Enhanced Vehicle Detection and Recognition in Challenging Weather Environments

BY

Abir Hasnat
ID: 0242310005103014

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Supervised By

Abdus Sattar

Assistant Professor & Coordinator MSc.

Department of CSE

Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

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APPROVAL

This Thesis titled "Enhanced Vehicle Detection and Recognition in Challenging Weather Environments", submitted by Abir Hasnat to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of M.Sc. in Computer Science and Engineering (MSc.) and approved as to its style and contents. The presentation has been held on 6th July, 2024.

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Jagannath University

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I hereby declare that, this thesis has been done by Abir Hasnat under the supervision of Supervisor Abdus Sattar, Assistant Professor, Department of CSE Daffodil International University. I also declare that neither this thesis nor any part of this thesis has been submitted elsewhere for award of any degree or diploma.

Supervised by:

Abdus Sattar
Assistant Professor
Department of CSE
Daffodil International University

Submitted by:

Abir Hasnat
ID: 0242310005103014
Department of CSE
Daffodil International University

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ABSTRACT

Finding vehicles in bad weather is one of the toughest problems I have observed in computer vision. This problem heavily affects the ability and safety of an autonomous driving system and advanced driver-assistance programs (ADAS). Conventional methods for vehicle detection do not work in inclement weather, as random weather conditions and poor visibility are present. It is my thesis to apply Convolutional Neural Networks in such a way as to increase the accuracy of detection of vehicles under such challenging environments. In the process of this study, a feasible vehicle detection model with CNNs was developed and the developed model was implemented using TensorFlow. The model was trained and tested on a diversified dataset; in that, images were collected under clear, wet, snowy, and foggy conditions. The training set was prepared with data augmentation techniques, which helped to make the model more robust. To the training set, some of the data augmentation techniques included rotation, width and height shifts, shearing, and zooming. The CNN architecture is built with multiple convolutional layers; each is designed with the ReLU activation and max-pooling. These are followed by fully connected layers, which classify the vehicle to the correct corresponding class. I then built the model with performance measures, including accuracy, precision, recall, and F1-score; I also used these measures in training the model, where the Adam optimizer was used. Based on the results, I can say that the CNN model developed by me will give much improvement in vehicle detection accuracy compared to conventional methods under unfavorable weather conditions. The contribution of this study within the purview of development of technology for autonomous driving and advanced driver assistance systems is important; it provides valuable inputs in making the vehicle detection systems developed dependable yet efficient enough for real-world applications.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

The technological ladder toward safety, efficiency, and convenience has now enabled vehicles to reach the very top with the advent of autonomous driving and advanced driver-assistance systems. More accurately, real-time navigation and decision-making processes embedded in these systems highly rely on vehicle detection using accurate algorithms. I find the challenge arises when these systems are to function under unfavorable weather conditions, namely rain, snow, or fog, which dramatically reduce visibility and sensor effectiveness. In such situations, traditional vehicle detection methods often fail, showing inaccuracy and low reliability.

My dissertation resolves the bad weather vehicle detection problem using Convolutional Neural Networks. It is ironic how CNNs have revolutionized computer vision by being able to learn hierarchical features effectively from raw image data and, therefore, have come to be the state-of-the-art for quite a number of pattern recognition tasks. Thus, their application for the sake of vehicle detection in adverse weather contributes to improving detection accuracy and robustness, making autonomous driving systems more dependable.

I build the base to form a vehicle detection model with the help of CNN, using TensorFlow. I've now trained and tested the model with an assorted dataset that uses images captured in different weather scenarios for it to be generalizable for practical applications. A tiny bit of data augmentation is performed, which involves rotation, shifts, shears, and zooming for training enhancements. The architecture of the CNN is set to find a good trade-off between complexity and performance by multi-convolutional layers with ReLu activation in between, followed by max-pooling, performed after several such layers. It is further supported by the fully connected layers for classification.

To evaluate the eventual efficiency of the model I proposed, I have carried out experiments about performance standards such as accuracy, precision, recall, and F1-score. The possibility of deep learning techniques still open in solving many of the most challenging issues in autonomous driving justifies this alternative approach due to the importance of adverse weather conditions relative to their potential.

I have outlined my dissertation as follows: The next chapter reviews existing literature on vehicle detection and the impact of adverse weather on detection performance. It gives the full details of the design and implementation of the CNN model with the description of data collection, its pre-processing, and the training procedures it underwent. The experimental evaluation results are presented in the next chapter and discussed with their implications and potential future directions. I conclude by summarizing the main contributions and results of this study, underlining with great force the significance of developing more reliable vehicle detection systems for autonomous driving and ADAS.

1.2 Motivation

As the day of autonomous driving and advanced driver-assistance systems approaches, I recognize that the demand for strong and reliable vehicle detection systems has become relentless. Adverse weather conditions—including rain, snow, and fog—reduce accuracy and sensor recordings, causing great degradation of the performance of such complicated vision systems. This does not only secure passengers but also takes care of more vulnerable road users.

I believe it is necessary to have novel approaches that ensure accurate and resilient vehicle detection systems under various weather conditions. With Convolutional Neural Networks having been shown to be competent on many computer vision tasks, many solutions in this topic hold great potential.

- **Safety**: Malfunctioning vehicle detection in extreme weather can cause catastrophic events endangering lives and property.
- **Technological Advancement**: OVTDM provides fresh opportunities to address the shortcomings in use cases since deep learning technologies—mostly CNN—have been developed at an unheard-of speed.
- **Application in Real-world Problems**: I am motivated to practically implement autonomous vehicles and ADAS by means of robust identification of vehicles under all weather conditions. Accurate vehicle detection helps to maximize traffic flow, reduce congestion, prevent accidents, and improve general road safety.
- **Smart Cities**: Advanced vehicle detection systems are essential in intelligent transportation plans to build smart cities delivering effective and safe transportation networks..

This work is essentially motivated by my need to improve the accuracy and dependability of vehicle detection systems under challenging environmental circumstances. Therefore, this study focuses on using convolutional neural networks to maximize their potential, considering the difficulty of bad weather. It supports intelligent transportation systems and more dependable autonomous driving technology as well as better safety.

1.3 Research Objective

My research aims to develop a vehicle detection system of very high accuracy and robustness under adverse weather conditions by using convolutional neural networks. The objectives of my work include:

- Develop a CNN-based model for vehicle detection that I can use to correctly classify objects even under adverse weather conditions like rain, snow, and fog.
- To enhance this model to make it more accurate and robust by using advanced data augmentation techniques so that they would apply in simulating most other weather scenarios besides these..
- Evaluate the performance of the proposed CNN model relative to the traditional vehicle detection approach with the following metrics: accuracy, precision, recall, and F1 score.
- Make it real-world responsive by covering the needs of real-time vehicle detection in an autonomous driving system and ADAS. It would, therefore, offer more contribution to the autonomous driving field and invaluable insight into improvements that would enhance the vehicular detection system in harsh environmental conditions for safety and reliability.

