HAZY: A $PM_{2.5}$ Estimation Application Using Traffic Footage

A Special Problem
Presented to
the Faculty of the Division of Physical Sciences and Mathematics
College of Arts and Sciences
University of the Philippines Visayas
Miag-ao, Iloilo

In Partial Fulfillment
of the Requirements for the Degree of
Bachelor of Science in Computer Science by

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May 5, 2023

Abstract

Air pollution is a global problem and the Philippines ranked third among countries with deaths relating to air pollution. Mobile sources are responsible for 65% of the pollutants in the atmosphere and for two decades the country has tried to mitigate these atmospheric issues but shows no improvement. Air quality monitoring is important for mitigating air pollution in the Philippines. However, The country is doing a poor job of maintaining air quality monitoring devices to keep them operational. Moreover, it is expensive to maintain these tools, and access to the data is limited. This project aims to utilize new technologies to develop an alternative air quality monitoring system to help bring a solution to this problem. this project will utilize an object detection algorithm, YOLOv5 to be trained to identify and count the number of vehicles on the road to estimate the amount of fine particulate matter ($PM_{2.5}$) present in an area.

Keywords: Machine Learning, Artificial Intelligence, Object Detection

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Chapter 1

Introduction

1.1 Overview of the Current State of Technology

The Department of Environment and Natural Resources (DENR) expressed in their website that monitoring air quality is essential in reducing air pollution and they plan to protect the environment and public health by strengthening their air quality monitoring systems (DENR, 2020).

An example of air quality monitoring system that the DENR uses is the Differential Optical Absorption Spectroscopy (DOAS). (DENR, n.d.). DOAS captures light that passes through the atmosphere, to measure different wavelengths that were absorbed by different gasses. This method can accurately measure trace gasses absorption and it is simpler and less expensive to operate. DOAS, however, is greatly affected by turbulence in the atmosphere (Platt & Stutz, 2008). DENR also has particulate matter stations that records PM 2.5 and PM 10. (DENR, n.d.)

DOAS equipment needs frequent maintenance to be able to operate normally. In a news report by (Enano & Subingsubing, 2019) regarding air pollution at EDSA it was stated that the maintenance of these equipment requires "hundreds of thousands of pesos".

Currently, The way to access the data from the AQMS stations is through the website (https://air.emb.gov.ph/ambient-air-quality-monitoring/) and the play store application. Figure 1.1 shows the contents of the application.

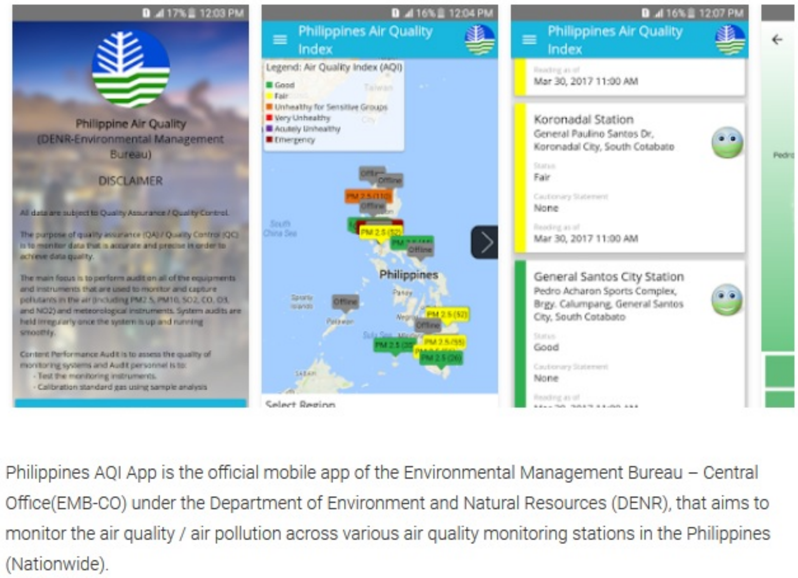


Figure 1.1: Screen capture of the mobile application of the Philippines Air Quality Index. Photo taken from https://air.emb.gov.ph/ambient-air-quality-monitoring/

In the mobile application disclaimer it is stated that the system audits are irregular and all data are subject to quality Assurance and quality control. This means that the end user may not get the accurate data that they expect when using the application. Moreover, monitoring stations are not online 24/7 which makes the data less accessible.

1.2 Problem Statement

Air pollution has become a global problem over the years. As stated by (Akimoto, 2004), the availability of the CO2 concentrations on the Measurement of Air Pollution from Satellite (MAPS) instrument in 1981 shows high concentrations of the greenhouse gas over tropical Asia, Africa, and South America. Not only does this date provide evidence that this has become an international issue, it also shows how fossil fuel combustion can have an impact on air quality.

