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基於熱影像視覺車流資料採集之電動車污染排放分析

ELECTRIC VEHICLE EMISSION ANALYSIS THROUGH THERMAL IMAGE-BASED VEHICLE CLASSIFICATION

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摘要:

城市地區空氣污染水平的上升已成為許多研究的焦點，因其對人口健康的不良影響。道路上的車輛排放被確認為污染的主要來源之一。許多國家提出將車輛完全電動化作為減少道路污染的措施，然而，電動車（EVs）相較於傳統車輛對污染的實際影響仍然不確定。因此，開發一種準確區分道路上的 EVs 的模型可以使我們更好地了解 EVs 對道路污染的影響。

由於 EVs 和傳統車輛在外觀上沒有顯著差異，基於可見光的目標檢測方法非常不可靠。然而，熱成像技術可以準確區分這兩種車輛之間的差異。

本研究提出了一種從深度學習模型和我們收集的熱數據中進行轉移學習的方法。特別地，我們使用車輛檢測模型計算不同類型車輛的比例，並應用車輛汙染排放分析來分析 EVs, EMs 對環境的汙染。

這項研究可應用於評估個人對排放物的暴露及相關健康影響。這項工作還提供了一種可靠的方法，使用熱成像技術區分道路上的 EVs 和傳統車輛，並可擴展到識別其他類型的 EVs，如電動摩托車（EMs）、電動巴士和電動卡車。提取的數據預計還可在環境分析、交通控制、智慧城市和其他相關研究領域中提供支援。

關鍵詞：轉移學習、深度學習、物體識別、熱成像、電動車、空氣污染、污染物

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Abstract:

The increasing level of air pollution in urban areas has become a focus of many studies due to its detrimental impact on the health of the population. Vehicular emissions on roads have been identified as one of the primary sources of pollution. Numerous countries have proposed the complete electrification of vehicles as a measure to reduce pollution on roads; however, the actual impact of Electric Vehicles (EVs) versus conventional vehicles on pollution remains uncertain. Therefore, developing an accurate model to distinguish EVs on roads can enable us to better understand the impact of EVs on road pollution.

Since EVs and conventional vehicles have no significant visual differences, visible light-based object detection is highly unreliable. However, thermal imaging can accurately distinguish the differences among these two types of cars.

This study presents a transfer learning approach from a deep learning model and an open-source dataset with the thermal data we collected. Particularly, we count the portion of different type of cars with the car detection model and applied vehicle emission analysis to analyze the emission contribution by EVs and electric motorcycles (EM).

This study could be applied for assessment of personal exposure to emissions and related health impacts. This work also provides a reliable method for distinguishing

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between EVs and conventional vehicles on roads using thermal imaging, which can be extended to the identification of other types of EVs such as EMs, electric buses, and electric trucks. The extracted data is expected to also facilitate in different domains such as environmental analysis, traffic control, smart cities, and other related research.

Keywords: transfer learning, deep learning, object detection, thermal imaging, electric vehicle, air pollution, pollutant

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1 Introduction

The purpose of this study is twofold: to construct a classification model for EMs and EVs, and to analyze the emissions from EMs and EVs. This chapter begins by providing the research background and motivation behind the study. Next, the objective of the study is introduced. The work flowchart is presented in the third section, outlining the step-by-step process of the study.

1.1 Background

Air pollution has been considered a severe environmental problem recently. Besides climate change [1], air pollution exposure is also harmful to the human health [2]. In the field of transportation, we focus on the air pollution generated by vehicles, especially the pollution generated by vehicles on roads, which directly impacts people in proximity to the transportation network. For example, long-term health of drivers, pedestrians, and even residents and business owners and customers near the roads could be affected.