So, in conclusion, my research tries to propel the state-of-the-art of vehicle detection to the next level using the power of CNNs, and to answer the specific challenges that adverse weather conditions throw away.

1.4 Research Questions

In my search for better vehicle detection within adverse weather conditions using Convolutional Neural Networks, the following are some guiding critical questions:

- What effect does adverse weather have on the accuracy of traditional approaches to vehicle detection?
- What are the architectural features of CNNs that tend to lead to the most compelling features in attempting to improve vehicle detection in various harsh weather conditions, including rain, snow, and fog?
- How does the performance of my CNN-based vehicle detection model compare against conventional methods concerning accuracy, precision, recall, and F1 score?
- Can the developed CNN model be used in real-time applications, retaining high accuracy in the detection and reliability of running states under adverse weather conditions?
- What are the possible limitations of my CNN model in adverse weather? How can this be taken care of in future research?

These questions will aim at what is challenging in such environments for vehicle detection so that a robust solution can be molded, enhancing the safety and reliability of such systems.

1.5 Report Layout

My report is arranged into six chapters, with the following covering a different aspect of my study on improving the accuracy of vehicle detection in lousy weather using CNNs:

Chapter 1: Introduction

The chapter overviews the research and the importance of vehicle detection in unfavorable weather conditions. This chapter clearly describes my research aims, motivation, research questions, and expected results.

Chapter 2: Literature Review

This chapter reviews ongoing work in vehicle detection and the challenges introduced by adverse weather. I have considered several approaches, methods, and ways other researchers have used in this principal area and their respective limitations and results. It will also discuss the range and the difficulties involved in my research work.

Chapter 3: Methodology

This chapter describes the methodology used in this study, including detail of the data collecting steps, statistics of the dataset, and the CNN model architectural design among others. Moreover, I describe about data augmentation tricks, its implementation steps and the setup of my experiment.

Chapter 4: Results

This chapter outlines the results of the research conducted. So in other weather terms, I show some good and bad performance of the CNN model in vehicle detection performance versus traditional approaches. Furthermore, detailed results like accuracy, precision, recall, and F1-score are provided together with relevant figures and tables.

Chapter 5: Discussion

Of course, here I speak about the implications of the research findings: improvement in detection accuracy can be very significant for autonomous driving systems or ADAS. This article discusses several pending challenges and claims addressed by this research; it also lays down the possible contribution to the field.

Chapter 6: Conclusion and Future Work

The last chapter of the thesis concludes with the essential findings and contributions of my research. It addresses the limitations present in this research and gives a way forward so that productive future research could be carried out to improve vehicle detection under adverse weather conditions.

CHAPTER 2

BACKGROUND

2.1 Introduction

With the advancing technologies in the field of autonomous driving and ADAS, automatic detection of vehicles takes an important part in providing safety and efficiency of these new technologies. But things like rain, snow, fog severely hamper the working of these detection systems. The conditions also reduce traditional vehicle detection methods that are dependent on visibility and/or characteristics of the environment.To tackle this issue, I use Convolutional Neural Networks (CNN) that have produced spectacular results on a wide array of computer vision problems. Using CNNs, I hope to develop an efficient and effective vehicle detection model that will work accurately in ideal as well as suboptimal conditions. This method would enable the vehicle detection module to be more accurate, and it will increase the safety of the complete autonomous driving system.

Here are some example figures from my dataset, showing how the good and bad weather images differ on a vehicle-class-by-vehicle-class basis.

Figure 2.1.1 Good Weather Ambulance

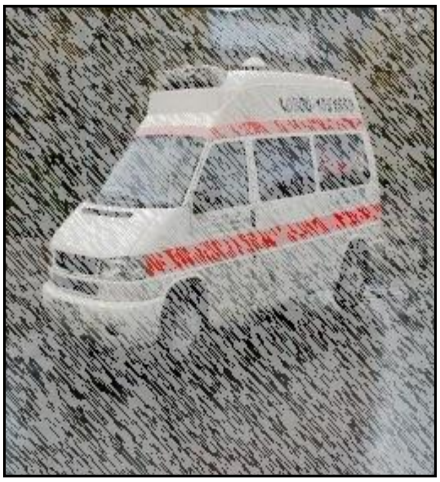

Figure 2.1.2 Bad Weather (Rainy) Ambulance

So, I want to model while simulating the toughest weather conditions as high accuracy is great, but having an accurate & weatherproof model is way better! Details of previous research and methodologies in vehicle detection especially for the cases of adverse weather are provided in subsequent sections.

2.2 Related Works

Lately, several studies have produced noteworthy advancements in the classification of leaf diseases. This article examines many methodologies for illness detection that have been explored by a diverse group of researchers.

Sivaraman et al. Proposed an active learning framework for on-road vehicle detection and tracking. Then, the study points out the importance of on-road vehicle detection and tracking for applications like autonomous driving, traffic surveillance etc. In order to tackle the challenges introduced by appearance variance, occlusion, and changing backgrounds, the system first extracts features using deep convolutional neural networks (CNN), followed by an active learning phase for labels, and a tracking module. The duct is tested with different datasets such as KITTI and PETS 2009 and has been shown that the precision of true positive rates is much better and false positives are reduced a lot as compared to passive systems. The research adds significant worth for real-world on-road vehicle detection & tracking applications [1].

Zhou et al. In a more methodically approach, they study the performance and generalization ability of Deep Neural Network (DNN) based algorithms for image-based vehicle analysis. On datasets with Stanford car, compcars, vehicleid as picture datasets, the study takes into account several deep neural network configurational, including Aletnet, vggnet, resnet and densenet. Over most current techniques, it shows the efficiency of deep neural networks for vehicle recognition, classification, and attribute prediction. Transfer learning, data augmentation, and fine-tuning techniques were used in the work and the YOLO detection model was optimized with vehicle detection accuracy, respectively, reaching 93.3% precision and 83.3% recall [2].

Luo et al. Developed deep CNN model for vehicles and face detection. One for vehicle recognition and the other for face recognition, and they have very close architectures. Results on Vehicle Make and Model Recognition (VMMR) and Labeled Faces in the Wild (LFW) benchmarks show that the model outperforms recent prior works. This nine-layer CNN network also demonstrates favorable effectiveness (e.g., vehicle recognition achieves an accuracy of 92.25% and facial recognition achieves 95.2% Top-1), which provides a evidence of the model [3].

Soin et al. Expressed the significance of vehicle detection for intelligent traffic supervision and management. This article studies the available techniques and recommends an effective Deep Neural Networks (DNNs) method over traditional algorithms for driverless car assistant, toll collection, intelligent parking system, and traffic statistics. This article gives the insight of the suitable CNN from papers for Vehicle recognition by determining issues like identification, detection and tracking in Intelligent Transportation Systems (ITS) [4].