The Philippines, a country located in tropical Asia, is not devoid of these issues. An article by (Abano, 2019) states that a 2018 study by the World Health Organization reports the Philippines has ranked third among the countries with air pollution related deaths. These deaths are tied to harmful particles entering a person's lungs, which can lead to multiple different ailments and diseases such as: heart disease, lung cancer, and respiratory infections, to name a few.

Air pollution can come from different sources, whether it be from stationary constructs like factories or mobile sources such as cars. (Environmental Management Bureau, 2015) An air quality status report by the Department of Environment and Natural Resources (2015) shows that 65% of the air pollutants come from these mobile sources. This worsened as the EMB's official site (Environmental Management Bureau, 2018) states that based on the Emissions Inventory of 2018, the pollutant contribution of mobile sources has increased to 74%. In places where traffic is congested could be a huge contributing factor to vehicular emissions. (Vergel & Yai, 2000) states that the congestion in the roads of Metro Manila contributes to the worsening air quality, especially in the vicinity of the road environment.

In the country's attempt to mitigate the atmospheric issues, the Philippine Clean Air Act of 1999 (Republic Act No. 8749) was passed. (Food and Agriculture Organization of the United Nations, n.d.) It entails the resolution of creating a national program of air pollution management, mainly focusing on pollution prevention. Two decades later and the country still sees increasing pollutants in the air and does not show signs of the improvement that was planned.

In addition to creating air pollution management programs, the Philippine Clean Air Act also aimed to utilize mass media communication in order to create awareness and active participation in air quality planning and monitoring. Considering that the available technology dedicated to monitoring the air quality in the country is sparsely spread throughout the country, being accessible to more citizens can help in creating awareness at a lower cost. With the aforementioned said, a system that could satisfy that goal can be created with the newer technologies that were not present in the decades prior. Thus, Hazy was constructed, a system that can gather information from vehicles – one of the biggest contributors of air pollution and provide an estimate to emissions produced, as a solution to these problems.

1.3 Research Objectives

1.3.1 General Objective

The general objective of the study is to develop an application that calculates the location's average amount of fine particulate matter ($PM_{2.5}$) emission from vehicles through the use of a vehicle detection system. This system will identify the vehicles on the street from a live camera feed. The system will integrate the values of $PM_{2.5}$ of different vehicles, which will be utilized to assign values to on-screen vehicles for their total average to be calculated. The average $PM_{2.5}$ value will then be displayed on the screen for the user to see.

1.3.2 Specific Objectives

This study specifically aims to:

1. To study YOLOv5 and its components to develop the application
2. To implement real-time vehicle detection and counting into a system that can be used on a live camera feed
3. To gather a collection of images of vehicles to be used for training for a system to detect real-time traffic footage to calculate the overall emission of an area based on the vehicles' average $PM_{2.5}$ emission.

1.4 Scope and Limitations of the Research

This application mainly focused on the PM2.5 emitted by traffic in the Philippines, where the researchers reside as of writing the paper. Thus, it will only be set up and used on the vehicles that travel within the country. For this reason, this project has some significant difficulties in using existing databases of vehicles that are mainly found locally (i.e. jeepneys and tricycles), with little to no readily available databases existing to be utilized in the study. To avoid said vehicles from not being detected, the researchers opted to take pictures and videos of the vehicles in traffic to be used as training data. These vehicles were recorded on a smartphone and were uploaded in Roboflow, which was used to annotate them as their respective vehicle type.

However, since the vehicles with no existing databases are taken and curated by the researchers within a small time frame, this could lead to inaccuracies as the frequency of a specific vehicle to appear on the road when recording is not guaranteed. Thus, lacking in representation compared to other common vehicles such as cars.

Furthermore, this study will be utilizing the YOLOv5 object identification framework and is thus limited to the features of that version. Any other features and upgrades that are present in future versions of the framework will not be included in the study.

1.5 Significance of the Research

The main objective of this study is to create an application that helps its users identify the $PM_{2.5}$ levels of a traffic congested area through a live video feed over the road. It serves as an example on how computer vision can be utilized to get an estimate of the pollutants in an area via tracking the vehicles they come from. This poses benefits to users that want to acquire information on the pollutant levels in traffic congested areas. Civilians such as joggers can plan their travel accordingly to avoid areas if $PM_{2.5}$ levels get too high.

For the environment sector, this study can help contribute to the air pollution awareness in the country, in which such data can be utilized when creating future plans and protocols to combat the rising concern for the country's air quality. The system is also open source so it is a benefit for the general public to use without needing a full set of gear to check on pollution levels.

Lastly, as interest in the computer vision field of vehicle identification and recognition systems increases, this study can contribute to future research on said field. The study can be of help to future researchers on the topics of: computer vision and tracking vehicular greenhouse gasses emissions. This may also provide data to vehicle image databases through the contribution of local vehicles from the Philippines.

