancing deep learning techniques and deep CNN has garnered significant interest among various research groups in recent years for the purpose of automatic recognition of weather conditions based on visual content. This section provides an overview of the existing literature pertaining to the recognition of weather conditions from images.

In their study [16] addressed the weather classification problem by employing CNNs. This study also examined the feature space introduced at various convolutional neural network (CNN) layers. The study focused exclusively on a binary weather classification task, specifically distinguishing between sunny and cloudy weather classes. The employed methodology incorporates a technique known as fine-tuning, wherein the researchers commence with a pre-existing network that has been previously trained, and subsequently modify it to suit the specific task of weather classification. The suggested CNN architecture in this study includes five layers: one for pooling and convolution, two for fully connectedness, and finally, one for output. Two nodes, one for each of the sunny and cloudy classifications, make up the Convolutional Neural Network's (CNN) output layer. In order to facilitate the training and evaluation processes, a dataset comprising a total of 10,000 images was utilized. This dataset was carefully curated to accurately represent two distinct classes. The methodology employed by the researchers yielded a normalized classification accuracy of 82.2%, with a corresponding regular classification accuracy of 91.1%.

Researcher in [17] introduced a novel approach in which cameras are employed as weather sensors for the purpose of estimating weather conditions based on captured images. In the present study, the researchers constructed an extensive image dataset comprising more than 180,000 images, encompassing various weather conditions such as foggy, sunny, cloudy, snowy, and rainy. Additionally, this dataset incorporated weather-related attributes such as temperature and humidity. The authors have successfully employed a support vector machine (SVM) for the purpose of indoor/outdoor classification, thereby effectively excluding indoor images from their dataset. The reported accuracy of this classification model stands at an impressive 98%. In addition, the algorithm employed by the system effectively excludes images in which the sky constitutes a proportion of less than 10% of the overall image. Geotags and temporal metadata linked to an image are employed to gather pertinent weather data from an online weather platform. This study employs random forests as a methodology to derive weather information from a provided image. The approach involves constructing a computational model that leverages the relationship between metadata and weather properties. The researchers documented a mean accuracy rate of 58% in the classification of weather types, achieved through the utilization of diverse weather-related features. The researchers developed a weather-informed landmark classification application, which incorporates weather data as a crucial component in the classification procedure.

Recognising the substantial impact of extreme weather on urban transportation and the progress in deep learning techniques motivated the authors of [18]. They came out with ResNet-15, a streamlined model, therefore. Based on the ResNet-50 design, the suggested model has 15 layers instead of 50. In order to extract relevant meteorological parameters from features like the sky and the road, their study's methodology depends on a deep CNN. This is achieved through the application of convolutional layers within the network architecture. The classification of input images is achieved through the utilization of fully connected layers in conjunction with a SoftMax classifier. The efficacy of this simplified model has been reported to be notable even when executed on a conventional central processing unit (CPU). The present study additionally generated a comprehensive dataset comprising weather-related images captured on traffic roads. The dataset comprised four distinct categories and encompassed approximately 5,000 images pertaining to weather-related phenomena. The system under consideration was subjected to a training and testing process using the dataset in question. Here are the comparable recognition accuracy rates that the researchers reported after examining four different weather conditions: 97.3% rain, 96.4% fog, 95.1% sunshine, and 94.7% snow.

In their seminal work, author in [19] proposed a novel framework aimed at extracting weather-related information from street-level images. The approach employed by the authors involves the utilization of deep learning and computer vision techniques through a unified methodology that does not rely on pre-established constraints within the images being analyzed. The proposed model facilitates the extraction of diverse weather conditions during distinct time intervals, including dawn/dusk, daytime, and nighttime, thereby enabling accurate time detection. The present study introduces a novel approach involving the utilization of four deep Convolutional Neural Network (CNN) models for the purpose of detecting various visibility conditions. The conditions that fall under this category include dawn and dusk, daytime, nighttime, glare, and weather-related factors such as rain and snow. It has been reported that the recognition accuracy for the various classes that are being considered falls somewhere in the region of 91% to 95.6%.