The electrification of transportation is a global trend, with many leading organizations and countries proposing similar policies to address pollution and carbon

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emissions. Examples include the United Nations Framework Convention on Climate Change [3], the Zero Emissions Transportation Association [4], the government of Norway which has set a target to sell only zero-emission cars by 2025 [5], and the United Kingdom which plans to phase out the sale of new gasoline and diesel cars by 2030 [6]. And research[7], [8]showed that the electrification of vehicle might have a chance to reduce those air pollutions generated by vehicles.

In line with the global trend, Taiwan is actively progressing towards the adoption of electric vehicles. According to the government open data [9], the car to motorcycle ratio in Taiwan is 59:100, Electric motorbikes account for 4.5% of all motorbikes and electric cars for 0.4% of all cars in 2022. And it was 3.9% and 0.2% in 2021. Hence, it is essential to delve into the environmental implications of vehicle electrification.

1.2 Objective

To assess the pollution impact of vehicle electrification, this study employs computer vision techniques to classify and count vehicles in traffic video. Subsequently, the collected data is utilized in conjunction with pollutant regression analysis. Specifically, the objectives of this research are

(1) Vision-based classification model of Ems and EVs from traffic flow video and count the proportion of each type of vehicle in the traffic flow.

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(2) Analyze the emission contribution of electrify vehicles on-road.

1.3 Research flowchart

The flowchart of the work is depicted in Figure 1- 1. This work includes transfer learning, traffic data extraction and emission analysis. The utilized data includes the following three types.

(1) Traffic counts: During the designated time period, the cumulative number of vehicles classified as Bus, Car, Truck, Motor, EV (Electric Car), EM (Electric Motorcycle), EV_ratio (Electric Vehicle ratio), EM_ratio (Electric Motorcycle ratio), Motor_ratio (Motorcycle ratio), and Electrify_ratio (Electrify vehicle ratio) are recorded and analyzed.

(2) Pollutant concentrations: The pollution data of NOx, No, O_3, CO, CO_2, NMHC, CH4, PM_1, CPN.

(3) Meteorological conditions: ambient temperature (T), Barometric Pressure (P), relative humidity (RH), and wind speed (WS).

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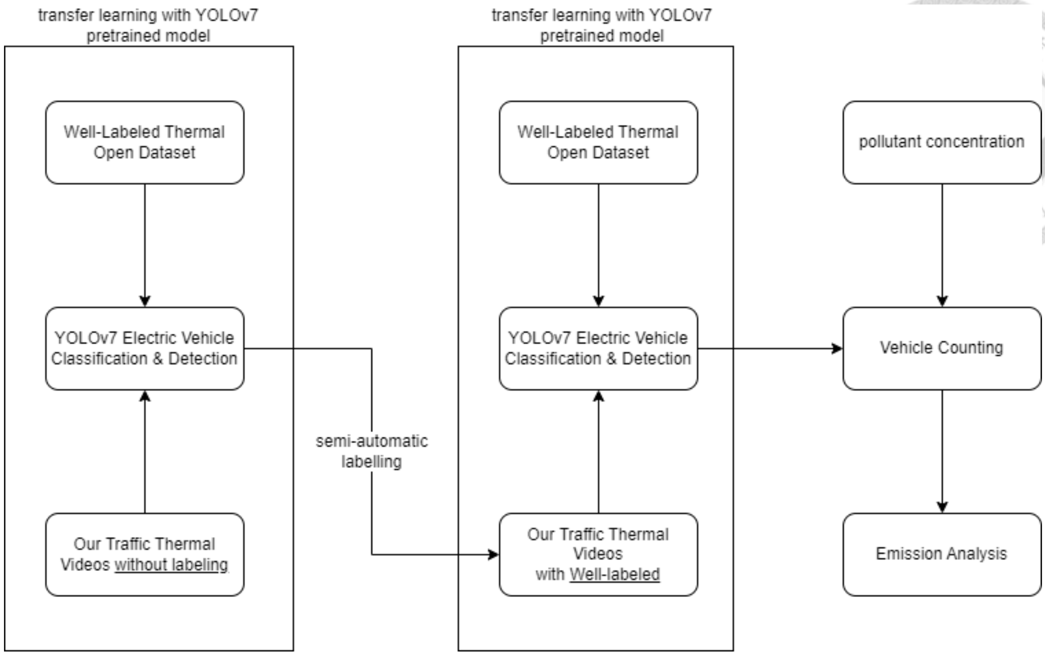

