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RESEARCH ARTICLE

Deep Learning-Based Object Detection and Classification for Autonomous Vehicles in Different Weather Scenarios of Quebec, Canada

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ABSTRACT The rapid development of self-driving vehicles requires integrating a sophisticated sensing system to address the various obstacles posed by road traffic efficiently. While several datasets are available to support object detection in autonomous vehicles, it is crucial to carefully evaluate the suitability of these datasets for different weather conditions across the globe. In response to this requirement, we present a novel dataset named the Canadian Vehicle Datasets (CVD). Subsequently, we present deep learning models that use this dataset. The CVD comprises street-level videos which were recorded by Thales, Canada. These videos were collected with high-quality cameras mounted on a vehicle in the Canadian province of Quebec. The recordings were made during daytime and nighttime, capturing weather conditions such as hazy, snowy, rainy, gloomy, nighttime and sunny days. A total of 10000 images of vehicles and other road assets are extracted from the collected videos. A total of 8388 images were annotated with corresponding generated labels 27766 with their respective 11 different classes. We analyzed the performance of the YOLOv8 model trained using the existing RoboFlow dataset. Then, we compared it with the model trained on the expanded version of RoboFlow using the proposed weather-specific dataset, CVD. Final values of improved accuracy of 73.26 %, 72.84 %, and 73.47 % (Precision/Recall/mAP) were reported upon adding the proposed dataset. Finally, the model trained on this diverse dataset exhibits heightened robustness and proves highly beneficial for both autonomous and conventional vehicle operations, making it applicable not only in Canada but also in other countries with comparable weather conditions.

INDEX TERMS Autonomous vehicles, convolutional neural networks, intelligent transportation, object detector, surveillance, YOLOv8.

I. INTRODUCTION

The implementation of recent artificial intelligence (AI) applications, such as self-driving vehicles, intelligent surveillance systems, and advanced urban infrastructures, can

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potentially contribute to the development of sustainable smart cities and communities [1]. The utilization of highly accurate real-time road object identification algorithms can significantly enhance automated driving systems' capabilities in effectively managing traffic flow and improving overall safety [2]. In order to effectively perceive and comprehend their surroundings, autonomous vehicles rely on a combination of essential sensory components. These include cameras, which capture visual information, the Global Navigation Satellite System (GNSS) for precise positioning and navigation, as well as range sensors such as radar or LiDAR. These range sensors enable the vehicle to measure distances and accurately detect objects in its vicinity. By integrating these crucial technologies, autonomous cars are able to interpret their environment with a high degree of accuracy and make informed decisions accordingly. The utilization of this system necessitates the implementation of sophisticated perception, fusion, and planning algorithms [3].

To fully comprehend pictures, we should classify them and estimate their concepts and object placements also referred as object detection [4]. Smart cities require object detection in conventional traffic or autonomous vehicle environments [3]. It can locate accurate traffic data for picture analysis and traffic flow control. This information includes vehicle counts, trajectories, tracking locations, flow, classification, traffic density, velocity, lane changes, and license plate identification [5].

Multiple object detectors can also detect pedestrians, diverse vehicle types, individuals, designated lanes, traffic signals, earthworks, drainage systems, safety barriers, signage, and lanes, as well as grasslands, shrubs, and trees [6]. Real-time object recognition and categorization from image/video data lays the groundwork for several analytical characteristics, such as population or traffic volume over time [7].

Automatic driving (AD) heavily relies on Deep Learning (DL). Deep neural networks outperform standard machine learning (ML) approaches in smart autonomous or self-driving automobiles, smart tracking, and smart city-based infrastructure [5].

Deep learning, a subfield of machine learning inspired by the structure and function of the human brain, has emerged as a powerful technique for addressing complex problems that are challenging to model using traditional statistical approaches [8]. Deep neural networks, such as the Convolutional Neural Network (CNN), have been widely employed in computer vision to recognize and categorize various components within images [9]. Algorithms can identify and classify objects such as street signs, automobiles, people, and other items.

One of the notable advantages of CNN is its ability to autonomously identify significant features without the need for human intervention following the training process. Numerous CNN architectures that exhibit a remarkable balance between high accuracy and efficient processing have been developed [10]. The You Look Only Once (YOLO) model, as described in [11], was developed with the primary objective of enhancing the efficiency of visual object classification and location computations.

The convolutional network employed in this study exhibits the ability to perceive and identify visual elements directly. The proposed approach involves the utilization of multiple feature maps with varying resolutions to account for objects of different sizes. This is achieved by aggregating predictions from these feature maps, enabling a more comprehensive analysis. The details of this methodology can be found in reference [12]. The accuracy and speed of YOLO have been significantly enhanced with the introduction of advanced algorithms such as YOLOv3, YOLOv5, and YOLOv8. YOLO serves the purpose of object identification, classification, and localization within images and videos [13].

Problems in Object Detection in Autonomous Environment such as Hue and excessive rain or snow might affect object detection in autonomous or typical situations [14]. Both driverless automobiles and human drivers encounter difficulties when it comes to accurately predicting traffic conditions, especially when there are dynamic weather conditions like snowstorms, fog, rain, and sunny weather [15]. Accurately identifying objects, especially in road environments, is a challenging process that often leads to incorrect determinations. Inaccuracies can have significant consequences, especially when it comes to identifying vehicles and other objects on the road. The decision-making process involves using prediction-based models that have been learned previously [16].

In all these cases, drivers or autonomous cars need pre-alerts to change lanes, save time, and avoid risks. Other object detection systems can forecast traffic and send drivers or autonomous cars signals or warnings [17].

In [18], authors enhanced the YOLOv5 deep learning neural network architecture to create an improved object detector for drones and self-driving cars. By merging three datasets (HDrone, VisDrone, and KITTI), they outperformed previous approaches in detecting objects of varied sizes and achieved state-of-the-art results. Reference [19] developed a YOLOX-based network model for multi-scale item identification in complex situations. They used a CBAM-G module in the network backbone to enhance semantic information with an object-contextual feature fusion module. The model outperformed alternatives in detection and had a 2.46% mAP improvement over the original model on the KITTI dataset.

The issue of foggy weather in autonomous driving is addressed by a novel domain adaptive object identification approach, as discussed in [20]. The study's authors employed image- and object-level adaptation techniques and a unique adversarial gradient reversal layer to identify and extract challenging samples effectively. The results obtained in this study demonstrated the effectiveness and accuracy of the employed methodology.