Author also introduced MeteCNN, a deep CNN, as a method for categorizing weather conditions. The present study involved the generation of a comprehensive dataset comprising 6,877 distinct images. These images were meticulously annotated and categorized into 11 distinct weather phenomena, namely hail, rainbow, snow, and rain. The categorization process employed in this study was predicated upon the analysis of visual shapes and color characteristics present within the images. The dataset employed in this study was utilized for both training and testing purposes to evaluate the efficacy of the proposed model. The model's design included a SoftMax classifier, thirteen convolutional layers, and six pooling layers. The proposed model achieved a reported classification accuracy of around 92% on the testing set.

Previous research conducted by Roser et al. aimed to improve the functionality of driver assistance systems (DAS) implemented in vehicles [20]. The researchers in this study devised histogram features for the purpose of weather classification. Additionally, they constructed a Support Vector Machine (SVM) classifier that relied on contrast, intensity, sharpness, and color features. The objective of this classifier was to accurately categorize images obtained from a camera affixed to a vehicle into distinct weather conditions, including clear weather, light rain, and heavy rain weather. The study presents the findings of accurate results achieved by employing a Support Vector Machine (SVM) classifier, utilizing a meticulously curated set of features. The reported results indicate an approximate error rate of 5%.

In addition to being driven by the necessity to enhance DAS and mitigate the interference of weather conditions, such as haze and rain, on its vision-assisted functionality, author introduced a weather recognition framework based on deep learning techniques [21]. The framework takes into account three prevalent meteorological conditions, namely hazy, rainy, and snowy weather. The present study conducted an experimental investigation employing widely recognized deep neural networks, namely GoogLeNet and AlexNet. The objective was to assess the efficacy of the proposed methodology following certain modifications aimed at achieving classification into four distinct output classes. In addition to assessing the deep learning methods, the study conducted a comparative analysis with the hand-crafted feature-based approach. The findings of the study indicate that deep learning methods exhibit superior performance.

The authors, have successfully developed a novel publicly available dataset that encompasses a diverse range of images pertaining to three distinct weather conditions, namely snow, rain and fog [22]. The present study additionally introduced an algorithm that employs super pixel delimiting masks as a means of data augmentation. The present study sought to investigate the potential benefits of super pixel masks on various Convolutional Neural Network (CNN) models, including CaffeNet, PlacesCNN, ResNet-50, and VGGNet16. By analyzing these models, we aimed to ascertain whether any of them exhibited a greater advantage when utilizing super pixel masks. The investigated categories encompassed weather conditions characterized by clear skies, overcast skies, foggy conditions, precipitation in the form of rain, and precipitation in the form of snow. The findings of this study indicate that the performance of all models evaluated ranged from 68% to 81%. Notably, the ResNet-50 model demonstrated the highest level of accuracy among all models considered.

In addition to employing conventional learning methods, this study incorporated transfer learning techniques from deep CNN [23,24]. Specifically, pre-trained models trained on the ImageNet dataset were utilized. The trainable parameters in the intermediate pre-trained layers were frozen, while the fine-tuning process was carried out on the input and output layers. This approach aimed to enhance the computational efficiency of the deep models. In contrast, we harnessed the computational power of Nvidia GPUs available in widely accessible machines to train a detection model. This model was trained on a comprehensive dataset, encompassing various weather conditions, and capable of classifying them into six distinct classes: rainy, cloudy, sandy, snowy, sunny, and sunrise. We developed a transfer-learning-based method to distinguish and assess three CNN models i.e. ResNet-50, EfficientNet-b0, and SqueezeNet. After numerous testing and comparisons, we found that our ResNet-50-based model outperformed the state-of-the-art models, EfficientNet-b0, SqueezeNet, and others.

III. MATERIALS & METHODS

The principal aim of this study is to advance the field by designing and implementing a sophisticated system that utilizes deep learning techniques for the purpose of accurately detecting and categorizing various weather conditions, encompassing both unfavorable and typical scenarios. The proposed system is designed to be deployed in conjunction with autonomous vehicles, facilitating the instantaneous recognition of outdoor weather conditions. The aforementioned capability endows autonomous vehicles with the capacity to make well-informed decisions and adjust their behavior in response to dynamic environmental circumstances.