Figure 1- 1The Flowchart of the Work

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2 Literature review

In this chapter, previous studies were introduced and discussed. This chapter has Six parts. First, we compared the EV emission method. Next, we find different of measurement of vehicle emission. Third, we summed up the method of collecting traffic data. Fourth, we took a closer look at distinguishing EV from other cars. Next, we conducted a systematic review of utilizing of thermal image. Finally, we discussed our finding of these research and summery.

2.1 EV emission on road

In analyzing air pollution related to traffic using pollution concentration monitoring methods, the contribution of electric vehicles is typically disregarded. However, with the widespread adoption and rapid growth of electric vehicles, the contribution of electric vehicles to pollution emissions cannot be ignored [10]. Although EVs can reduce pollution caused by burning gasoline, other sources of pollution caused by their heavier weight [11], such as tire wear and road dust, are also worth investigating.

In recent studies on the pollution of EVs, both laboratory tests [8] and analysis using pollution models [12] have been conducted and indicated that a positive relationship exists between vehicle weight and non-exhaust emissions, and electric

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vehicles are 24% heavier than conventional vehicles. Research [13] also indicated that there is a positive relationship exists between vehicle weight and non-exhaust emissions. EV penetration would reduce pollution episodes in Taiwan's major cities by up to 60% [7] .

According to researches [14]–[16],that employed the life cycle assessment (LCA) approach to assess the emissions of air pollutants throughout the entire lifecycle of vehicles, including production, usage, and end-of-life. The findings revealed that EVs exhibited a decrease in CO2, VOCs, and NOX emissions and an increase in PM2.5 and SO2 emissions.

2.2 Measurement of Vehicle Emission

Study [17] indicated that measurement methods for vehicle exhaust emissions are typically categorized into two main types: laboratory measurements and real-world measurements. Laboratory measurements involve conducting emission tests on vehicles within a controlled environment and vehicle emission models. On the other hand, real-world measurements encompass various approaches such as tunnel testing, remote sensing testing, near-road measurements, and on-board testing.

To estimate the emission rates, [18],[19] applied a comprehensive approach involving the application of dynamometer testing on a substantial number of laboratory

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vehicles has been employed.

Mobile source factor model (MOBILE)[20] is developed by the US EPA and the California Air Resources Board (CARB). A macroscopic emission model was developed for China based on MOBILE by [21].

Another model called computer program to calculate the emissions from road transport (COPERT) was developed by the European Commission (EC). A comparative study of both emission models was made by [22]. MOBILE and COPERT are compared to 8 others model by [23].

Motor vehicle emission simulator (MOVES) model is a state-of-the-art vehicle emission factor model developed by the US EPA's office of transportation and air quality (OTAQ).[24] [25] applied MOVES for application in their city. MOVES and a traffic simulation model VISSIM are combined to predict emissions by [26] .

Models used for assessing vehicle emissions may not always accurately reflect the vehicle's actual operating mode and the corresponding emissions on the road. [27], [28] applied on-road measurement models for vehicle exhaust emission test. Fuel type, road elevation, road grade or other indicators may lead to the change of the vehicle pollution emission results were resulted by [29], [30]. On-board measurements with portable emission measurement systems (PEMS) to determine solid particle number (SPN) emission factors was applied by [31]. Comparison between models and on-road test

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was made by [32].