Researchers examined the intrinsic fault tolerance of camera-based object detection (CBOD) methods [21] through various approximations. Despite the utilization of lower precision arithmetic and the occasional occurrence of errors, the level of accuracy achieved was found to be within a margin of 1% when compared to the established baseline. Additional dimensions of error tolerance encompass the utilization of LiDAR and radar-based sensors, which have the potential to mitigate the intricacy of hardware systems.

The comprehensive investigation of the dataset revealed several components associated with the research criteria. The dataset did not include all weather conditions. To address this issue, we integrated various images from Roboflow's open-source annotations and custom-generated Canadian vehicle-based annotations. The compilation of Canadian weather images included a variety of scenes, ranging from bright and sunny days to dreary and foggy conditions, as well as rainy and snowy landscapes. The collection also featured both daytime and nocturnal shots. This study used the YOLO technique to focus on 2D object recognition using camera sensor data. YOLOv8 [22] is an updated version of the YOLO approach for object detection in autonomous driving. This approach has been further developed and expanded upon by several researchers.

RoboFlow and other datasets for training models only cover generic traffic and road conditions, not changing weather. Addressing multiple weather concerns requires training a model for different weather circumstances [23]. In industrialized countries like Canada, harsh winters and shifting weather (snowstorms and rain), as are summer and winter precipitation, are common and unexpected. The new model is trained to recognize and categorize numerous item classes accurately in this challenging object identification circumstance in bad weather.

Error-free performance requires high-quality, diverse data from real-world everyday settings. Autonomous driving (AD) data focused on temporal thinking and 360° vision may ignore variety and long-term capacities [24]. To address this issue, we propose a Canadian Vehicle Dataset (CVD) for AD. It's a vast, diversified multimodal picture collection from Quebec, Canada, collected over one year under different weather conditions. CVD applies to traffic sign identification, semantic and instance segmentation, and road categorization.

This study used the deep learning-based YOLOv8 algorithm to identify and detect automobiles in vigilance camera recordings under snowy, sunny, rainy, fog, and nocturnal conditions. Our model is weather- and location-specific. This study lays the basis for a global uniform prediction-based trained model for road item identification and categorization. It is extremely useful in typical and autonomous situations. The primary contribution of the proposed study is based on model performance analysis assessment results:

- A heterogeneous dataset of 10000 images extracted from videos captured from a vehicle-mounted camera in Quebec, Canada, is proposed.
- This study analyzes the applicability of the Canadian approach for identifying and categorizing road objects.
- Using transfer learning to train the model on two vehicle data sets to improve object recognition accuracy.
- A comparison of model performance on existing and mixed datasets (proposed weather-specific datasets and existing dataset) is presented.

The present study is structured in the following manner: the dataset and technique are presented in Section II. Section III shows the pre-trained algorithm's performance, followed by transfer learning detection findings. Section IV presents quantitative indicators statistical results and visualization graphs to evaluate the algorithm's performance. The study closes with suggestions in Section V.

II. DATASET AND METHODOLOGY

The present section provides a comprehensive overview of the data sets utilized in the study, as well as an in-depth discussion of the model training procedure. The findings derived from the evaluation of the model are systematically presented and organized into distinct subsections. The initial focus of this discussion pertains to the performance of pre-trained algorithms. Next, we will outline the procedures involved in annotations and training the model.

The testing and validation process utilizing simulated datasets has been successfully concluded, and the algorithm's performance has been thoroughly assessed through the application of diverse quantitative metrics. The initial segment of this section provides an overview of the methodology employed in this study, as well as the pre-existing vehicle dataset. Subsequently, a detailed description of the proposed dataset utilized in this research is presented.

The study was conducted in a systematic manner, ensuring a logical progression from the beginning to the end.

1. Existing dataset RoboFlow is utilized, and a baseline model is trained. The model performs well on the Roboflow dataset; however, when tested for varying weather conditions in Canada using a subset of the proposed CVD dataset, the performance of the RoboFlow model degrades significantly. This results in the need for a new model to suit the requirement of autonomous vehicles in varying weather conditions in Canada or other countries.

2. To address the aforementioned need, we propose using the CVD dataset along with the existing RoboFlow dataset and training a new model with improved robustness.

In this work, the model is first trained using the RoboFlow dataset utilizing the weights of YOLOv8 pre-trained on the MSCOCO dataset. Next, transfer learning is applied to train YOLOv8 using a combination of RoboFlow and CVD datasets. The additional training enhances the vehicle detection system accuracy. We have chosen the YOLOv8 model as it's a lightweight model that effectively reduces around 40% of parameters and 50% of computation compared to previously existing real-time object detection models, achieving improved detection accuracy and increased inference speed [4].

First, we extracted images from the street-level recordings captured by RGB Cameras installed in Quebec by Thales Canada on the vehicle's windshield. The Canadian Vehicle Dataset (CVD) comprises ten thousand images. We labeled 8388 images for 11 distinct classes and then combined them with the publicly available dataset RoboFlow. The study then entails training and evaluating a Deep Convolutional Neural Network (DCNN) model for detecting and classifying objects under different weather conditions.

In this study, we investigate the viability of YOLO-based approaches by recognizing and classifying vehicles and other road assets in real-time images using deep learning. A first-order object identification technique called the YOLO family of algorithms integrates a localization of numerous objects using an anchor box. The YOLO family of algorithms has had eight iterations released so far.

We are motivated to choose the latest YOLO version (YOLOv8) detection model due to its smaller architecture, high confidence score in their detection targets, and much faster detection abilities than the old families of this model. These capabilities make the YOLOv8 algorithm a better choice when compared to previous vehicle detection algorithms. We proposed highly accurate vehicle detection in real-time with model parameters optimization.

We have trained our models on RoboFlow and mixed (RoboFlow + CVD) datasets in bad weather conditions, which are further adjusted to be used in congested traffic conditions. We compared the efficiency of our trained versions with existing publicly available RoboFlow datasets.

This study focuses on detecting and classifying vehicles under diverse traffic and adverse weather conditions, including rain, sunlight, haze, nighttime, and snowfall. We gathered an extensive CVD in difficult weather conditions to improve image accuracy from our local traffic patterns and employed transfer learning on YOLOv8-based trained models.

The knowledge that is already present in our local datasets can be used in a transfer learning strategy [25]. A real-time image is the system's input, and its output is a bounding box for every object in the image, coupled with the class of each object in the box.

Rapid and accurate vehicle recognition and categorization are needed for ITS-based applications. Small distances between vehicles on the road and interference from image frames holding vehicle images make it difficult to identify various vehicles abruptly and precisely. As a result, our proposed technique offers a useful perspective on locating automobiles in congested settings.

A. VEHICLE DATASET

1) ROBOFLOW VEHICLE DATASET

RoboFlow introduced the self driving vehicle dataset, which several researchers have used to generate novel techniques for road asset detection.