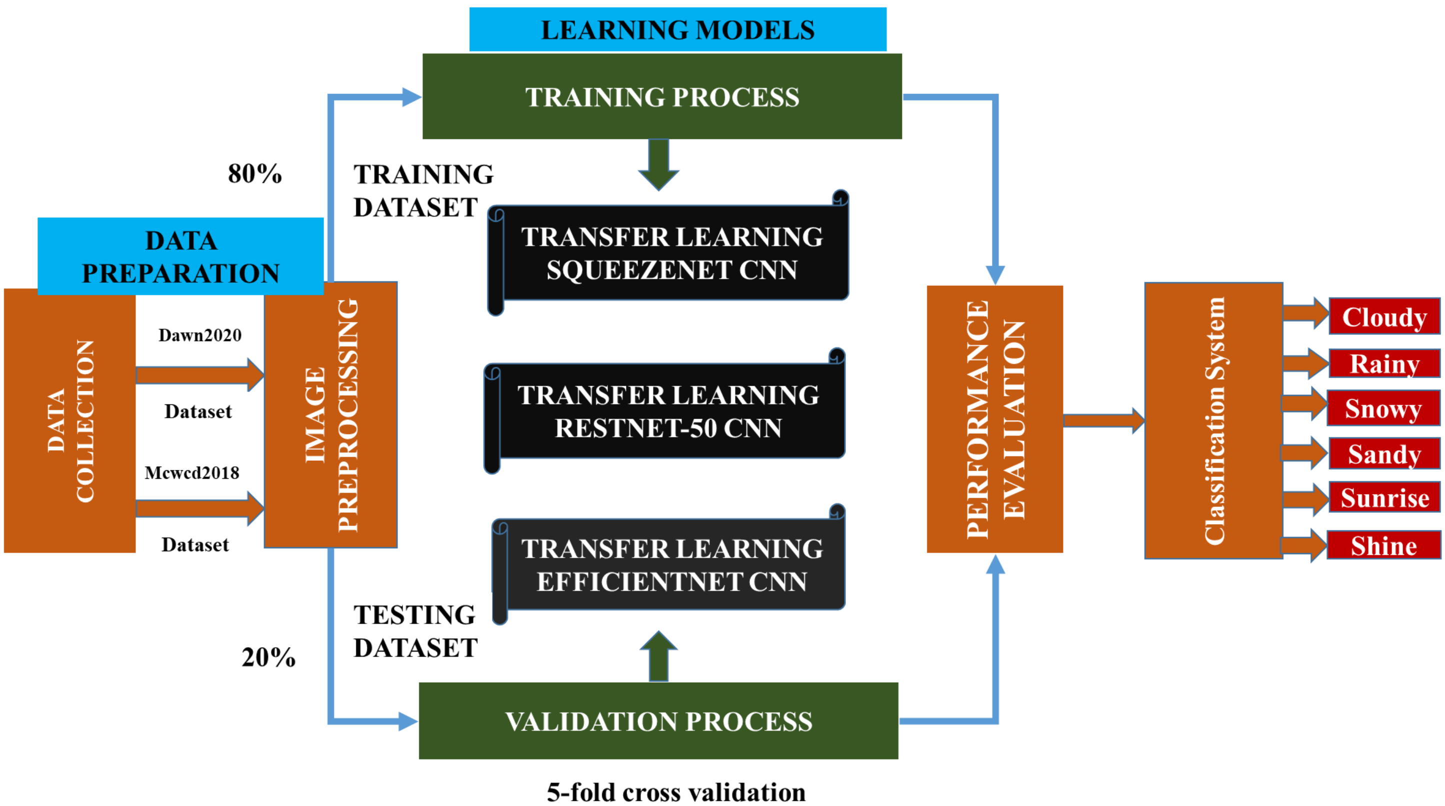

Figure 1. Developed Methodology Block Diagram

The system under consideration comprises three interconnected subsystems, as depicted in Figure 1. The system consists of three subsystems i.e. the Data Preparation (DP) subsystem, which collects and preprocesses datasets containing weather condition images, The Learning Models (LM) subsystem, which trains, validates, and tests using deep learning algorithms and the Evaluation and Deployment (ED) subsystem, which assesses system performance and generates categorizations using a multiclass classifier.

A. The Subsystem for Data Preparation

In this phase, the integration of two primary weather conditions datasets, namely DAWM2020 dataset [16] and MCWCD2018 [17], was conducted, yielding a comprehensive dataset comprising 1656 image samples. These samples were rigorously divided into six distinct weather situations, namely sandy (319 images), sunrise (365 images), rainy (215 images), overcast (300 images), snowy (204 images), and shine (253 images). Figure 2 illustrates a visual depiction of example images that match to each unique weather condition in the collection.