Chapter 2

Review of Related Literature

This chapter discusses the features, capabilities, and limitations of existing research, algorithms, or software that are related/similar to Hazy. Hazy, as an application, identfies the vehicles passing across the camera feed and calculates their CO2 emssion average

2.1 Air Quality Monitoring Systems

Air quality monitoring systems are systems that collects data to record and or or analyze atmospheric emission levels. There are various systems for air quality monitoring. (Zoogman et al., 2017) showcased in a journal the use of satellite imagery for large-scale air quality monitoring. They call this instrument TEMPO (Tropospheric Emissions: Monitoring of Pollution). It is an instrument that collects data on tropospheric emissions such as NO_2, SO_2, H_2CO, Methane, etc from a satellite in a geostationary orbit. This system is wide-range and precise, however, access to the equipment is limited. A more accessible air monitoring system was made by (Zheng et al., 2016) using several sensors. This system makes use of low-power wide-area network (LPWAN) to give it a wider coverage compared to the IoT (Internet-of-Things) and the air quality data can be accessed through a mobile application. These systems make use of dedicated sensors to collect emission data whereas this project will make use of computer vision and machine learning.

2.2 Air Pollution from Vehicles

The Philippines currently has a problem with air pollution. According to (Tantengco & Guinto, 2022), the Philippines' PM2·5 concentrations in urban areas exceed the WHO guideline value. They further state that the Philippines' PM2·5 levels reaches 58·4 ug/m3 in traffic sites of Metro Manila during the dry season. Though there could be different sources of air pollution, 65 percent of the air pollutants come from mobile sources such as: cars, motorcycles, trucks, and buses (Environmental Management Bureau, 2015).

Furthermore, CO2, a component of greenhouse gasses, totaled to "30 million tons and 56 thousand tons of particulate matter" (Fabian & Gota, 2009) in the Philippines and the transport sector contributed to 38 percent of fuel combustion back in 2000. The authors have noted that the motorized vehicle count would double by 2020. The increase of motorized vehicles also means an increase in its air pollution contribution.

A study by (Lu, 2022) analyzes the emissions of vehicles due to its impact on air pollution and road-environmental safety. The results show that in 2018 to 2019, two hundred eighty-two vehicle emission standard violations were recorded by the Land Transportation Organization (LTO) office. All of these violations were due to smoke-belching from vehicles. Another result to note was that all the violations were during work hours (6:00 AM to 5:00 PM). The vehicles caught for dangerous emissions were more than 10 years old, with one-third between 10 to 19 years old. The paper concluded that not only ensuring safe vehicle emissions can play an important role in reducing air pollution, there is a need for implementation and monitoring of said vehicle emissions to be within a safer threshold. The researcher notes that the Philippines still needs improvement in addressing the concerns of vehicles contributing to air pollution.

A recent paper by Rito, Lopez, and Biona (2021) raises the concern of quantifying traffic flow, which in this context, is also used for calculating the emission and energy consumption factors. The researchers state that calculating traffic flow has other researchers "deal with complex and arduous tasks, especially when conducting actual surveys". In this paper, the researchers instead utilized crowd-sourced data from Google Maps to estimate mobile emissions and energy use from the traffic flow of the road. The method was used on the EDSA highway in the Philippines, and managed to garner a 8.63% error with respect to the total vehicle count.

2.3 Vehicle Detection and Tracking

Vehicle detection is a method of identifying a vehicle via a camera. Research on this method started being conducted during the late 1970s (Nath & Deb, 2012) and as more vehicles enter our roads, there has also been more interest in the topic. (Meng, Bao, & Ma, 2020) defines vehicle detection based computer vision as aiming at identifying and locating vehicles by digital images or videos. They further simplify the idea by stating that vehicle detection detects “blocks”, which reflects the vehicle’s position from the images and videos.

A paper by (Yang et al., 2020) proposed an “object tracker–detector combined with an object tracking algorithm” for tracking vehicles in traffic. They created the tracker by combining strategies for the You Only Look Once (YOLO) model (which will be talked about in 2.4) with a correlation filter (CF) tracker. To elaborate on the object detection, a detection box merge strategy was used for YOLO. This is to prevent the algorithm from partially detecting an object or detecting it more than once. For the tracker, a “deep feature-based CF tracker” was designed. Lastly, to combine both into a tracker-detection program, a tracker was “first used to predict location of an object in the subsequent frame.”

Another process to detect and track the vehicle would be through background subtraction. Background subtraction, according to Huang BJ. et al. (2017), is used to extract the moving objects and then filter the unwanted images through image processing tools.