2.3 Collect traffic data

Traffic flow studies have focused on the interactions among various traffic participators and infrastructure. Beside the traditional method which is manual roadside observations with handheld counters, [33] collected traffic data using radar-based devices. Loop detector was applied by [34]. Pneumatic-tube counter was applied by [35]. Light Detection and Ranging (LIDAR) was applied by [36]. GPS was applied by [37]. Unmanned aerial vehicles (UAV) was applied by[38]–[40]. Vehicle-to-everything (V2X) communication equipment was applied by [41]. Cellular phone data was applied by [42]. Based on traffic video collected by CCTV or camera was applied by [43], [44]. Computer vision-based vehicle detection was applied by [45] [46].

Computer vision-based vehicle detection has improved dramatically in recent years due to the increased speed of computer graphics. an appropriate image detection model plays a crucial role in extracting traffic data from videos. Convolutional Neural Networks (CNNs) have exhibited excellent performance in object detection. CNN-based object detection models can be categorized into two-stage methods and one-stage methods. two-stage method is a two-stage process: proposing regions (region proposal) and then classifying and location-correcting predictions for these regions. R-CNN [47],

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Mask R-CNN [48], Faster R-CNN [49] are the best known. One-staged methods skip the region proposal stage and get the final localization and content prediction at once. SSD [50] and YOLO [51] are the commonly used one stage detection methods. While one-stage methods may not achieve the same level of accuracy as two-stage methods, they offer higher efficiency. In practical applications, one-stage methods are well-suited for handling large volumes of image data.

2.4 Distinguish EV from other cars

As our means of transportation continue to evolve and new ways of getting around emerge, it becomes necessary to develop innovative sub-classification methods for Transportation Mode Detection (TMD) to effectively differentiate these novel forms of transport. With the transition from fossil-fueled cars to electric vehicles, the adoption of electric motorcycle, the utilization of hybrid buses, unique challenges arise when it comes to distinguishing these modes of transport.

Inductive power transfer (IPT) was applied by [52], which is a method that can transfer power to EVs without physical contact. Once these systems are integrated on the road and activated, we are able to identify the presence of EVs.

Data on vehicle dynamics and acoustic parameters to investigate potential differences between EV and combustion cars was collected by [53]. Analyses revealed

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notable distinctions in both interior acoustics and external acoustic emissions.

EVs using the unique high-frequency switching noise only generated by the motor unit in EVs was detected by [54]. This can be conveniently accomplished by utilizing a smartphone carried by the pedestrian.

A method that utilizes features built on frequency analysis to identify idle-engine motor vibrations was presented by [55]. But this method is limited by the requirement of placing sensors on the vehicle, even if a smartphone with built-in inertial sensors can be used to measure.

The differences in thermal characteristics between EV and combustion cars were indicated by [56]. EVs do not generate heat in the engine compartment while in operation, which is typically located beneath the front hood of the vehicle.

The available literature on the classification of electric motorcycles is relatively limited. Computer vision-based classifier based on the visual appearance of the motorcycle was applied by [57]. We agree that relying computer vision-based on the visual appearance may not achieve the same level of effectiveness in distinguishing EVs. This is because certain car manufacturers, such as Volkswagen and Toyota, offer electric versions of their popular internal combustion engine vehicles, such as golf and C-HR, resulting in similar external appearances. This adds complexity to the task of differentiation.

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In Taiwan, EVs are required by regulations to have a distinctive label on their license plates, indicating 'Electric Vehicle' in Chinese, and their license plate numbers typically start with the letter 'E' for electric. While using conventional license plate recognition methods[58] may address the identification issue for electric vehicles, we recognize that this approach may not be universally applicable worldwide.

2.5 Utilize of thermal image

thermal imaging technology has found wide-ranging applications across various research fields, providing researchers with a valuable tool. By detecting and recording the thermal radiation emitted by objects or scenes, thermal imaging technology can provide valuable information about temperature distribution and heat transfer.

In biomedical research[59][60], thermal imaging is widely utilized for thermal physiology studies of organisms and medical diagnostics.