We used this datasets as one of the datasets in our study as they are open-sourced and widely accessible. RoboFlow Self Driving Car Dataset has image dimensions of $512 \times 512 \times 3$, with the number of annotations 97,942 and the number of classes is 11, including car (64399 labels), pedestrian (10806), biker (1864), traffic Light – Red (6870), traffic Light – Yellow (272), traffic Light – Green (5465), Traffic Light - Red Left (1751), Traffic Light – Yellow Left (14), Traffic Light – Green Left (310), Truck (3623), Traffic Light (2568). Preprocessing techniques such as - Auto orient, Discard EXIF rotations, standardized pixel ordering, and Adaptive Equalization were applied to the data. The RoboFlow Dataset did not undergo any data augmentation.

2) THE PROPOSED CANADIAN VEHICLES DATASET (CVD)

The datasets, such as RoboFlow that are accessible to the public show less diversity in lighting or weather conditions, driving scenarios, and geographical coverage. Additionally, these datasets have limited annotations in terms of both tasks and range.

These issues can lead to overly specialized solutions, which may not generalize to real-world AD systems' full operational design domain. Our prepared dataset, referred as the Canadian vehicles dataset (CVD),consists of road images from Quebec province in Canada.

The dataset includes 10000 images, including 11 different classes; therefore, the proposed CVD is robust and heterogeneous. CVD contains images extracted from street-level videos from Thales Inc. Canada.

The surveillance videos were recorded during the day and night, capturing various weather scenarios, including snow, rain, fog, and gloomy and sunny days. The videos were captured using high-quality cameras mounted on a car in the province of Quebec, Canada.

To ensure consistency across all datasets, all images were manually annotated using labeling software and resized to 512×512. Here are the key points of difference:

- RoboFlow vehicle datasets contain images of normal traffic and road conditions, not environment-specific or varying weather-specific. Therefore, RoboFlow is a more generalized case.
- New images collected from the Quebec, Canada street is more heterogeneous as this dataset is collected in changing environments as well as weather situations such as snowy, fog, rain and sunny, and nighttime. The model trained on such datasets is more robust and highly useful in autonomous vehicle driving and can be applied to countries with similar weather conditions.

Table 1 compares datasets used in this study (Roboflow and proposed Canadian Vehicle datasets) based on different criteria.

B. ACQUISITION SYSTEM

Figure 1 shows the framework of the proposed system. In this framework, a vehicle was initially equipped with cameras and sensors to gather real-time data for an AI-driven autonomous vehicle in a diverse Canadian scenario, as depicted in Figure 1. The collected data was transmitted to the cloud or

TABLE 1. Comparison of roboflow and proposed canadian Vehicle Datasets based on different criteria.

Parameters	Roboflow	Proposed dataset CVD
Size (Number of images)	30000	8388
Number of instances	97,942	27766
Video resolution	1920x1200	1920x1200
Annotation type	Bounding box based	Bounding box based
Classes	11 distinct classes (car, pedestrian, biker, Traffic light-red, Traffic Light – Yellow, Traffic Light – Green, Traffic Light - Red Left, Traffic Light – Yellow Left, Traffic Light-Green Left, Truck, Traffic light)	11 distinct classes (car, pedestrian, biker, Traffic light-red, Traffic Light – Yellow, Traffic Light – Green, Traffic Light - Red Left, Traffic Light – Yellow Left, Traffic Light-Green Left, Truck, Traffic light)
Image acquisition methods	Vehicle-based	Vehicle-based
Extracted frame size	512x512	512x512
Camera used	Specifications not provided	4x DALSA Nano C-1920 Couleur PoE (Resolution- 1920x1200)
Location covered	California and neighboring cities	Quebec, Canada
Regions covered	Urban, Sub-urban	Urban
Weather scenarios covered	Daylight conditions	Daytime and nighttime images with weather conditions covered (Rainy, foggy, sunny, gloomy and snowy)

an on-premises data center using wireless or cellular communication technology.

This step involved collecting raw data from the various sensors installed on the vehicle. This data was then preprocessed to make it easily accessible and usable for the stakeholders.

After completing the data preparation task, a web-based repository was created and implemented on Laval University's cloud-based server.

This repository serves as a platform for authorized users to access the dataset. The repository will be regularly updated and maintained according to the requirements of cellular communication technology.

Furthermore, in this study, we exclusively used videos captured by RGB cameras for object detection.

The main goal was to use a deep learning model on RGB videos for object detection, while driving a car. Additionally, we wanted to evaluate the effectiveness of the trained model by preparing training datasets for various weather conditions.

C. DATA PREPARATION AND PREPROCESSING

Since object detection in varying weather conditions is the main challenge of our project, highly accurate and specific data collection and preparation is a very challenging and time-consuming task. Therefore, the most crucial step is data collection and preparation.

In this work, we used video data (captured from a camera placed on a car driven on the street) collected from Canadian streets in different weather conditions (prepared explicitly for our study). The car traveled at an average speed of approximately 40 km/h.

After data collection, we extracted images from videos using Python scripts with a frame rate of 2 fps (minimum) and 10 fps (maximum). In data preprocessing, all photos were resized to 512×512 pixels to maintain uniformity and stored in jpg format. No other preprocessing steps were applied manually.

1) DATA ANNOTATION

Data annotation plays a key role in ensuring the accurate functioning of numerous machine learning models. The aforementioned study outlines the foundational steps necessary for instructing a deep neural network to accurately identify and differentiate objects among a diverse range of input images [25].

The process of annotating objects in images is labor-intensive in nature, and it involves significant time commitment since it necessitates the initial manual evaluation of the entire dataset on a screen.