A recent study by Li et al. (2022) studies another method of vehicle detection and recognition – via Infrared Image and Feature Extraction. The paper states that due to infrared images having shortcomings such as poor contrast or blurred edges, they mainly studied the color space preprocessing of the image with the use of threshold segmentation method and infrared image enhancement to separate the vehicle and the background. Techniques such as the Median filter and the Improved Histogram Equalization are then used to remove the noise from the infrared image and to enhance the contrast of the image, respectively. Vertical Sobel operator is then selected to enhance the vertical edge of the image. Vertical Sobel operator is used to enhance the vertical edge of the image. Lastly, vertical edge symmetry, aspect ratio, and gray-scale symmetry are utilized for the vehicle detection and recognition.

2.4 A case for YOLOv5

Yolov5 is a pretrained algorithm that uses a system of grids to detects objects from images or videos (https://docs.ultralytics.com/). This tool will be used for the vehicle detection in this project.

2.4.1 Application of YOLOv5

One application of this algorithm was done by Yan et al. (2021) for an apply picking robot. YOLOv5 was used to identify apples, however the algorithm cannot detect apples that are safe to pick and those that are not. This may cause the picking arm of the robot to break if it tries to grasp an apple that is occluded by a solid object. They solved this problem by improving on the modules used for the algorithm. This is not a problem for this project as it only counts the number of vehicles without interacting with them.

In a study done by Zhou et al. (2021), they applied YOLOv5 algorithm to detect safety helmets on workers. The algorithm had an average detection speed of 110 fps in real-time. With a 94.7% effectiveness (The model was trained and tested using 6045 data sets) the algorithm proved to be viable for real-time detection.

2.4.2 Advantages of YOLOv5

YOLOv5 is one of the commonly used algorithm for object detection. It is faster that other object detection algorithms like Region-based Convolutional Neural Networks (RCNN), Fast RCNN, and Faster RCNN. Gandhi (2018) wrote in an article the comparism between the RCNN algorithms and YOLOv5. He said that the major drawbacks of RCNN is that it classifies 2000 regions per image everytime it runs, it cannot run in realtime and it is a fixed algorithm. Fast RCNN employs a similar algorithm to RCNN but instead of classifying regions everytime, it uses CNN to generate a convolutional feature map where the bounding regions are derived. Faster RCNN improves upon this by using a different network for predicting the regions of proposal. In his comparison he found that Fast RCNN improves on the speed of RCNN significantly. He also mentioned that Faster RCNN, the fastest of the RCNN algorithms, is viable for realtime object detection.

2.5 Vehicle Recognition/Identification Applications

In this study, Vehicle Recognition or Identification Applications would be considered as applications that either use any form of video-based software in locating the vehicle on the display feed, or software where static images can be used in identification. Chintalacheruvu and Muthukumar (2012) state that video based vehicle detection technology has features such as: "non-intrusiveness and comprehensive vehicle behavior data collection capabilities", that it has become an integral part of f Intelligent Transportation System (ITS)

V-App Vehicle Detection is a real-time vehicle detection system that utilizes the visual analytics provided by Meraki Smart Cameras and a License Plate Recognition function to 'overcome the limitations of common sensors'. It also has features such as: vehicle distribution, which detects transit vehicles in an area by grouping them into categories; vehicle count and directions, which gets info on the total amount of vehicles transited and their direction details; and average busiest hours, which shows the higher transit and occupancy peaks in a graph. (V-App - Vehicle Detection, n.d.)

BitRefine Heads is a computer vision platform that "utilizes deep learning algorithms to perform high-level visual analysis" . It is a platform that detects everyday objects from any angle and also has a vehicle detection system. The recognition module is pre-trained and can detect vehicles as well as recognize the car's model based on the visual features. It gets its video source from an Real Time Streaming Protocol (RTSP) stream from an IP-camera. The video then goes to a neural classifier that locates the vehicle in the frame and identifies its class using their own vehicle recognition module's database. The tracking module then takes the results and builds the vehicle's movement track. Then it passes additional images of said vehicle to the neural module to check whether the class is correct. (BitRefine Heads, n.d.)

2.6 Vehicle Emission Calculator Applications

In this study, a vehicle emission calculator application would be regarded as applications that provide the total emission count or estimate of a vehicle after given inputs such as: a car's make and model, car type, fuel type, and the like.

The PM2.5 Footprint Calculator v1.01 is an online web browser tool by the constituents of Mahidol University, Thailand. It calculates the primary and secondary PM2.5 emissions (PM2.5, NOx, NH3, and SO2) by asking for the distance traveled, age of vehicle, fuel type, and city location. Due the calculator being "developed as a tool for enhancing environmentally sustainable passenger transport in Thailand," it also displays information that assesses the health costs of health impacts of a vehicle. The effect of the emissions on humans' health are calculated using Disability-Adjusted Life Years (DALY) – which, according to the (*WHO-Disability-adjusted life years (DALYs)*, n.d.), One DALY represents the loss of the equivalent of one year of full health. The calculator is divided into different vehicle types, each having their own dedicated page for calculating the PM2.5 levels. (*PM2.5 footprint calculator-Overview*, 2021)

The Myclimate Car calculator is an online web browser application that determines the CO2 emissions of a car during its travel. The application asks for the distance traveled, along with the fuel type and fuel consumption. Users also have the option to enter the cart type (compact, mid-range, luxury/SUV/Van) to add to the calculation of the CO2 amount. The basis of this calculation is through the utilization of the ecoinvent database (Version 3.6), using the IPCC 2013 (Intergovernmental Panel on Climate Change) evaluation method. The emissions are calculated per vehicle kilometer (vkm). The application creators further note that there is an uncertainty margin of 5% added to the emissions due to statistical values used in the calculations. (myclimate Foundation, n.d.)