The datasets that were collected underwent preprocessing using MATLAB2021b. This involved the unification of image types to JPG format, resizing all images to dimensions of 224 × 224 × 3 (representing RGB images), and the application of data augmentation techniques to enhance the training dataset. The process of data augmentation encompasses various operations, including but not limited to resizing, cropping, rotation, reflection, and invariant distortions. Utilizing the technique of data augmentation, a collection of novel images have been generated.

Figure 2. Dataset attributes

The Image Data Store (IMD) is a collection of both original and augmented images. The dataset consists of approximately 5000 JPG images, each with a size of 224 × 224 × 3. To mitigate biases, the images have been randomly shuffled. The dataset has been partitioned into two distinct subsets, namely the training set, which accounts for 80% of the combined dataset, and the testing set, which represents the remaining 20% of the combined dataset. To ensure the robustness of system performance, a 5-fold cross-validation approach is employed in the developed methodology.

B. Subsystem Model Learning

The focus of this subsystem is to train and validate a model for the classification of weather conditions. This would be achieved through the utilization of deep supervised convolutional neural networks (CNNs). This research makes use of transfer learning as a technique to improve the application-specific performance of three pre-trained CNNs i.e. EfficientNet-b0, SqueezeNet, and ResNet-50. The process involves fine-tuning these CNNs to adapt them to the specific task at hand, thereby leveraging the knowledge and features learned from their pre-training on large-scale datasets.

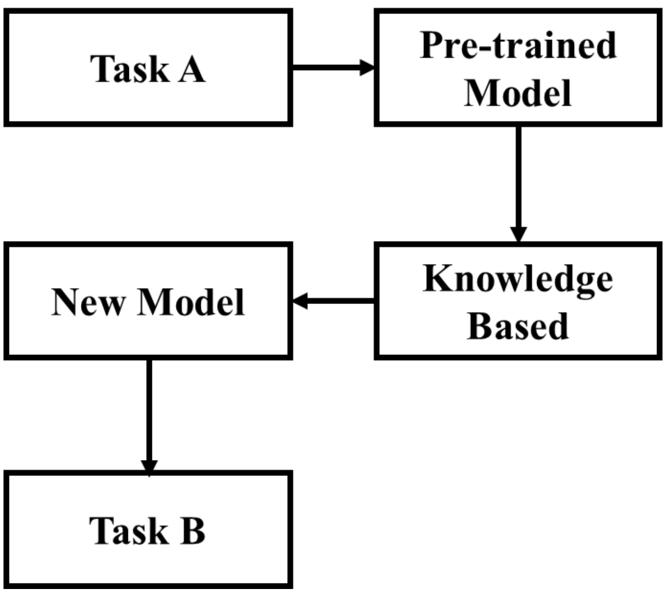

Figure 3. Dataset attributes

The Input Layer is responsible for receiving preprocessed RGB images with dimensions of 224 × 224 × 3. These images serve as the initial input for the Processing Layer, which is responsible for extracting relevant features and performing image classification tasks. The Output Layer, which incorporates trainable parameters derived from pre-trained CNNs, facilitates the generation of SoftMax probability functions to yield the ultimate classification outcome.

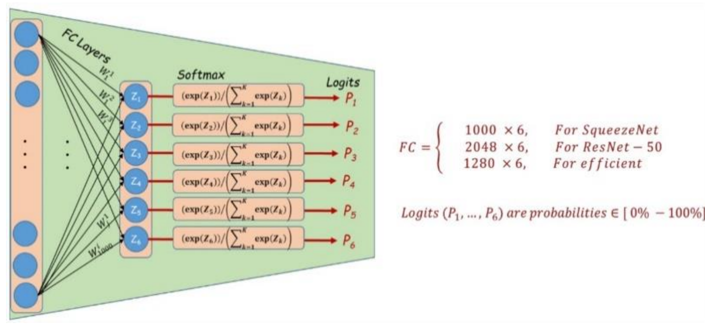

Figure 4. Learning model output layer development.