Subsequently, all identified classes were annotated by including them within bounding boxes and categorized by

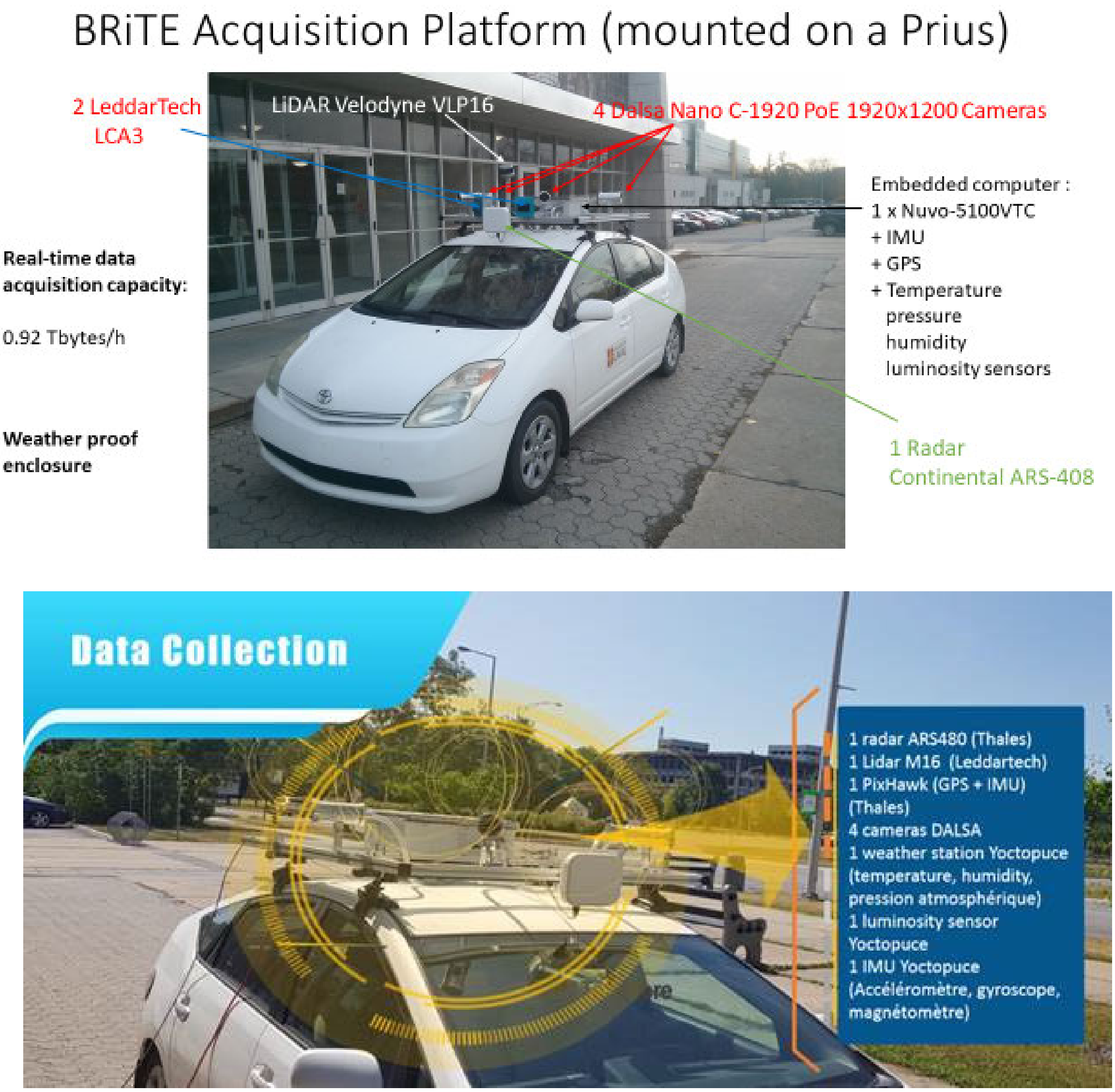

FIGURE 1. **A vehicle, equipped with cameras and sensors to collect real-time data for AI-driven AV in a Canadian heterogeneous scenario.**

assigning the appropriate label. Additionally, the image should be annotated only once for a particular scenario, and on receiving more than one image for the same scenario, the image should be skipped for annotation. Keeping repetitive images may cause the overfitting of the model.

A total of 10000 images were extracted from the video captured in conditions such as sunny, light rain, snow, overcast, and fog. A total of 8388 images were chosen for inclusion in this study.

We used Labeling software for image annotation. Annotated 8388 images with corresponding generated 27766 labels with their respective 11 different classes are presented in Table 2.

For the annotation of images, we used Labeling software. The XML format was used to hold class labels and bounding box coordinates, which were represented by four decimal numbers (xmin, ymin, xmax, ymax), identical to the PASCAL VOC format.

Subsequently, the data was converted into the TFRecord file format, in accordance with the specifications of the TensorFlow Object Detection API. Example images for labeling different types of objects in various weather scenarios are shown in Figure 2.

As we can see from statistics (Table 2), CVD data could be more balanced. Still, it is sufficient for our training and experimentation due to the high number of instances in each class except the biker class, traffic light yellow and traffic light yellow-left.

We expected that combining CVD with other existing datasets (RoboFlow in our case) could help in representing these classes better while training the requisite neural

TABLE 2. Selected class types and instances per class of total Canadian Vehicle dataset (CVD).

Sr. No.	Class types	Number of Labelled Objects
1	Car	16676
2	Pedestrian	2917
3	Biker	48
4	Traffic Light - Red	1728
5	Traffic Light - Yellow	213
6	Traffic Light - Green	1566
7	Traffic Light - Red Left	618
8	Traffic Light – Yellow Left	63
9	Traffic Light – Green Left	465
10	Truck	1292
11	Traffic Light	2177
	All	27766

network model. Furthermore, it has the potential to generate a balanced representation of classes and training highly effective models.

III. EXPERIMENTAL SETUP

The presented study includes the training and evaluating the YOLOv8 network model, considering diverse weather conditions by using distinct combinations of test and train datasets. The development of an optimized deep convolutional neural network using RGB image data for the automatic classification of selected class types (Table 2) to identify different types of objects while driving a car is presented in this section.

We utilized pure modeling and mixed modeling approaches in model training. In pure modeling, a model is first trained and tested only on a dataset captured from the same country. The model underwent training and testing on two distinct datasets, namely RoboFlow consisting of 29800 images and RoboFlow + CVD comprising 38215 images, in order to determine the suitability of integrating two different image database.

Figure 3 demonstrates the proposed deep neural network-based vehicle detection system. In training, we first train a YOLOv8 model on publicly available RoboFlow dataset. The training is initialized from pre-trained COCO weights.

FIGURE 2. Labelled dataset for selected images for different weather scenarios.

The training runs for 300 epochs with a batch size of 64. The default hyperparameters for the training include the initial learning rate = 0.01, momentum= 0.937 (SGD momentum/Adam beta1), and weight decay: 0.0005. A mixed modeling case includes mixing the local data of some other country, generally the target country (Canada in our case, and the dataset is Canadian Vehicle dataset), with openly accessible data to train the models, i.e., (CVD+RoboFlow).

Further, the YOLOv8 model performance was tested using these two databases [RoboFlow $\in$ 29800 images, RoboFlow + CVD $\in$ 38215] in different weather scenarios. For both cases, training is performed on 90% of the dataset and testing on 10 %. Therefore, for the RoboFlow case (Training=26820, Validation=2980) and for mixed case (RoboFlow plus CVD) (Training=34394, Validation=3821), images were used.