The Next Greencar Make/Model Search Tool is an online car make and model search tool by Nextgreencar.com, a website established in 2007 in the purpose of helping car buyers transition from "fossil cars" to electric cars. This search tool takes the input of a car's manufacturer and/or a specific model to provide results of : tail-pipe CO2, NOx, particulate emissions and the NGC Rating. NGC Rating or Next Green Car Rating is a rating developed by the company to assess the environmental impact. (Lilly, n.d.) The site then lists all the cars that satisfy the query, allowing users to compare them between their emissions.

The aforementioned applications use different techniques to calculate the harmful emissions from different vehicles but they commonly share the same process of asking for input: from the user via typing in the required information to output the estimated PM2.5, CO2, NOx, etc. emissions. Hazy, while utilizing the same process of using predetermined pollutant levels being assigned to a vehicle, relies on computer vision training instead of user input to determine the vehicle and estimate the amount of the pollutant they would emit.

2.7 Summary

As the usage of vehicles in the Philippines rapidly increases through the years, it also starts becoming the main contributor to the air pollution in the country – a problem which the Philippines is still trying to mitigate. The studies mentioned above mention that in an attempt to solve this concern, emissions such as fine particulate matter ($PM_{2.5}$) from mobile vehicles are collected and analyzed through making applications that can keep track of the emissions by identifying the type of vehicle on screen.

The type of vehicle can be identified through a collection of images of vehicles gathered by the researchers, being used for the model training of Hazy. This can be utilized to create a system to identify vehicles via either still images and/or video. This chapter presented studies from different researchers that produced vehicle identification and recognition systems through machine learning and computer vision. Some of the applications used as an example can identify objects from a live video feed and produce results that list the vehicle type. Most of the related applications for vehicle tracking all use an in-house system that are not publicly available to use without having to pay for them. The researchers instead utilized YOLOv5, an open source pre-trained algorithm that uses a system of grids to detect objects from images or videos to be used in the study.

The recent studies make note of the interest in vehicle tracking systems and its benefits in managing traffic. This information, combined with the goal of reducing the emissions from vehicles that contribute to pollution, can be used to support the researchers' purposes of the study.

Chapter 3

Research Methodology

This chapter lists and discusses the specific steps and activities that will be performed to accomplish the project. The discussion covers the activities from preproposal to Final SP Writing.

3.1 Technologies Used

The technologies that will be utilized for this project are the following in the following subsections

3.1.1 Roboflow

Roboflow offers a suite of browser applications to preprocess and preparation of the data for computer vision and machine learning. Roboflow annotation will be used to manually set bounding boxes for model training and image augmentation for the manipulation of images. (*Overview - Roboflow*, n.d.)

3.1.2 Jupyter Notebook using Google Colab and Python

Jupyter Notebook and Python will be used for training and fitting the data. Jupyter notebook, using google colab, offers free GPU with CUDA for processing, and Python, the programming language, offers essential libraries for machine learning. (*Google Colaboratory*, n.d.)

3.1.3 YOLOv5

YOLOV5 is an object detection algorithm which simplifies the workflow of training the dataset. It will serve as the object detection algorithm that will be used for training the dataset and counting vehicles in a video or live footage in this project.

3.2 Research Activities

To explore YOLOv5 two models will be used. One model is a pre-trained model that comes with YOLOv5 and a custom model trained with a dataset taken from Kaggle. YOLOv5 has options to download and use pre-trained models on the YOLOv5 GitHub page (*Revolutionizing the world of Vision Ai*, n.d.). This model will serve as a basis to benchmark the performance of the custom data.

3.2.1 Data Gathering

This study plans to identify an area's pollution level through calculating average of the emissions coming from the cars on the road. In doing so, data of the vehicles, its identification, and its emission rates are needed for the study. Through the use of a camera, a live feed of the vehicles in traffic can be recorded to gather the data of cars in traffic. Image samples of the vehicles (Cars, Motorcycles, and Trucks) will be taken from the Kaggle dataset, Traffic Images Of Vehicles (Shihavuddin & Rashid, 2020). This can be utilized in training and testing for the software to recognize the vehicles on the video feed. The vehicle emissions will be taken from an average CO2 emissions of vehicles (four-wheelers and motorcycles) from a dataset provided by Gov.Uk (2020).