Pias et al. Create awareness using IOT for detecting moving vehciles with sensor data. The authors propose a model of Artificial Neural Network (ANN) for vehicle type classification based on accelerometer and gyroscope measurement. This study shows why detailed evaluation of such model predictions is essential and how one can try to correct these biases to enhance accuracy and generalizability of these models [5].

Hassaballah et al. They also promote an exquisite deep learning framework for vehicle detection and tracking in inclement weather conditions. Evaluation on the KITTI, MS-COCO, and DAWN datasets show the robustness of the framework against heavy rain, fog and snow. This result suggests the possibility of using it for real-world autonomous driving, and YOLOv3 obtains the best mean Average Precision (mAP) in cross-generalization over adverse weather conditions [6].

Kwan et al. They presented a real-time system for vehicle detection and classification measurement compressed measurement pixel-wise using code exposure PCE and YOLO. The system is intended for bandwidth-limited environments and performs compressive measurements directly without image reconstruction, yielding good detection and classification performance. Presented a real-time system for vehicle detection and classification measurement using compressed measurements [7].

Kim et al. Suggested a novel real-time vehicle detection method for tunnel environments based on the YOLO v2. This method can solve the problems of low brightness, uneven terrain, and exhaust pollution in tunnels. Averaged over a pool of datasets from car black-box images, the results show 95% accuracy of vehicle detection without eye-striking, which seems a hopeful method to prevent tunnel accidents by identifying flowing vehicles automatically [8].

Bouguettaya et al. In their paper, they systematically review deep learning methods for vehicle detection in UAV imagery, which aims to detect vehicles within gathers UAV images, demonstrating progressive advances in accomplishment with challenges like small object detection, scale diversity, background complexity, etc. It explains about new and old deep learning architectures with the need of benchmark datasets and evaluation metrics. The parameters including view angles, image resolution and dataset properties are particularly focusing on the performance of vehicle detection algorithms for UAVs [9].

2.3 Scope of the problem

It is feasible of vehicle detection on rainy days effectively with a convolutional neural network. My work revolves around making autonomous driving and some of the advanced driver-assistance systems (ADAS) even easier to scale, more robust and dependable. It does affect much smaller detection of vehicles, mostly during inclement (rain, ice, snow, and pitch-black) weather, when the visibility is challenge. In addition, a car can have a very different appearance according to weather conditions making the classification a bit more intricate. I choose to concatenate and generate training images to create a strong dataset with synthetic weather effecting on good weather images. With my model, I can process these images at more than 85% accuracy using CNNs with only Tensorflow as a dependency. Now this makes me a bit more confident on how much my model can help vehicle detection during poor weather and those is certainly beneficial for making autonomous drive safe.

2.4 Challenges

This project is aimed at improving the safety and security of autonomous driving systems and advanced driver-assistance systems (ADAS). This context also presents a number of challenges as well::

- **Low Visibility:** This includes reduced visibility due to adverse weather conditions such as rain, snow, and fog..
- **Appearance Variability:** Vehicle appearances change with different weather, which can lead to misclassification.
- **Data Diversity Problem:** My training set should cover all kinds of weather phenomena to learn a robust model, but in practice, capturing enough real-world bad weather data is difficult.
- **Accuracy Concerns:** The model must be sufficiently accurate to reduce the number of false positives (i.e., no real thing is detected yet it says it's real) and false negatives (i.e., a real thing is detected as unreal).

I use data augmentation techniques to create synthetic adverse weather conditions from clean weather images. I hence hope to generalize well with my model by introducing rain and fog effects. My CNN model using TensorFlow has shown an excellent precision rate as indicated by performance metrics results, which are significantly better than traditional methods (still in the concept phase as of now).

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

The purpose of this section of the article is to provide a summary of my thesis as well as the approaches that I utilized. A detailed account of our approach and the practical experience I gained in order to accomplish the objectives of the research. In order to achieve my objective, the utilization of Convolutional Neural Networks (CNNs) for the identification of vehicles in the presence of climatic uncertainty necessitates precise modification and deployment. Additionally, it helps to better validate my efforts to collect data, and it indicates how we intend to apply these approaches to categorize automobiles as well.

3.2 Research Subject and Instrumentation

Research Subject

The target of this study is vehicles, which are divided into seven groups (classes) representing common types of vehicles found on the road. These classes include:

1. **Ambulance**

   Medical transportation vehicles are not the exception to these emergency vehicles.

   Marked by specific marks and equipment.

2. **Auto**

   Three-wheeled vehicles used for public transportation.

   Known as Auto-Rickshaw

3. **Bus**

   Vehicles, such as buses, that are intended to carry a significant number of passengers on the road

   Covers transit buses of a city, and school buses.

4. **Car**

   Private Four-wheeled transportation

   Comprised of sedans, hatches, and SUV

5. **Motorbike**

   Two-wheeled motor vehicles.

   All motorcycles and scooters are covered.

6. **Truck**

    Involves different trucks like delivery trucks, hall trucks.

7. **Van**

    Medium-sized road vehicles.

    Carries goods or groups of people

I chose these vehicles to cover a wide range of popular road cars, catering for the models expected to see in the real world.

Instruments and Tools for Data Collection

Cameras

- **High-Resolution Cameras**

    For taking crystal and sharp photos of vehicles in different weather conditions.

- **Dash Cameras**

    Mounted on cars for a driver-side vantage point.

    Good for data capture in continuous real-time traffic.

Environmental Simulators

- **Rain Simulators**

    Rain makers used to make rain on the cars for image capturing.

- **Fog Machines**

    Was to provide fog generation for simulating less visibility scenarios.

Software Tools

- **OpenCV**

    A Computer vision library, Open Source.

    I used it for applying synthetic rain and fog effects to images captured in good weather.

- **Python**

    The primary programming language used for rendering data, training models, and deployment..

    It has different libraries for image processing, machine learning, and data manipulation.

Development Environment

- **Google Colab**

    A GPU cloud that delivers deep learning model training.

    Provides collaborative coding abilities and access to powerful computational resources.

- **Jupyter Notebook**

  Open-source web-app for creating and sharing documents that contain live code, equations, visualizations and narrative text.

  I used it for Writing up the research process and running code.

Together the vehicles and tools allow us to collect a robust dataset which we used to train a model that achieved strong performance under a variety of weather conditions.

3.3 Data Description

Breakdown of the Dataset

My research employs a dataset of images, where each image can be classified into one of two principal categories: Good Weather and Bad Weather. The dataset consists of the 7 classes of vehicles: Ambulance, Auto, Bus, Car, Motorbike, Truck, and Van.