In the realm of building construction[61][62], thermal imaging can help detect thermal losses in buildings, thus providing recommendations for energy-saving improvements.

Recently, the application of thermal imaging technology in the field of autonomous vehicles has gained significant attention[63]–[65]. Traditional visual-based systems may have reduced visibility at night, but thermal imaging technology

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can detect the thermal radiation of objects, unaffected by lighting conditions. The extensive research and successful implementation of thermal imaging technology in the autonomous vehicle domain have led us to believe in its potential for providing stability and precision in object detection, including vehicles and pedestrians.

2.6 Research gap and summery

Currently, there is a lack of a reliable method to differentiate between a traditional internal combustion engine vehicle and an EV with absolute certainty. While there are certain visual cues and characteristics that can be indicative, such as the license plate or engine noise for internal combustion engine vehicles, these methods are not foolproof. In some cases, EVs designed to resemble traditional vehicles may exhibit similar visual features. Therefore, additional measures and technologies may be required to accurately and reliably distinguish between these types of vehicles. We believe that thermal imaging technology has the potential for significant breakthroughs in this field. EVs typically have lower heat emissions from the engine compartment compared to traditional vehicles[56]. By utilizing advanced image processing algorithms and machine learning techniques, thermal imaging technology can potentially analyze the thermal patterns and characteristics specific to electric vehicles, enabling more accurate and reliable identification.

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In addition, the review of pollution aspects highlights the importance of measuring the pollution caused by vehicles. Many researchers approach this issue from multiple approach, including laboratory measurements, roadside monitoring, pollution model simulations, on-board measurements, and more. However, when it comes to the pollution generated by EVs, the research is mainly limited to laboratory measurements and pollution model simulations. This limitation can be attributed to the relatively low proportion of EVs in the real world.

Taiwan's unique development of motorcycles has resulted in a higher number of motorcycles compared to cars, and the proportion of electric motorcycles is also significant. We aim to utilize real-world roadside measurement data to validate the findings of other studies regarding pollution from EVs. This approach will contribute to a better understanding of the environmental impact of EVs and provide valuable insights for future research and policymaking.

3 Methodology

In this chapter, we will provide an overview of the methodology employed in this study. The chapter comprises six parts. We first discussed the techniques and procedures utilized for collecting traffic data. In subsection one we delve into the application of transfer learning techniques using YOLOv7 and the FLIR dataset. And soon on, we present the methodology for vehicle counting, specifically focusing on

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categorizing vehicles using the StrongSORT algorithm. Second, we outline the procedures and methodologies employed for data collection. Finally, we explain the analytical framework used to determine the pollution emission contributions by different vehicle types.

3.1 Traffic data collection

In this chapter, we will present our methodology for collecting traffic data. Our approach involves utilizing transfer learning techniques to leverage an existing open dataset, followed by training our own object detection model using the collected data.

3.1.1 Transfer learning with YOLOv7 and FLIR dataset

We employ the latest YOLO version, YOLOv7[66], as our object detection model. YOLOv7 is an advanced version that builds upon previous iterations and incorporates improvements in terms of accuracy and speed. To train our YOLOv7 model, we utilize a large-scale and well-annotated dataset. Specifically, we leverage the MS COCO[67] (Microsoft Common Objects in Context) dataset, which is a widely used benchmark dataset for object detection tasks. MS COCO consists of a diverse range of images with over 80 object categories, making it suitable for training

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a robust and versatile object detection model.

This model is good at general object detection in regular video, which refers to visible light video. However, when it comes to using thermal imagery, the performance of such a model is bound to be significantly affected. Fortunately, FLIR[68] provides a comprehensive annotated thermal dataset that we can utilize. A total of 26,442 fully annotated frames with 520,000 bounding box annotations across 15 different object categories are provided. After transfer learning process, our model can easily classify vehicle into different categories under thermal image. Due to the lack of specific labels for EVs and EMs in the dataset, they are not distinguished as EVs and EMs. Instead, EVs are categorized under "car," while EMs are categorized under "motor." This labeling limitation is a result of the MS COCO and FLIR thermal dataset not providing distinct labels for EVs and EMs. We will solve this problem in the next chapter.