Due to the study being conducted in the country of the Philippines, vehicles such as the local jeepney and tricycle do not have readily available image datasets.Videos and Images of said vehicles in traffic were taken from different angles using a phone camera.

3.2.2 Preprocessing

Preprocessing the data includes defining the bounding box of the vehicles in the training data and augmenting the images to make the model perform better. Roboflow has an annotation tool that can be used for training the model to detect a vehicle in an image and its type. Augmentation of the images will be done by the YOLOv5 algorithm automatically given that the Albumentation library is installed. Augmentation can be used for transforming the images allowing the model to diversify its training data set making it perform better.(Dilmegani, 2021)

Annotation of the vehicles consist of: full image annotation and vehicle cropping. In full image annotation, the entire image or video frame is used and every vehicle present is then selected and categorized for the Roboflow tool to save. Vehicle cropping is when a vehicle/small group of vehicles is/are cropped from the source image/video frame and is then annotated by the tool. This was done when a specific type of vehicle was needed for the database.

3.2.3 Training and Performance Testing

The training data will be separated into classes: cars, jeepneys, motorcycles, tricycles, trucks, and utility vehicles. These classes will be the bases of classification for the training. For performance testing, there are visualization tools available to visualize the performance of the model. In this project, Tensorboard will be used since it is already available in python and can be rendered using Jupyter notebook. The training time will be based on the performance parameters (Precision and Recall being the most important). If little to no improvement is being done by subsequent iterations on the performance parameters the training will be interrupted. To benchmark the performance of the custom data it will be compared against the pre-trained weights available for YOLOv5.

3.3 Model Applictation

The program detect.py will be run to detect objects from an external device or video file using the trained model. When detect.py is run it will start to list the objects it detects. An average emission of each vehicle type will be used. The study from (Rito et al., 2021) provides a table that quantifies the emission factors of energy consumption of multiple vehicle types, 6 of which are to be used in this study. The emission data from the study will be utilized for the application.The table below shows the grams of emissions per kilometer. The averages of the vehicles' $PM_{2.5}$ emissions at a given time will be displayed in a real-time chart and will be periodically updated as vehicles enter and leave the camera's or video's line of sight.

Table 3.1: Emission factors per vehicle type ($g_{emissions}/km$)

Vehicle Type	$PM_{2.5}$	CH_4	N_2O	CO_2
Tricycle	0.0562	4.0906	0.0021	66.8747
Motorcycle	0.0336	2.3022	0.0015	60.0983
Jeepney	0.8466	0.2357	0.0316	668.7415
Car	0.0221	0.7408	0.0099	109.8958
Utility	0.1430	0.3538	0.0063	92.4039
Light Truck	0.7519	0.3648	0.0226	842.0852

3.4 Calendar of Activities

Table 3.2 shows a Gantt chart of the activities for the development of Hazy. Each bullet represents approximately one week worth of activity.

Table 3.2: Timetable of Activities

Activities	Sept	Oct	Nov	Dec	Jan	Feb	Mar	April	May	June
Finding and Choosing Final Topic	●●									
Review of Related Literature		●●●●	●●●●					●	●	
Identifying Problem Statement	●●	●								
Formation of Possible Solution		●●	●							
Constructing the Methodology			●●	●●●						
Documentation	●●	●●●●	●●●●	●		●●		●●	●	
Model Training							●	●●	●	
Data Gathering						●●●●	●●●●	●●●●		
Testing				●●●			●	●	●	
Interpretation of Results				●●●				●	●	

Chapter 4

Results and Discussions

4.1 Training the Data Set

Given that the Vehicle Traffic dataset was already preprocessed using Roboflow, it only needs to be trained in YOLOv5 using the available "train.py" file. The following is the code used for the Google Colab Notebook for training the data:

```
!git clone https://github.com/ultralytics/yolov5
%cd yolov5
%pip install -qr requirements.txt
import torch
import utils
display = utils.notebook_init()
```

The data was trained with 16 batches and 300 epochs. These are reflected by the following terminal command for training.

```
!python /content/yolov5/train.py --batch 16 --epochs 300 --data
    /content/drive/MyDrive/College/SP/data/data.yaml --weights
    yolov5m.pt --cache
```

The “/content/drive/MyDrive/College/SP/data/data.yaml” is the yaml file that contains the information about the different classes in the dataset. Below is an example of data.yaml.

```
train: ../train/images
val: ../valid/images
test: ../test/images

nc: 6
names: ['Car', 'Jeepney', 'Motorcycle', 'Tricycle', 'Truck',
    'Utility Vehicle']

roboflow:
workspace: special-project
project: sp-cmsc198.1
version: 3
license: CC BY 4.0
url:
    https://universe.roboflow.com/special-project/sp-cmsc198.1/dataset/3
```

The file contains the directory to the train, validation, and testing data as well as other important information such as the number of objects and their names that is needed by”train.py”.