C. Assessment and Implementation Module

The assessment of deep learning models' effectiveness commonly involves the utilization of standard evaluation metrics, with the inclusion of confusion matrix analysis during the testing phases. The metrics encompassed in this study comprise of true positive (TP), true negative (TN), false positive (FP), and false negative (FN). The metrics of model accuracy, sensitivity (recall), precision, and F1-score are calculated based on the information provided by the confusion matrix. The selection process for real-time deployment of autonomous vehicles involves identifying the optimal model that demonstrates superior evaluation metrics. Upon deployment, the system has the capability to interpret SoftMax probabilities in order to accurately classify various weather conditions. In the event that the SoftMax outcomes for a particular image demonstrate notable probabilities for inclement weather conditions (as depicted in Table 1), the self-driving vehicle adapts its configuration correspondingly.

Table 1. SoftMax classifier samples output

P_{Cloudy}	P_{Sandy}	P_{Snowy}	P_{Rainy}	$P_{Sunrise}$	P_{Shine}
1.25%	1.0%	1.75%	93%	1.2%	1.8%

IV. Results & Discussion

This study presents the development of a computational intelligence model that utilizes deep learning techniques to detect adverse weather conditions. The model is specifically designed to cater to the needs of autonomous vehicles. The effectiveness of the proposed methodology is evaluated by conducting a comprehensive analysis of the system's performance, utilizing the metrics that were previously outlined. The following section presents the empirical findings.

A. Performance Trajectories

Performance trajectories seen throughout the classification process of the proposed weather detection system are illustrated in Figures 5, 6, and 7. The system employs three CNNs namely, EfficientNet-b0 C, SqueezeNet, and ResNet-50. The accuracy curves of all Convolutional Neural Networks (CNNs) demonstrate a consistent and gradual improvement as the learning epochs progress. These curves exhibit a notable trend of approaching a higher accuracy level, nearing 100% with each subsequent epoch. After approximately 60 learning epochs, it is observed that there are slight variations in saturation levels as well as thresholds for accuracy and loss values. The models demonstrate exceptional performance in terms of training accuracy, achieving a remarkable rate of 100%. In evaluating the models on the testing dataset, we observe high levels of accuracy as well. Specifically, SqueezeNet achieves an accuracy rate of 98.48%, ResNet-50 achieves 97.78%, and EfficientNet-b0 achieves 96.05%. These results further validate the efficacy and reliability of the models in accurately classifying the given dataset. The observed variations fall within the acceptable thresholds, thereby ensuring the prevention of both underfitting and overfitting [26].

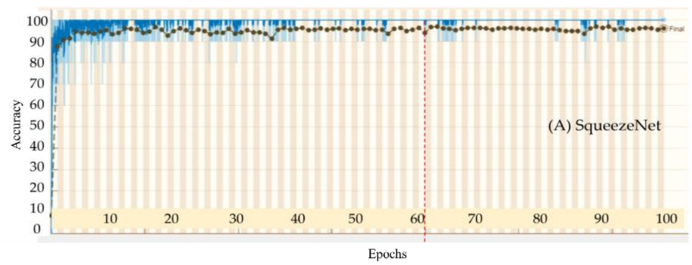

Figure 5. SqueezeNet performance trajectories.

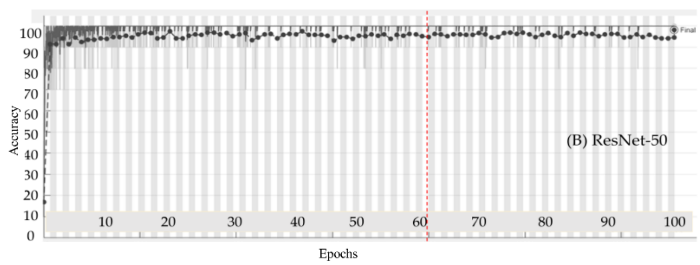

Figure 6. ResNet-50 performance trajectories.

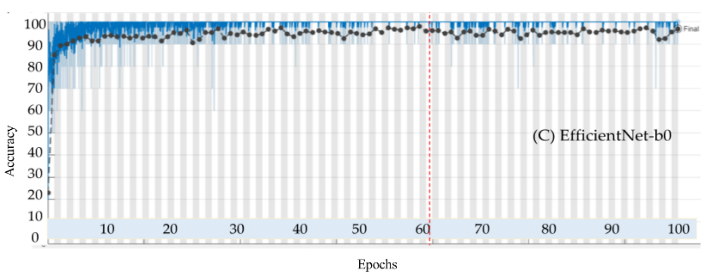

Figure 7. EfficientNet-b0 performance trajectories.