Transfer learning is a machine learning technique where knowledge gained from training a model on one task is applied to a different but related task. The idea behind transfer learning is that the features learned by a model on a large and general dataset can be useful for solving other related problems. Transfer learning is particularly beneficial when the new task has limited training data or when training from scratch would be computationally expensive or time-consuming. Compared to the MS COCO

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dataset, the FLIR dataset is relatively smaller in terms of data volume. This poses a challenge for complex tasks like object detection. However, utilizing transfer learning is indeed a good approach in such cases.

3.1.2 EV and EM classifier construction

Once we have collected data using our thermal imaging device on the road and labeled the EVs and EMs accordingly. After we gather a sufficient amount of data. We can utilize transfer learning once again in our model training process. Indeed, considering that the dataset we collected is relatively smaller compared to the FLIR dataset and that our task shares similarities with the previous objective, transfer learning is an ideal approach. Which allows us reduce our workload while maintaining or even improving the model's performance. This is especially advantageous when working with limited data, as it allows us to make efficient use of available resources and achieve better results.

3.1.3 Vehicle counting by categories by StrongSORT

We applied StrongSORT[69] as our vehicle counting system. StrongSORT is a improvement method of DeepSORT[70] . The DeepSORT method operates based on

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the following principle: it starts by predicting the trajectory of the current frame using the trajectory obtained from the Kalman filtering algorithm[71] and Hungarian Algorithm[72]. It then determines whether to confirm the predicted trajectory. Next, it detects objects in the current frame and correlates the detected objects with the predicted trajectory. The algorithm updates the trajectory after the correlation process is completed. This process continues by predicting the trajectory for the next frame, observing the actual detection results, and updating the trajectory accordingly. This cycle repeats for subsequent frames. If a track fails to match with any detected object, it will be deleted from the tracking list if it exceeds the maximum age threshold. On the other hand, if a detection result does not match any existing track, a new track is created, and the prediction process continues using the Kalman filtering algorithm.

3.2 Data collection

Based on the previous chapters, the vehicle counting system provides us with classified traffic flow data, including the following categories: Bus, truck, car, EV, motor, and EM. In this context, "car" refers to all vehicles, excluding EVs. "Motor" refers to all motorcycles, excluding EMs. Moreover, EV_{ratio} (Electric Vehicle ratio), EM_{ratio} (Electric Motorcycle ratio), $Motor_{ratio}$ (Motorcycle ratio), and $Electrify_{ratio}$ (Electrify vehicle ratio) are also included. Those additional variables are calculated by

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Equation (3- 1)(3- 2)(3- 3)(3- 4). The reason for creating these variables is because I believe that the proportion of vehicles may also impact the results. Additionally, the total number of vehicles on a road is limited, so the proportion is likely to vary. The reason for not including variables for buses and trucks is because our main focus is to differentiate between EVs and EMs in terms of emissions.

$$\mathrm{EV}_{\mathrm{ratio}} = \frac{EV}{EV+car} \tag{3- 1}$$

$$\mathrm{EM}_{\mathrm{ratio}} = \frac{EM}{EM+motor} \tag{3- 2}$$

$$\mathrm{Motor}_{\mathrm{ratio}} = \frac{EM+Motor}{EV+car+EM+Motor} \tag{3- 3}$$

$$\mathrm{Electrify}_{\mathrm{ratio}} = \frac{EV+EM}{EV+car+EM+Motor} \tag{3- 4}$$