Training of the algorithm across these two different vehicle data sets using transfer learning is analyzed and we expected an improvement in the performance of objects detection in different weather scenarios.

The proposed experiment are in line with the previous experiments performed rigorously in the field of automatic road inspection by [26], [27], [28], when dataset available from some countries is extended by small amount of dataset from other countries to suit the target domains better. Python programming language was used with the following PC specifications:

- CPU: Intel Core i9-12900F
- GPU: NVIDIA® GeForce RTX™ 4090, 24 GB GDDR6X
- RAM: 64 GB DDR5, 4800 MHz
- Storage: 2TB NVMe SSD
- Operating System: Windows 11 Home

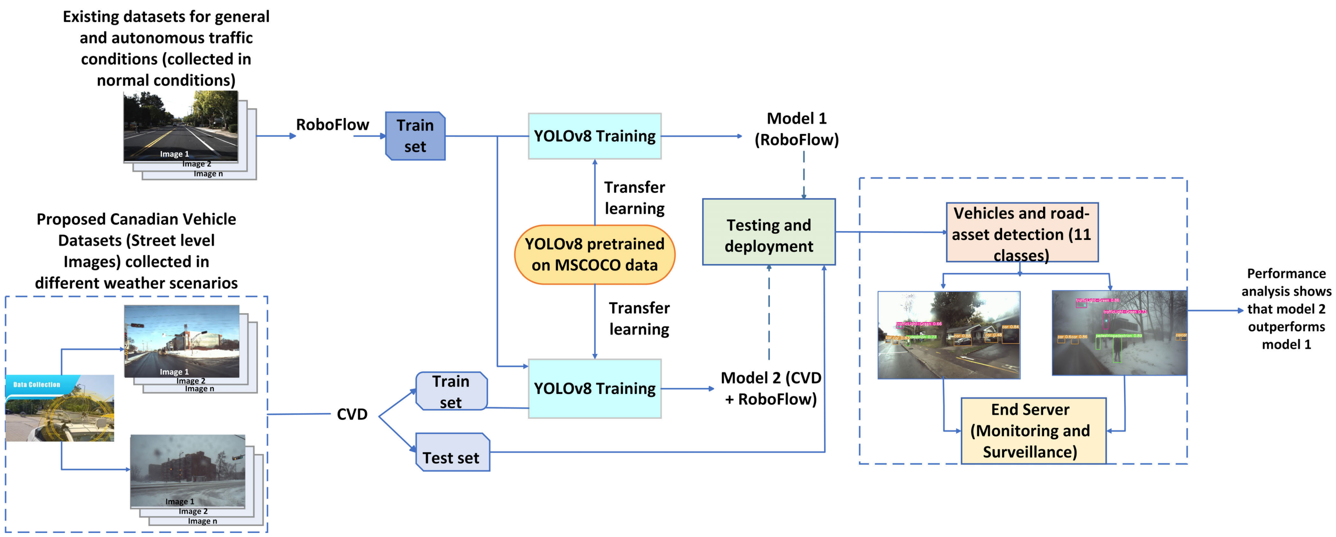

FIGURE 3. **Proposed YOLOv8 based deep learning model architecture to detect objects in self-driving/autonomous vehicles.**

In addition, we used Google Colab with a Tesla T4 GPU, which has a total memory capacity of 15109MB, for training our models.

The PyTorch deep learning framework is employed for the execution of the model algorithm. The model is constructed using SGD as the optimization function.

During the trial, we employed the original data augmentation technique of the YOLOv8 algorithm. The effectiveness of the optimized model for classifying objects in various weather conditions was evaluated using RGB movies that were gathered (Figure 1). Ultimately, we performed a thorough evaluation of the effectiveness of the YOLOv8 model on both RoboFlow and mixed case datasets.

Figure 3 showcases the YOLOv8 trained model, which utilizes a transfer learning approach and optimized hyper-parameters to provide automatic object recognition and categorization.

Table 2 displays the composition of each database, which includes samples from 11 distinct classes. Furthermore, the hyperparameters (learning rate, epoch, mini-batch size, and momentum) were fine-tuned to enhance performance. The efficacy of the created models was assessed by comparing the performance of the YOLOv8 on two separate benchmarks.

IV. RESULTS

A. EVALUATION PARAMETERS

The model performance was measured using a number of accuracy measure indices such as recall, precision, F1-score, class loss, and mean average precision (mAP) [29]. The evaluation of the classification model relies on these parameters. All the indices frequently depend on the parameters of the confusion matrix, which encompass true positive (TP), true negative (TN), false positive (FP), and false negative (FN) [30]. On the contrary, false positive (FP) and false negative (FN) are the results in which the model makes inaccurate predictions for the positive and negative classes, respectively. Further, these parameters are calculated using Eqs. (5.1) - (5.3). The representations of true positive, true negative, false positive, and false negative are illustrated below:

1) *True Positive (TP)*: occurs when a class is accurately identified in the ground truth, and both the label and the bounding box of the instance are correctly predicted with an Intersection over Union (IoU) >0.5.
2) *False Positive (FP)*: occurs when the model makes a prediction of a class at a certain position inside an image, but the instance of that class is not actually present in the ground truth for the image. This also includes the case in which the predicted label doesn't match with the actual label.
3) *False Negative (FN)*: refers to a situation when a certain class is actually present in the ground truth, but the model fails to accurately forecast either the right label or the bounding box of the instance.

Recall measures the proportion of accurately predicted features relative to the total number of features in the true class, encompassing both true positives and false negatives.

$$Recall = \frac{(TP)}{(TP + FN)} \tag{5.1}$$

Precision is a metric that quantifies the proportion of accurately predicted features, namely the true positives, relative to the overall number of predicted features, which includes both true positives and false positives.

$$Precision = \frac{(TP)}{(TP + FP)} \tag{5.2}$$

Precision and recall are inversely related, meaning that an increase in one measure typically leads to a decrease in

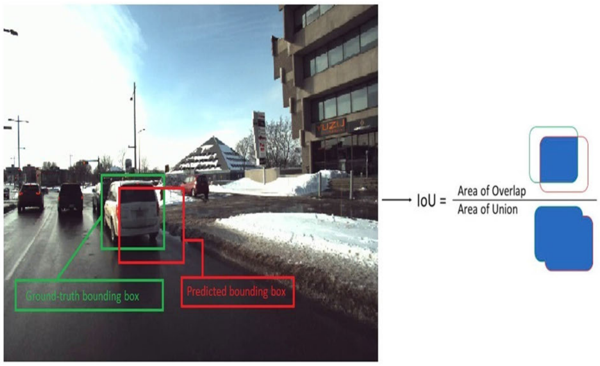

FIGURE 4. An illustration for calculating Intersection over Union (IoU).

the other. The predominant approach for achieving balance between these metrics is to use the F1-score, which serves as model's overall accuracy and is computed in the following manner:

$$F1Score = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)} \tag{5.3}$$

The increase of the F1-score gives a substantially higher level of Precision and Recall. Both Precision and Recall metrics rely on the assessment of Intersection over Union (IoU). IoU is a measure that quantifies the extent of overlap between predicted and ground-truth bounding boxes for a given class. It is calculated by dividing the area of overlap between the two boxes by the area of their union [31], as shown in Figure 4.