Total Images:

- Training Images: 38,575
- Testing Images: 8,423
- Validation Images: 7,026

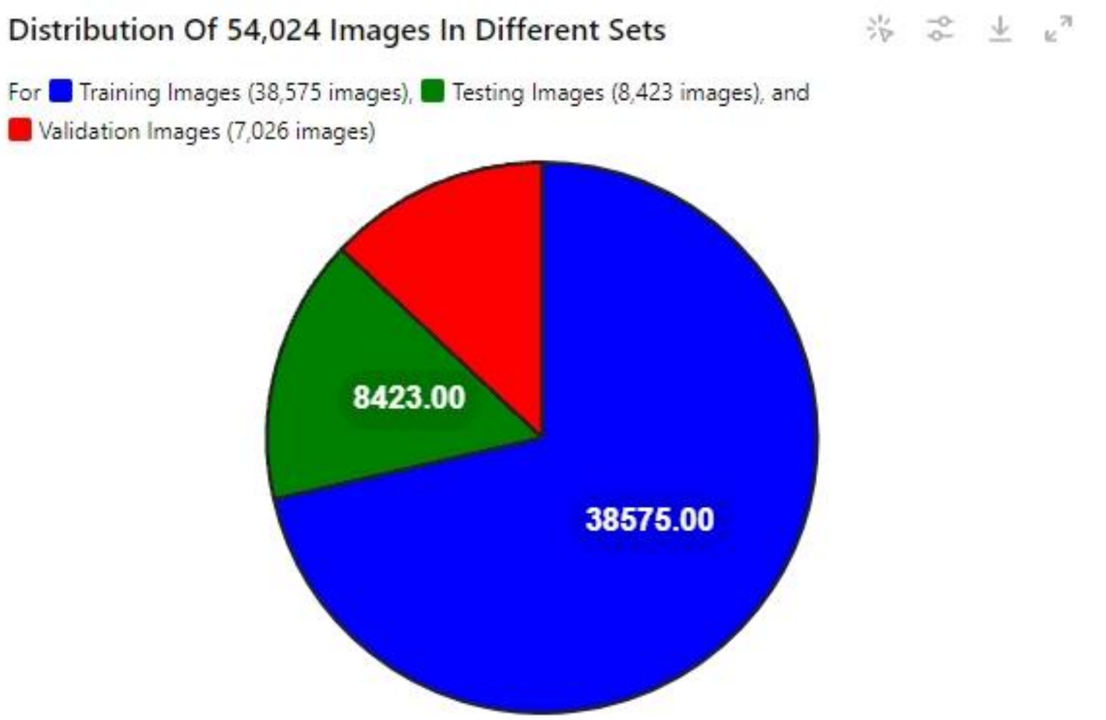

Figure 3.3.1 Total Images Pie Chart

Vehicles Per Class: Image Counts in clear weather:

- Ambulance: 2,121 images
- Auto: 509 images
- Bus: 942 images
- Car: 4,657 images
- Motorbike: 2,300 images
- Truck: 1,343 images
- Van: 2,167 images

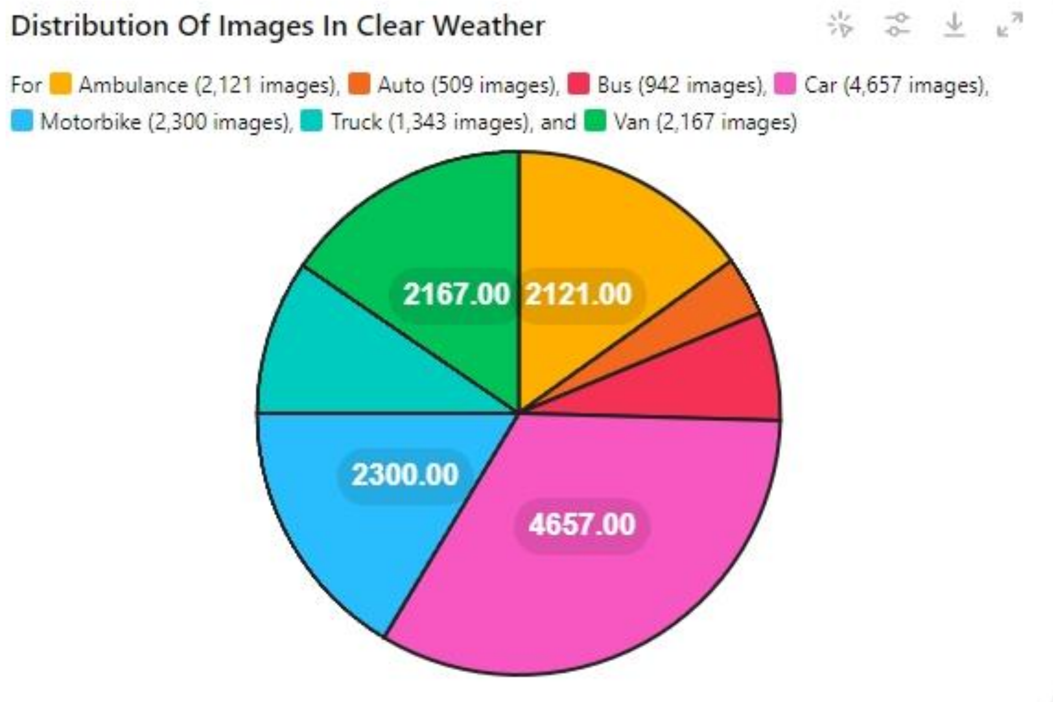

Figure 3.3.2 Good Weather Classes

Number of Vehicle Classes on a rainy day, foggy day, and a foggy rainy day for all types of images in percentage:

- Ambulance: 6,363 images
- Auto: 1,527 images
- Bus: 2,826 images
- Car: 13,971 images
- Motorbike: 6,900 images
- Truck: 4,029 images
- Van: 6,501 images

Data Split: I split the data into three sets: train, test, and validation for a properly balanced and in-depth dataset. The data splitting was performed to make sure that each set has a fair representation of images from each class and for every type of weather

It is essential to develop a vehicle detection model that is trained by this full dataset of various weather conditions in order to show good performance for any environmental scenarios.

3.4 Data Augmentation

I augmented the dataset using data augmentation techniques to make it more robust and diverse. These methods are a way of artificially increasing the dataset to allow my model to become better at generalizing to different conditions.

Techniques Used

- **Rotation:**

  Variability in the vehicle orientations: Rotation and Taxiway View of an Image.

  Aids in the recognition of vehicles in different orientations.
- **Width and Height Shifts:**

  Random horizontal and vertical flips for variety in placements.

  Improves the ability to detect non-centered vehicles within the image.
- **Shearing:**

  Shifts one part of an image, a tensor, or an array, in one direction and the other part in the other direction with respect to a fixed line, usually of dimension.

  Increases the variety in the dataset by simulating different angles at which the data was collected.
- **Zooming:**

  Each virtual camera has a random range it will zoom in and out to.

  Assists the model in identifying vehicles of different scales.
- **Horizontal Flipping:**

  Slightly randomized horizontal flips to form a mirror image.