B. Confusion Matrix Analysis

As illustrated in Figure 8, the validation/testing dataset, which encompasses all of the developed models and encompasses six classes, underwent confusion matrix analysis. True positives and true negatives are both represented by the huge number of accurately predicted samples along the diagonal of the matrix, which shows that the models are persistent. In the present study, it is observed that the model based on ResNet-50 exhibits superior performance. Specifically, the model achieves a commendable outcome, with a total of 326 true positives/negatives accurately identified, while only four false positives/negatives are reported, out of a sample size of 330. The efficacy of all models has been validated, with ResNet-50 exhibiting a marginal edge.

Predicted Classes

True 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

Predicted Classes

True 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

Predicted Classes

True 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. Confusion Matrix for deep learning Model

C. Performance Indicators

Table 2 provides a detailed summary and comparative examination of key performance metrics, including detection sensitivity, accuracy, F1-score, and precision, for the weather detection system that utilizes SqueezeNet, ResNet-50, and EfficientNet-b0 models. The ResNet-50 model demonstrates superior performance, outperforming other models by a range of

0.72% to 2.45%, 0.77% to 3.00%, 0.45% to 2.45%, and 0.60% to 2.76% in terms of precision, accuracy, F1-score, and sensitivity, respectively. The ResNet-50 model is considered the optimal choice for implementation in autonomous vehicles for the purpose of real-time weather detection.

Table 2. Developed methodology KPIs.

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%

D. Comparative Analysis

Table 3 presents a comprehensive comparative analysis of our ResNet-50-based weather detection model in relation to other contemporary state-of-the-art models that have been developed within the past five years. Our model exhibits exceptional performance, attaining the highest level of accuracy in the six-class weather detection model. Furthermore, it significantly enhances the classification accuracy of the six weather conditions classifiers by a range of 0.5% to 21%. Moreover, the ResNet-50 Convolutional Neural Network (CNN) model exhibits a notable efficiency in detecting objects, with an average time of 5 milliseconds for the inference step when utilizing the Graphics Processing Unit (GPU) component. The aforementioned statement highlights the efficacy of the proposed framework in facilitating real-time implementation, thereby facilitating prompt and accurate decision-making for autonomous vehicles in relation to weather conditions.

Table 3. Results comparison with existing Literature

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

V. CONCLUSION

This research paper introduces a sophisticated and autonomous weather detection system that utilizes deep learning techniques to augment the decision-making capabilities of autonomous vehicle systems. The proposed system utilizes a combination of three deep CNNs namely EfficientNet-b0 CNN, SqueezeNet CNN, and ResNet-50 CNN. The present study involves a comprehensive assessment of a merged dataset derived from MCWDS2018 and DAWN2020. This dataset encompasses six distinct weather categories, namely cloudy, rainy, snowy, sandy, shine, and sunrise. The findings of this evaluation highlight the system's commendable performance and its ability to handle diverse weather conditions effectively. The obtained experimental results highlight the notable efficacy of all three models, as evidenced by their respective accuracy rates of 98.48%, 97.78%, and 96.05% for the ResNet-50, EfficientNet-b0, and SqueezeNet models. The proposed model demonstrates noteworthy performance metrics and a rapid time-per-inference step when utilizing the GPU component. This emphasizes its efficiency for real-world applications. One notable characteristic of our methodology lies in the integration of the DAWN2020 dataset, which is being employed for the first time in deep learning applications for weather classification, in conjunction with the MCWCD2018 dataset. The amalgamation of these variables yields a dataset comprising six distinct classes, thereby affording a more comprehensive depiction of meteorological circumstances. Although a standardized dataset for weather conditions across detection systems is currently lacking, the utilization of accuracy as a metric enables meaningful comparisons to be made among different models. This study presents a comprehensive evaluation of weather detection models, taking into account the distinctive amalgamation of datasets and classes. In forthcoming endeavors, our intention is to expand the scope of our experiments in order to assess the efficacy of the proposed lightweight architecture across a diverse range of devices. This evaluation would encompass the examination of both processing time and model accuracy as key performance metrics. Moreover, it is worth noting that the system's capabilities could be extended to encompass a more extensive array of objects present on urban streets, including but not limited to signs, mailboxes, and street lighting fixtures. Through the implementation of experimental methodologies on a wide range of autonomous driving datasets encompassing intricate scenarios and diverse objects, our primary objective is to augment the system's practicality and effectiveness in real-world contexts.

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