For evaluating the model's efficacy, we kept the IoU threshold as 0.5, which is a PASCAL VOC object detection competition evaluation metric [32]. mAP is also utilized for quantitative analysis. The mean Average Precision (mAP) of a model is calculated by taking the average of the Average Precision (AP) values for each individual class.

The calculation of Average Precision involves determining the area under the Precision and Recall Curve for each class. This metric offers information about the performance of a model throughout the complete range of Recall values [33].

B. STATISTICAL ANALYSIS

As mentioned, the YOLOv8 models were trained and tested on two datasets [RoboFlow $\in$ 29800 images, RoboFlow + CVD $\in$ 33419 images] to identify the optimal image database. Table 3 presents the results obtained for individual and specified classes with their precision, recall, and mAP values and accuracy curves for both models. Graphs for precision, recall, mAP, and class loss for 300 epochs for Roboflow and combined case are plotted in Figure 5 a and Figure 5b. These plots illustrate the model's performance by visually representing various performance measures for validation and training datasets.

The classification loss of the validation data displayed a significant decrease after the 50th epoch. The loss function is used as a metric to evaluate the performance of a specific predictor in accurately classifying the input data components within a provided dataset. A classifier model's ability to accurately represent the relation between input data and output targets improves as the loss decreases.

It shows the algorithm's efficacy in accurately predicting the correct class of an object in the context of classification loss. The results of our investigation show that the suggested methodology can be employed to detect and localize various objects among countries with similar weather conditions.

The findings indicate that the detection results significantly improve after additional training and with the application of transfer learning in the RoboFlow + CVD case. When applied to two different datasets, the mAP with an IOU value of 0.5 was set for both models. In this model, we utilized early stopping to choose the best weights. The presented model indicates better mAP, recall, and precision between 50 to 100 epochs, respectively.

From the statistical results it's clear that publicly available RoboFlow dataset alone is not sufficient, that's why we are proposing the new CVD dataset which can be added to RoboFlow (or other existing datasets) to improve their performance in several weather conditions in Canada or other countries.

Table 3 presents the results for precision, recall, and mAP for different object classes. In this table, the results for the RoboFlow-trained model and the model trained using a combination of the proposed dataset CVD and RoboFlow are compared. As mentioned earlier, we targeted training the models for detecting and classifying 11 types of objects.

However, the number of instances captured in the dataset from Canadian Roads for some categories, like a biker, trafficLight-Yellow, and traffic Light-Yellow Left, is less than 0.5% of the total number of instances in CVD. Consequently, the performance results for these classes might be insignificant and could be subject to variation. Still, the corresponding results are reported in the paper to convey the exact information to the readers.

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The results show an overall improvement of 29.1% precision and 33% recall across all classes, with varying improvements for individual classes on adding the proposed CVD dataset for training. This indicates that utilizing CVD for training made the model more effective at capturing all instances of the object classes and enhanced its ability to classify the objects correctly. However, as mentioned earlier, the impact of results for some classes with fewer instances

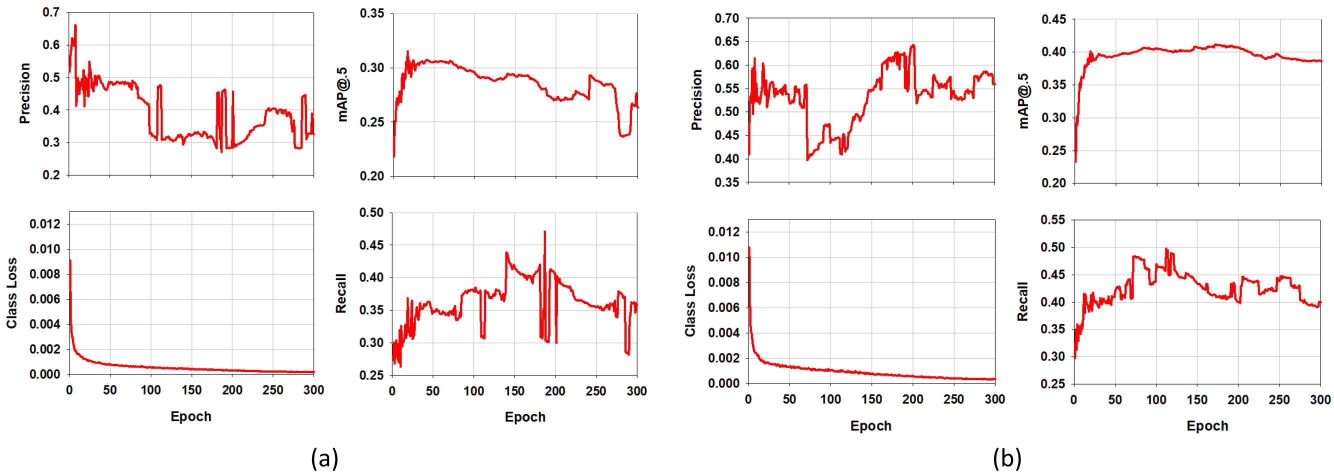

FIGURE 5. Plots of the Precision, Recall, mAP (0.5) and class loss with 300 training epochs for (a) Roboflow dataset (b) Combined (CVD and RoboFlow) datasets.

TABLE 3. Performance of the model YOLOv8 on in case of RoboFlow dataset and combined (CVD+RoboFlow).