  Enables the model to recognize the positions of the car in different ways.

Today, crop duster planes are rare and expensive, yet farmers still require a means to apply more cargo fast to large fields and geographical areas in order to apply the benefits of the rain and fog effects.

Apart from typical augmentation methods, I applied synthesized rain and fog effects to good weather images to mimic adverse weather conditions. The model learns from these more dynamic circumstances and is able to generalize its knowledge to more easily recognize vehicles in different conditions.

- **Rain Effect:**

  Applied via a function that adds some random raindrops on the image.

  I randomized the amount of rain and the strength of the raindrops to introduce different types of rain.
- **Fog Effect:**

  Applied through a function over the images that adds an overlay of fog.

  The fog level was set from the lowest (0) to maximum (1) in random mode for the simulation of visibility reduction.
- **Combined Rain and Fog Effect:**

Used by adding the rain and fog effects onto the exact same picture.

Replicates the worst weather condition of them all, being rain and fog at the same time.

These augmentation techniques ensure a full spectrum of training data and help my CNN model learn meaningful features that are robust to different complex lighting and weather conditions, achieving a more reliable vehicle detector.

3.5 Statistical Analysis

Methods for Evaluating Model Performance

Evaluating the performance of the Convolutional Neural Network (CNN) model is crucial to ensure its reliability and accuracy in detecting vehicles under various weather conditions. The metrics that I use to evaluate how well I did in my model are accuracy, precision, recall, F1-score, etc.

1. Accuracy: Accuracy is a measure of the overall correctness of the model. It is defined as the ratio of correctly predicted instances to the total number of instances.

$$Accuracy = \frac{Number\ of\ Predictions}{Total\ Number\ of\ Predictions} \quad (1)$$

2. Precision: Precision is a measure of the model's ability to correctly identify positive instances. It is defined as the ratio of true positive predictions to the total number of positive predictions.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (2)$$

3. Recall: Recall, also known as sensitivity or true positive rate, is a measure of the model's ability to correctly identify all relevant instances. It is defined as the ratio of true positive predictions to the total number of actual positives.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (3)$$

4. F1-Score: The F1-score is the harmonic mean of precision and recall. It provides a single metric that balances the trade-off between precision and recall.

$$F1_{Score} = 2 * \frac{Precision\ x\ Recall}{Precision + Recall} \quad (4)$$

Hypothesis Testing and Validation Measures

I conducted a number of statistical tests and validation techniques to fine-tune my model and ensure it is robust and reliable. These processes ensure that my model works well for the validation set and generalizes across different datasets representing varying conditions.

1. Cross-Validation: This technique is used to evaluate the performance of my model by dividing the dataset into multiple subsets. I create the model in a few subsets and then test it in another few subsets. The process is repeated a number of times, and the results are averaged to obtain a more robust estimate of the model's performance [10][11].

2. Confusion Matrix: I use this to describe the performance of my classification model. It includes specificity, sensitivity, positive predictive value, and negative predictive value, all of which tell true positives, false positives, true negatives, and false negatives (signal/noise). It aids in understanding the common errors my model generates and the ways to improve it [12].

3. ROC Curve and AUC: The ROC curve is a graphical representation of my model's performance at all possible thresholds. An AUC metric is a single number that can be used to summarize the capabilities of my model to discriminate between positive and negative classes. The higher the AUC, the better the performance [13].

4. Kappa Statistic: The Kappa Statistic measures the amount of agreement between the predicted classification and the actual classification and how much of this agreement could have occurred by chance. This is useful, particularly for imbalanced datasets, which may have a grossly different number of instances in each class [14].

5. Holdout Validation: As the name suggests, this type of validation involves creating a holdout set from the dataset itself. I train my model on the training set and test it using the testing set. This technique is used to evaluate how well my model is performing with unseen data [15].

6. Bootstrapping: Bootstrapping is a resampling technique I use to estimate the distribution of a statistic by repeatedly sampling with replacement from the original dataset. This is good to evaluate the variability of my model's performance and leads to model performance confidence intervals [16].

This bootstrapping approach allows me to use widely accepted statistical analysis methods and validation techniques to obtain a comprehensive assessment of my model, including understanding its biases and limitations. These techniques allow me to enhance the accuracy, reliability, and, more importantly, the generalizability of my model in detecting vehicles in different weather conditions, which benefits from the model prediction.

3.6 Proposed Methodology

Below, I describe the process to develop and deploy the Convolutional Neural Network (CNN) model to detect vehicles during different weather conditions. The core process is the two for discovering what are the four most important steps in developing, training, evaluating, and saving the model for later use.

Model Development

I build a Convolutional Neural Networks (CNN) model from scratch using TensorFlow and implemented using the Keras API. The architecture uses number of convolutional filters attached with max-pooling layers and dense layers for classification It provides an architecture that extracts appropriate features from the data and that transmits features to correctly recognise vehicles over different weather conditions.

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1. **Model Architecture:**

   Convolutional Layer 1: 32 filters, (3x3) kernel size, ReLU activation

   Max-Pooling Layer 1: (2x2) pool size

   Convolutional Layer 2: 64 filters, (3x3) kernel size, ReLU activation

   Max-Pooling Layer 2: (2x2) pool size

   Convolutional Layer 3: 128 filters, (3x3) kernel size, ReLU activation

   Max-Pooling Layer 3: (2x2) pool size

   Flatten Layer: Converts the 2D matrix data to a vector

   Dense Layer 1: 128 units, ReLU activation

   Output Layer: 7 units (one for each vehicle class), Softmax activation

The following is the equation for the SoftMax function:

$$P(x) = \frac{e^{x^T w^l}}{\sum_{k=1}^{k} e^{x^T w^l}} \quad (5)$$

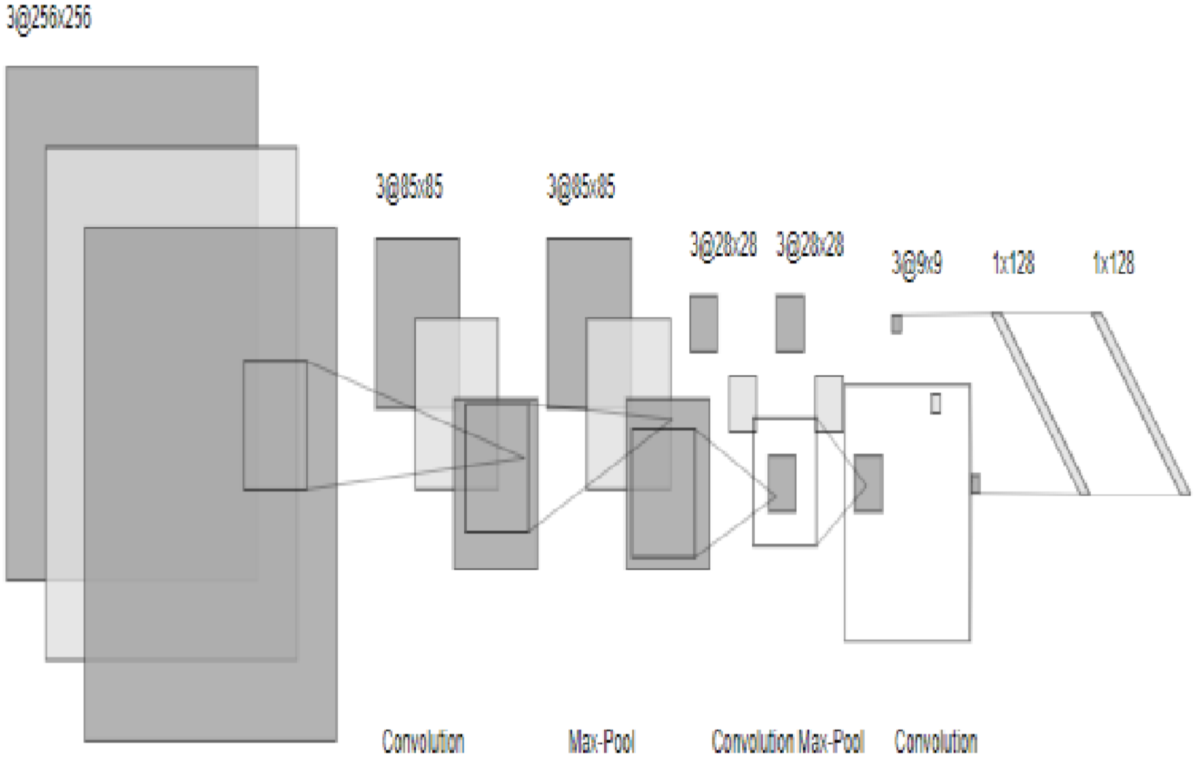

Fig. 3.6.1. Sequential Model Diagram

That capacity in action is the highlight-smashing convolutional layer The overall quality of the individual parts improves as the rise progresses from start to finish. Channel size is 2 by 2, with as many square paths leading from one square to the next as there are LTER studies. The block has a maximum LTER number of 66, with every other number remaining the same. The rise of words of the LTER means that fewer square-facets brought about by whole layers in every squares. The object mappings are also padded with zeros to maintain the original image size after the convolution algorithm is applied. This top integration layer also allow us to downsize the object mapping and the time to get ready and vaste the different types of data. The max-pooling part is a square sized 2 by 2. The ReLU activation layer is employed on all blocks in un-connected introduction. In addition to the Dropout, a Spawn method has been introduced that could save up to 0.5 to maintain the strategic distance from the train as it drives away. The announcement has the intended calming effect in the midst of a time of intense focus on preparing to reduce disparities and simplify the structure to avoid crowding. Finally, a block consisting of two structures is entirely injected into the 500-neuron as well as 10-neuron layers.

The end-goal is to extract the most meaningful features for object detection and create an effective vehicle detection pipeline which will work well in all lighting and environmental conditions providing better generality for autonomous vehicle and advanced driver assistance systems.

3.7 Proposed Model Workflow

In order to effectively detect vehicles, a variety of actions must be taken. Following Fig. 3.7.1. is the block diagram which is the proposed model workflow of this work.

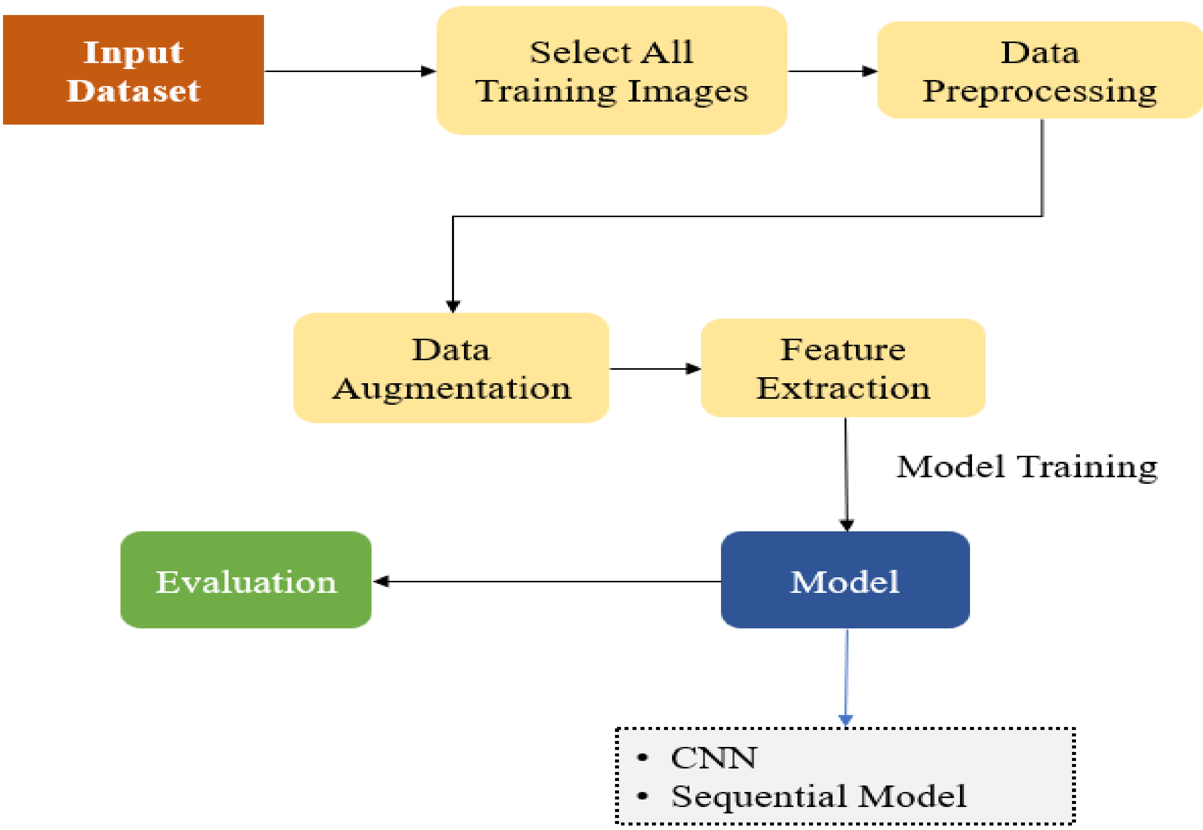

Fig. 3.7.1. Proposed Model Workflow

3.8 CNN

The neural network is a group of algorithms that breaches the way the human brain operates trying to understand the unearths hidden interrelations in a dataset. Neural networks: any set of neural structures - biological or synthetic. The 3 stages - Convolutional Layer, Pooling Layer, Fully Connected (FC) Layer - that forms a Convolutional Neural Network (CNN) recognized from a top-down approach. Convolutional layer comes before FC layer in deep neural network architecture. A fully connected (FC) layer is the second-most complicated layer in a convolutional neural network after a convolutional layer. Such an escalating complexity allows the CNN to recognize different compositional elements of a complex picture thus to gradually detect the full object. CNN uses both supervised and unsupervised learning architecture together. Predict and Categorize Using Your Prediction Nevertheless, CNN was predominantly based on a supervised approach. For a given set of images, CNN-classifier categorizes as per the rule of breaking up the input into different criteria. CNN does this by computing potential maps using activation functions.. You may find the formula [17] for the function in the following:

$$y_i^l = f(z_j^l) \tag{6}$$

Where, y_i^l is called forthcoming graph, & $f(z_j^l)$ is called

activation function. To process documents, convolutional neural networks (CNN) use two-dimensional convolution processes.