4.2 Results

Figure 4.1 shows the statistics of how the data set performed during training. Notice that as the training progresses the loss values drop. This is the desired behavior as it shows that the training is making fewer mistakes as training continues.

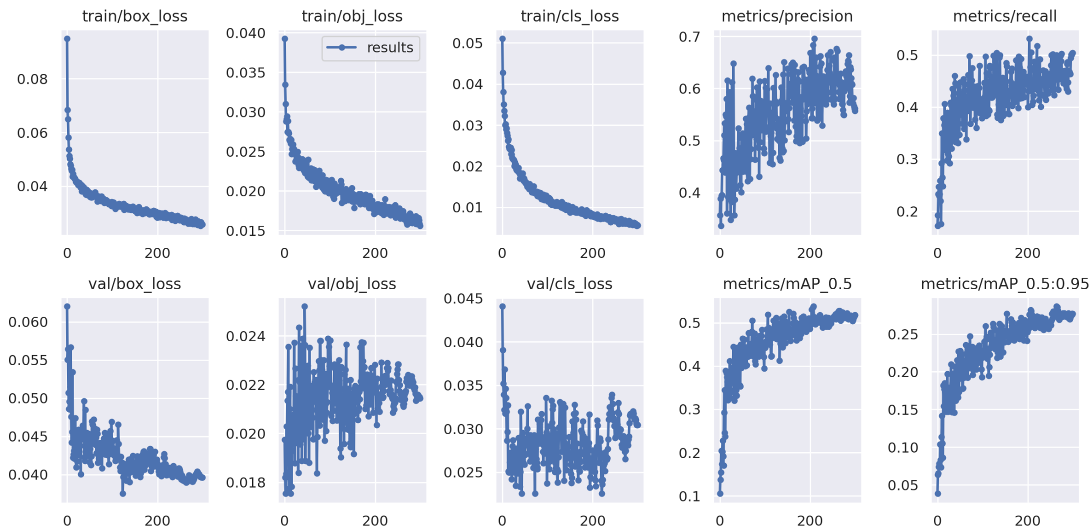
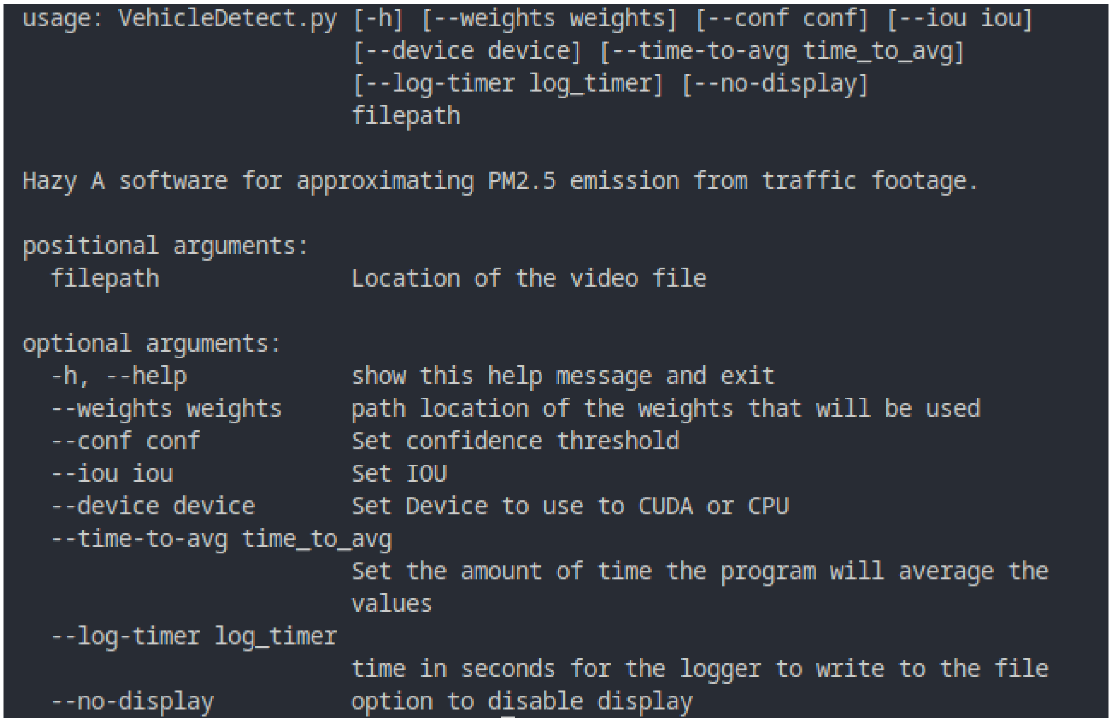


Figure 4.1: Statistics of the prototype training

The precision is expected to increase however in the results displayed the opposite. This is not desirable as it means that the model is getting less precise as training goes on. Although, the model that will be used is the best performing one.