Precision		Object Classes											
		All	Biker	Car	Pedestrian	Traffic Light	Traffic Light - Green	Traffic Light - Green Left	Traffic Light - Red	Traffic Light – Red Left	Traffic Light – Yellow	Traffic Light – Yellow Left	Truck
Data used	Model considered	3518	2	2212	333	330	144	68	214	69	17	13	116
RoboFlow	YOLOv8	0.338	0	0.487	0.678	0	0.076	0	0.12	69	1	1	0.165
Proposed CVD (Canadian Vehicle Dataset)+RoboFlow	YOLOv8	0.629	1	0.767	0.656	0.542	0.497	0.599	0.471	0.452	0.379	1	0.55
Recall		**Object Classes**											
		All	Biker	Car	Pedestrian	Traffic Light	Traffic Light - Green	Traffic Light - Green Left	Traffic Light - Red	Traffic Light – Red Left	Traffic Light – Yellow	Traffic Light – Yellow Left	Truck
Data used	Model considered	3518	2	2212	333	330	144	68	214	69	17	13	116
RoboFlow	YOLOv8	0.123	0	0.737	0.316	0	0.042	0	0.0514	0.0855	0	0	0.121
Proposed CVD (Canadian Vehicle Dataset)+RoboFlow	YOLOv8	0.453	0	0.91	0.807	0.603	0.869	0.147	0.519	0.145	0.288	0	0.697
mAP		**Object Classes**											
		All	Biker	Car	Pedestrian	Traffic Light	Traffic Light - Green	Traffic Light - Green Left	Traffic Light - Red	Traffic Light – Red Left	Traffic Light – Yellow	Traffic Light – Yellow Left	Truck
Data used	Model considered	3518	2	2212	333	330	144	68	214	69	17	13	116
RoboFlow	YOLOv8	0.126	0.022	0.691	0.385	0.012	0.017	0.0611	0.0242	0.0963	0.0078	0	0.0875
Proposed CVD (Canadian Vehicle Dataset)+RoboFlow	YOLOv8	0.475	0.251	0.924	0.8	0.517	0.713	0.379	0.431	0.22	0.304	0.068	0.615

is limited. Still, the improvement reported in other classes is substantial.

For example, CVD enhanced the prediction of cars (2212 instances in CVD) in varying weather situations with an improvement of 28% precision and 17.5% recall. Likewise, a gain of 38.5% precision and 57.6% recall was reported in detecting trucks (116 instances in CVD) in different weathers. Further, although the precision for detecting and classifying pedestrians (333 instances in CVD) decreased by 2.2%, the recall was improved by 49.1%.

Similarly, for traffic lights (various sub-classes), mostly the detection has been improved substantially by adding

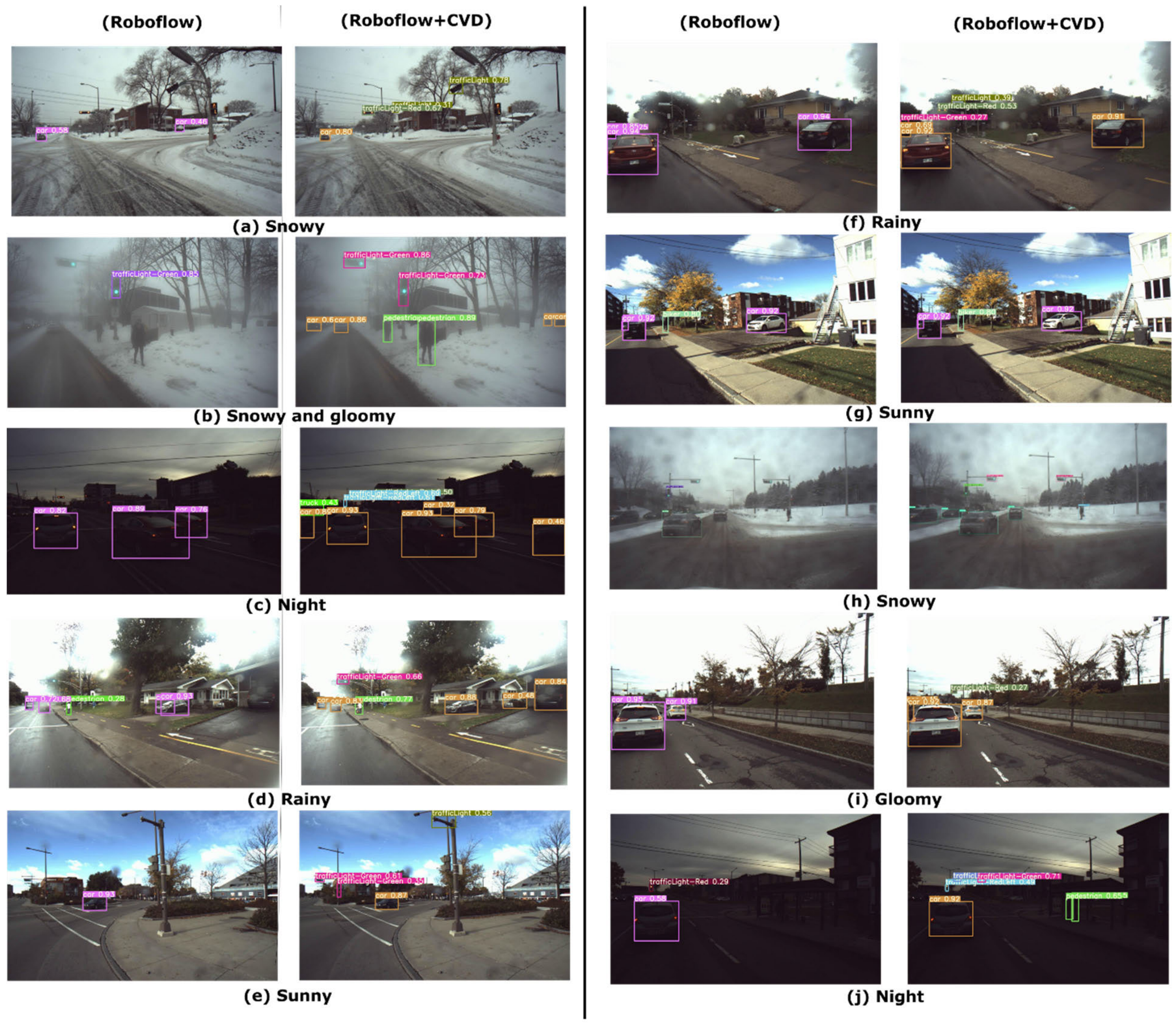

FIGURE 6. Results of DCNN model trained on RoboFlow and combined RoboFlow and CVD datasets in different weather scenarios (snowy, night, rainy and sunny, daytime, gloomy, hazy).

CVD dataset for training the model, except for trafficLight-Yellow and trafficLight-YellowLeft, where the impact may not be considered due to a significantly less number of instances.

For the classes trafficLight and trafficLight-GreenLeft, we conducted a visual analysis to confirm the inability of the model trained using only RoboFlow data to detect these classes. Autonomous vehicle controllers in urban areas face a significant challenge in perceiving traffic lights. Urban driving introduces intricate scenarios with complex interactions involving traffic controls, vehicles, pedestrians, and more. The difficulty is heightened when it comes to traffic lights, posing a formidable computer vision challenge due to varying lighting, view distances, and weather conditions.