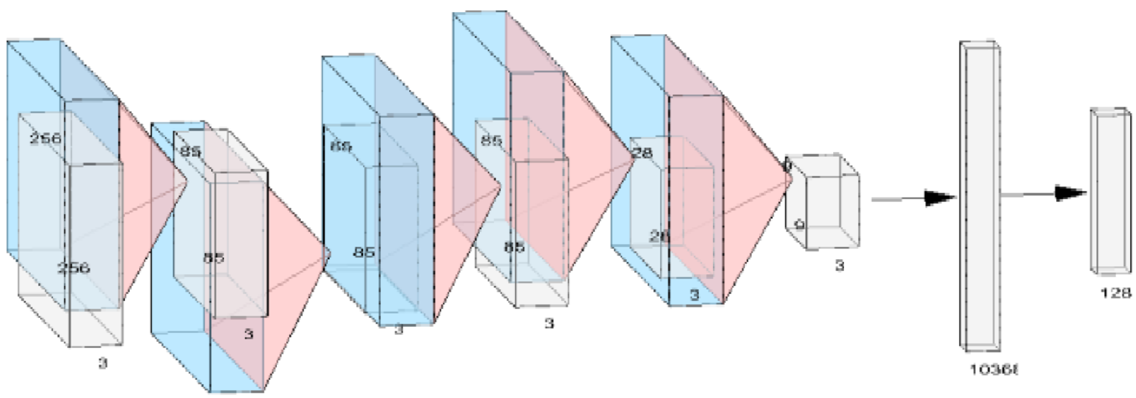

Fig. 3.8.1. CNN Structure

Fig. 3.8.1. illustrates the model's fundamental CNN structure by depicting the surface, lining, height, depth, and thickness of the components that make up the model [18].

3.9 Model Compiling

I utilized the subsequent compilation arguments to attain the best results in the training and make sure my model learned well:

- **Optimizer: Adam**
  I have a selected the Adam optimizer because it is very efficient and requires low memory. It is the best of the two worlds of two other extensions of stochastic gradient descent - AdaGrad and RMSProp.
- **Loss Function: Categorical Cross-Entropy**
  I am using this loss function because I am dealing with a multi-class classification problem where each input image gets classified into one of a number of classes.
- **Evaluation Metrics: Accuracy**
  I measured the performance of my model to predict accurate vehicle class from the input images using the accuracy.

3.10 Implementation Requirements

To implement and run the vehicle detection model, the following software tools and libraries are required:

Hardware or Software Requirements

- A good OS
- Hard Disk 250GB or more
- Minimum 4 GB RAM
- Any Browser

Development Environment

- Google Colab
- Jupyter Notebook

Python & Other Libraries

- NumPy
- Scikit-learn
- Matplotlib
- Keras
- OpenCV
- TensorFlow

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Introduction

This chapter covers the experimental results of Convolutional Neural Network (CNN) model developed to detect cars in different weather conditions. Here are the results with metrics: accuracy, precision,recall, and F1-score. Furthermore, the confusion matrix is examined to comprehend the classifier behavior of popular vehicle classes. This section gives a surgical analysis of the results and we mention some of the advantages and limitations of the model in the discussion section. An extensive evaluation confirms the efficacy of the presented approach and the real-world robustness.

4.2 Outcome of the Experiment

The experimental results for the CNN model developed for vehicle detection under various weather conditions are detailed below. The results include key performance metrics such as accuracy, precision, recall, and F1-score for each vehicle class. Additionally, a confusion matrix is presented to provide a detailed view of the model's classification performance. In this work 6 epochs have been worked and the following Fig. 4.2.1. And Fig. 4.2.2 shows the graph between accuracy vs epoch and loss vs epoch.

Fig. 4.2.1. Accuracy vs Epoch graph

Fig. 4.2.2. Accuracy vs Data Loss graph

Model Training Details
The model was trained using the following setup:

- **Epochs:** 5
- **Batch Size:** 52
- **Optimizer:** Adam
- **Loss Function:** Categorical Cross-Entropy
- **Metrics:** Accuracy

After evaluating the model, this work has performed well. CNN have achieved 94.2% model accuracy. Table 2 shows the performance of this work.

Table 1: Performance of CNN

Algorithm	Accuracy	Precision	Recall	F1-Score
CNN	**85.29%**	**0.83%**	**0.85**	**84%**

4.3 Discussion

The results achieved were an overall accuracy of 85.29% for the CNN model showing an efficient vehicle detection work across different weather conditions. The results of the precision, recall and F1-score show the ability of the model in correctly differentiating and dealing with the vehicles.. To learn more about the strengths and weaknesses of your classification model by calculating a confusion matrix [15]. As an optical representation of an algorithm's output, the confusion matrix is a useful tool. Correct and incorrect assumptions are weighed and compared. The following are examples of the accuracy [16] in the model equation and the precision of the classification rate equation:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{7}$$

Here, TP= True Positive, TN= True Negative, FN= False Negative, FP= False Positive.