4.3 Hazy Command Line Help



```
usage: VehicleDetect.py [-h] [--weights weights] [--conf conf] [--iou iou]
                        [--device device] [--time-to-avg time_to_avg]
                        [--log-timer log_timer] [--no-display]
                        filepath

Hazy A software for approximating PM2.5 emission from traffic footage.

positional arguments:
  filepath              Location of the video file

optional arguments:
  -h, --help            show this help message and exit
  --weights weights     path location of the weights that will be used
  --conf conf           Set confidence threshold
  --iou iou             Set IOU
  --device device       Set Device to use to CUDA or CPU
  --time-to-avg time_to_avg
                        Set the amount of time the program will average the
                        values
  --log-timer log_timer
                        time in seconds for the logger to write to the file
  --no-display          option to disable display
```

Figure 4.2: Hazy command line help shown

Figure 4.2 shows the command line help for the "VehicleDetect" program. This helps the user to determine what the different arguments do and what is needed to run the program. This can be accessed via the terminal by inputting the command "python VehicleDetect.py -–help" or "python VehicleDetect.py -h".

4.4 Object Detection

The trained weights obtained by training were used in pre-recorded videos to determine if the weights were trained successfully and to see how they perform in actual video footage. Figures 4.3 and 4.4 are screenshots of video recordings taken at Luna St., Lapaz and Diversion Road, Mandurriao, Iloilo City, Iloilo, Philippines , respectively. These recordings were then processed using the custom vehicle detection python file. The processing includes detecting the vehicles, drawing bounding boxes, and calculating and displaying the approximation of the emission of that area. The "detect.py" file that comes with yolov5 will not be used because it is an all-purpose detection algorithm and it cannot do the calculations needed for the project whereas the custom vehicle detection file has the sole purpose of calculating the emissions.

The trained model correctly identifies several vehicles on the road as shown enclosed in bounding boxes with the class name and confidence score above them.

Figure 4.3: Object Detection Prototype used for Traffic recorded in street view

Figure 4.4: Object Detection Prototype used for Traffic recorded in bird's eye view

The researchers compared the frame of the detected vehicle (Figure 4.4) from manual vehicle counting and below are the results:

Table 4.1: Comparison of manual counting versus detection from Figure 4.4

	Actual		**Detected**	
Vehicle type	Count	Total $PM_{2.5}$	Count	Total $PM_{2.5}$
Tricycle	3	0.1686	0	0
Motorcycle	3	0.1008	1	0.0336
Jeepney	7	5.9262	6	5.0796
Car	46	1.0166	36	0.7956
Utility Vehicle	3	0.429	1	0.143
Truck	2	1.5038	1	0.7519
Average $PM_{2.5}$		9.145		6.8037

There is a difference in the number of vehicles in the detection and manual counting and this might be due to low detail on some vehicles, for example on the upper right corner of Figure 4.3 there are several vehicles, like the three tricycles, that are not detected by the program, or obstruction of objects, like on the case of one truck that is obstructed by the tree on the upper left corner of Figure 4.3. The actual value of PM2.5 using manual counting is 9.145 while the detection only shows 6.8037.

4.5 Log File

datetime	PM2.5	Cars	Jeepney	Motorcycle	Tricycle	Truck	Utility Vehicle
2023-05-05 15:10:20.879357	8.6	13	8	1	0	2	0
2023-05-05 15:10:26.295809	9.43	14	9	0	0	2	0
2023-05-05 15:10:31.356844	6.3	21	6	0	0	1	0
2023-05-05 15:10:36.468247	11.33	19	12	0	0	1	0
2023-05-05 15:10:41.551151	8.87	21	9	1	0	1	0
2023-05-05 15:10:47.244026	7.94	19	8	0	0	1	0
2023-05-05 15:10:52.511129	8.86	22	9	0	0	1	0
2023-05-05 15:10:57.780215	7.05	17	7	0	0	1	0
2023-05-05 15:11:02.913040	8.72	16	9	0	0	1	0
2023-05-05 15:11:08.139784	7.15	15	7	0	0	1	1

Figure 4.5: Example Logfile where each entry was generated for approximately 5 seconds

To record the data, the results were saved in a CSV file as shown in Figure 4.5. The recorded data was written using the current frame that it was recorded in, not the average, hence why the values on the recorded data vary a lot between time periods. The data in Figure 4.5 shows that Cars have the most contribution to particle emissions with an average of 17.7 cars per recording, followed by the jeepney having an average of 8.4 jeepneys per recording. Tricycles and Utility Vehicles came last with almost none of them per recording.

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