Our model addresses this challenge by detecting traffic lights, distinguishing between red, yellow, and green states in input raw images at each timestep. The model's training is tailored to different weather scenarios, and the inclusion of a specific classes for three different colors of traffic light enhances its overall performance. This strategic approach involves incorporating three distinct classes for traffic light colors, a crucial adaptation for navigating varying weather conditions during autonomous vehicle operation.

The robustness of our trained model is evident, particularly when combining CVD data with the Robolow dataset. This resilience is consistent with findings from previous studies that focused on traffic light detection in urban settings for autonomous vehicles, reinforcing the effectiveness of our approach ([33], [34], and [35]).

The visual analysis presented in section IV-C confirmed that the RoboFlow model could not detect any instances of these classes in the weather considered for capturing the data from Canadian roads. The addition of CVD to the train set results in improvement of the detection ability of the model for these classes, as reported in Table 3.

In summary, the detection system has seen significant improvements in precision and recall for various object classes, particularly for cars and ''traffic-light'' and their subclasses. A similar improvement was reported in mAP values. However, certain classes with a smaller number of instances available might require attention to enhance the system's overall performance [36], [37].

C. VISUAL ANALYSIS

The observation reveals that the RoboFlow model exhibits limitations in detecting specific objects, whereas the implementation of a mixed modeling approach demonstrates improved accuracy in detecting said objects.

The visualization results of models trained on RoboFlow and integrated with CVD datasets in various weather conditions are displayed in Figure 6.

After the training phase is over, the algorithm is tested again using the same test images discussed earlier. The experimental results indicate a significant improvement in the detection outcomes following extra training and transfer learning.

The results of the visualization demonstrate that the mixed model exhibits a high level of efficacy in the detection and classification of vehicles and other objects across various weather conditions, in contrast to the RoboFlow case.

The model successfully detects road objects in different weather conditions (snowy, night, rainy, and sunny) at various locations (close or distant), as depicted in the sample images of Figure 6.

Results of the model trained on Roboflow and model trained on mixed datasets in snowy as well as snowstorm with gloomy conditions are shown in figures 6a, 6b and 6h. It is clear that traffic light, traffic lightRed, and traffic light-Green and other objects such as cars and pedestrian are effectively detected by the proposed mixed model. In another case these objects are not detected in snowstorm with gloomy conditions.

In Fig. 6c and 6j, the trained algorithm is tested for many objects in night conditions, and the mixed model effectively detects all objects with high confidence scores compared to algorithm tested on RoboFlow.

It is also clear from figure 6f (rainy) and 6i (gloomy) conditions that the mixed model effectively detects the road objects in these weather scenarios while model trained on Roboflow can detect only few objects. Similarly, the mixed model efficiently detected other objects in snowy and gloomy conditions (Figure 6b)

In figures 6e and 6h, it becomes apparent that the trained model exhibits a notable degree of precision in its ability to identify and classify objects under sunny conditions. In all the findings it is observed that a reduced number of road objects are detected when the algorithm is exclusively evaluated using the RoboFlow dataset. The detecting algorithm has superior accuracy in comparison to RoboFlow when tested on combined Roboflow and CVD.

V. CONCLUSION

This study presents a comprehensive dataset comprising 8388 annotated images encompassing diverse vehicles. In total, there are 27766 labels distributed among 11 distinct classes. The dataset was collected in various meteorological conditions within the province of Quebec, located in Canada. The present study has successfully showcased the application of deep neural networks for road item detection in the specific domain of smart cities and communities.

The evaluation of deep learning-based object detection and classification models encompasses various weather conditions, thereby assessing their performance across diverse environmental contexts. Transfer learning, in combination with the YOLOv8 algorithm, was employed in this study to address the task of detecting road objects in challenging weather conditions.

The experiments illustrate how combining datasets containing normal and varying weather scenarios can lead to developing an efficient road object detection model tailored to a specific country. The experimental results showed that the YOLOv8 algorithm achieved an overall accuracy of 91% for car identification, 80.7% for pedestrian identification, and 86.9% for traffic light-green identification, with a mean average precision (mAP) of 0.5.

The research presented here has potential applications in detecting autonomous vehicles under different weather conditions in the future. In addition, the proposed generalized hybrid model can detect and classify vehicles in other countries with similar weather conditions.

This study establishes the foundation for developing a universally applicable and standardized predictive model to effectively identify and categorize road objects. The findings of this study have significant implications for variou contexts, including both regular scenarios and autonomous environments.

Overall, the study underscores the substantial improvement in model performance when trained on mixed datasets, encompassing diverse day and nighttime scenarios and variable weather conditions in Quebec, Canada, as compared to traditional datasets. However, the summary still lacks an explicit analysis of whether the improved model performance meets the needs outlined by driving regulations for autonomous vehicles.

It's noteworthy that the current regulatory landscape may not explicitly define the requirements for autonomous vehicles. Despite this, the study lays the foundational steps for developing a comprehensive pipeline of trustworthy AI tailored for autonomous vehicles, indicating a promising trajectory in addressing future regulatory considerations.

A. FUTURE WORK AND RECOMMENDATIONS

The present study aims to explore the application of pre-existing data and models in developing vehicle object detection and classification models adaptable to countries with diverse weather conditions. The data utilized for this research was obtained in Canada. In subsequent iterations, there is potential for further development of the aforementioned prototype to establish a singular standardized model that can be universally implemented or, at the very least, applied to a cohort of countries sharing similar weather conditions.

Furthermore, it is important to note that this study holds significant value as a fundamental reference point. Its findings can facilitate the replication of experiments by obtaining supplementary images from a wide range of countries and diverse seasonal conditions.

This approach aims to improve the depiction of individual classes and strengthen the overall resilience of the detection system across all categories of items. One potential avenue for augmenting coverage and expediting response time involves the integration of a vehicle detection system on mobile devices, alongside the deployment of car vehicle recorders on various municipal-operated vehicles, encompassing a range of transportation modes such as conventional automobiles, public transit vehicles, and waste management trucks, among others.

In future research endeavors, it is recommended to undertake a thorough assessment of the accuracy of the optimized model through a comparative analysis with contemporary deep learning models that are considered to be at the forefront of the field. Implementing this approach would allow us to determine the most attainable degree of precision. The model that has been presented exhibits the potential for expansion in order to accommodate the distinctive weather conditions observed in developing and less developed nations.

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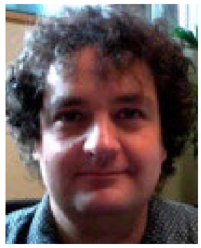

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