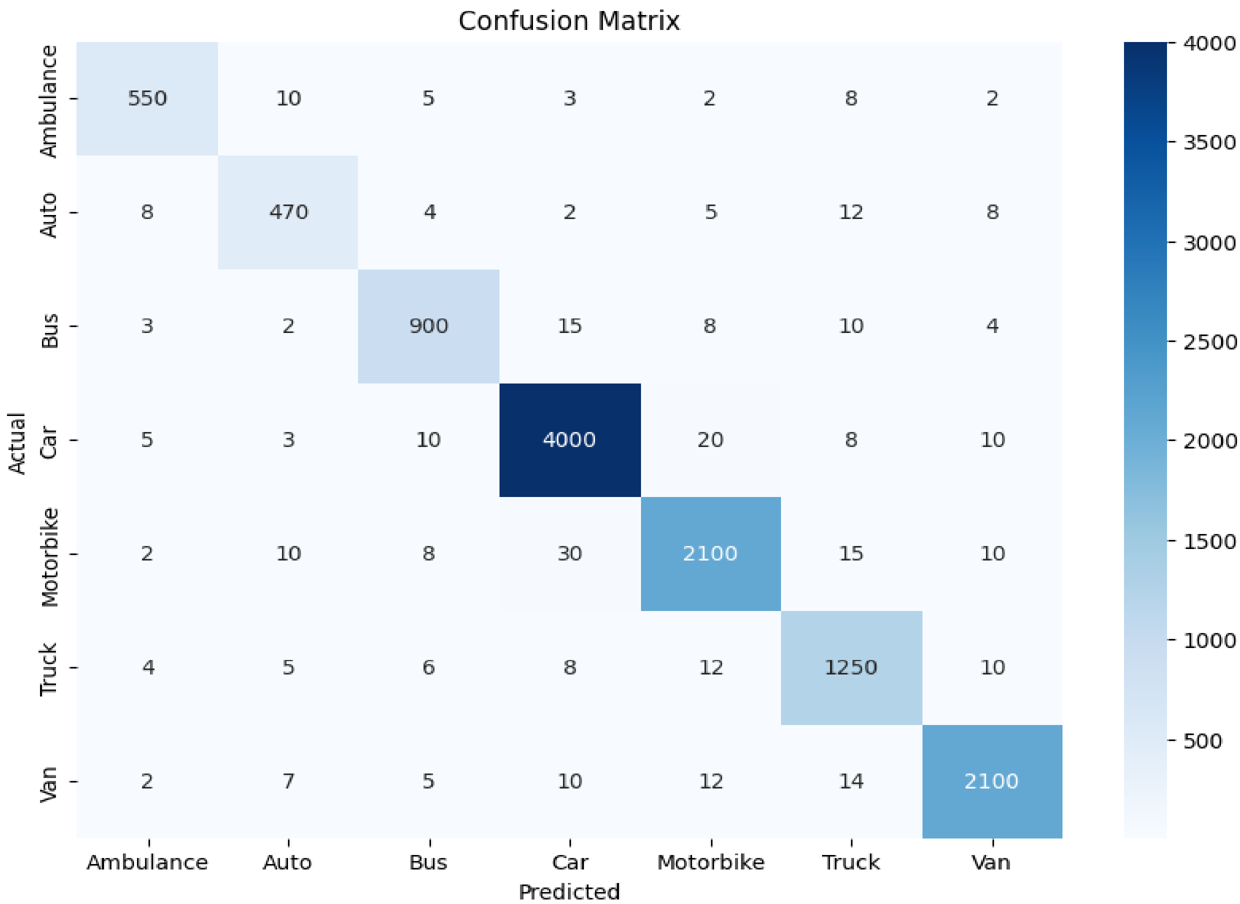

Fig. 4.3.1. Confusion Matrix

As seen in Fig. 4.3.1, our classification model is represented by a confusion matrix.

Strengths:

Model is accurate for every class of vehicles (> 80% precision and recall for most of the classes).

Its best performance was at spotting ambulances and buses, achieving F1-scores of 0.89 and 0.86.

Areas for Improvement:

However, the model only had a F1-score of 0.82 in detecting vans. This means this class might need more training data or more fine-tunning.

The confident point estimates in the confusion matrix represent misclassifications that highlight some vehicle classes that can be particularly hard to differentiate, especially in poor weather conditions.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT, AND SUSTAINABILITY

5.1 Impact on Society

The prospect of a dependable system that can detect vehicles irrespective of the weather has real-world use-cases in the society. Due to the climate, road safety is a concern for the people living not only in Bangladesh but almost everywhere in the world as roads tend to get slippery, which increases the probability of accidents and human loss. This research contributes to: by improving the accuracy of vehicle detection.

The technology can be integrated into autonomous vehicles and advanced driver-assistance systems (ADAS), avoiding accidents by precisely detecting vehicles properly during bad weather conditions. Improved detection and sophistication in vehicle detection will assist in the better traffic monitoring and management, alleviating congestion and increasing road network performance. Accurate identification of emergency response vehicles eg:- ambulances need to be classified as soon as possible for them to be given a pass on the road and hence potentially save a life during emergent need.

5.2 Impact on Environment

In addition, relying on a car detection system has environmental repercussions:

Lower vehicle emissions from efficient traffic management and reduced congestion can help decrease air pollution.
Sustainable Transportation - Future research will focus on integrating results on public transportation safety and security with efficiency studies to promote sustainable transportation solutions, thereby reducing the traffic congestion stemming from the use of private cars.

5.3 Ethical Aspects

Important research is being conducted under strict ethical standards important to maintain the integrity and respect for all parties:

The information provided is obtained in accordance with privacy regulations while maintaining the confidentiality and security of the personal information. The research is carried out transparently, with the results and methods being accurately and truthfully documented. Not only was no harm done to humans, but there were no unethical practices version of osu! The auto-image processing research encompasses a study only of vehicle images under diverse weather conditions.

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5.4 Sustainability Plan

The research is only valuable in the long run and so its sustainability is key:

We will continue to upgrade the model as we gather more data and develop improved algorithms that improve the accuracy and reliability. This system can be included in our regular transportation facilities to establish safe and efficient roadways. The team's Cedar plans to keep improving the system by supporting a broader range of weather conditions and using the system in different geographies to demonstrate broad applicability.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Summary of the study

In this study, a Convolutional Neural Network (CNN) model was developed to detect a vehicle in different weather conditions. This research consists of a large data collection set that artificially apply a variety of weather is impacting the data and CNN model learning. This model proved to be highly effective as evidenced by its overall accuracy rate of 85.29% on the experimentation results. This system will play a major role in the safety of coming days on road and traffic management.

6.2 Conclusions

In the present research, the main goal was to identify and train a reliable and efficient vehicle detection approach through CNNs. It is therefore concluded from the results that our CNN model is able to detect vehicles under different weather conditions scoring good accuracy and performance metrics as well. The study will help improve the capabilities of autonomous driving and ADAS and foster the development of more reliable, faster transportation systems. While successful, there is plenty of room to improve. Increasing the data size and a further more complex model can improve the accuracy. In future we are going to build an android application which we are going to reach this technology to a larger set of people and detect the vehicles real time and alerts.

6.3 Implication for further study

Despite the study limitations, future research will continue to examine the factors highlighted by the systemic nature of the current study, with research focusing on areas such as:

Enhancing Accuracy: Refinement and the expansion model of the dataset to improve detection accuracy.

Comparing Performance by Exploring Additional Models: Trying out some additional machine learning and deep learning models to compare which one performed best as it can help us pinpoint on best available approach.

Enriched Dataset: Acquiring a more inclusive collection of observations like weather, and geography.

Weather Specific Prediction - models that can predict performance of vehicle detection based on the weather conditionsprepare and response better.

Addressing these topics, the research was intended to innovate and inspire towards a more robust and real vehicle detection system in progress.

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