In addition to the traffic flow data, Coarse Particle Number (CPN) concentration, mass concentration of PM1, CH4, NMHC, CO, CO_2, NO, NOx are the pollution data used to analyze in this study. PM1.0 is the PM with diameter smaller than 1 μm. CPN is the particle number measured by Aerodynamic Particle Sizer (APS). NMHC stands for Non-Methane Hydrocarbons. It refers to a group of organic compounds that contain carbon (C) and hydrogen (H) atoms but do not include methane (CH4). Besides, ambient temperature (T), relative humidity (RH), wind speed (WS), wind direction

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(WD), and Barometric Pressure (P) were also recorded because of the sensitivity of ambient concentration to meteorological conditions. Table 3- 1 shows the time resolution, the unit, and the used instrument of collected data.

Table 3- 1 Measurement Time Resolution and Unit

	Time Resolution(sec)	Unit	Instrument
CPN	120	$\#/cm^3$	Aerodynamic Particle Sizer (APS; TSI, 3321)
$PM_{1.0}$	360	μg/m3	Tapered Element Oscillating Microbalance (TEOM) with Filter Dynamics Measurement System (FDMS) Monitor (Thermo Fisher Scientific, TEOM 1405-f)
CH4	60	ppb	Horiba apha-360
NMHC	60	ppb	
CO	60	ppm	Ecotech EC9830
CO_2	60	ppm	PICARRO G3101
NO	60	ppm	Ecotech serinus 40
NOx	60	ppm	
Vehicle counts	360	Veh/6min	Optris Xi400 thermal camera
T	60	˚C	Smart Air Temperature and Relative Humidity Sensor (AMES, TPR159S)
RH	60	%	
WS	60	m/sec	Wind Speed and Direction Sensor (AMES, VMT107C)
WD	60	degree	
P	60	mbars	Smart Air Temperature and Relative Humidity Sensor (AMES, TPR159S)

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3.3 Analysis of Pollution Emission Contributions by Vehicle Types

Multilinear regression analysis is a common method used in air pollution analysis to compare the importance of different features to the objective value[73][74]. We employed this method to actualize our emission analysis. First, we identify the contribution of EM and EV by comparing the importance of different features. The multilinear regression model is shown in Equation (3- 5) .

$$Y_p = \sum_i \beta_i \cdot x_{p,i} + \beta_0 \tag{3- 5}$$

Where Y_p is the ambient concentration of the pollutant P, while $x_{p,i}$ and β_1 is the contribution factor and coefficient of the feature i, and β_0 is the bias term. “Exhaustive Feature Selector method” is adopted to find significant features. Exhaustive Feature Selector method, also known as exhaustive search, is an infrequently used approach not because of its poor performance, but rather due to its high computational time complexity. The time complexity of this method is 2^n, where n represents the number of variables. Fortunately, in our case, we only have 14 variables, which leads to a relatively short computation time. This allows us to find the optimal solution based on the criterion of model R-squared.

Furthermore, to emphasize the investigation of the impact of traffic flow, we

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attempted to replace the weather variables in the obtained optimal solution with highly correlated traffic flow variables. For example, we replaced temperature (T) with the traffic flow variables Car (correlation coefficient: 0.82) or Motor_ratio (correlation coefficient: -0.88). The decision to replace variables was based on the changes in R-squared and the p-values of the newly added variables. Because the confidence level of statistically significance was set at 95%. In other words, the features with P-Value smaller than 0.05 were considered as significant.

Due to the difference in the time resolution of different data sources as shown in Table 3- 1, we pre-processed the data into six-minute averages as [57] suggested.

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4 Result

In this chapter, we present the results obtained from our study. First, we describe the process of constructing the models used in our study. Second, we evaluate and validate the performance of the trace and vehicle counting models developed. The last section focuses on the analysis of pollution emission contributions by different vehicle types.

4.1 Model construction

For EM and EV classifier training tasks, samples images are needed. An Optris[75] Xi400 Infrared (IR) camera is used for thermal video recording as Figure 4- 1. The 80 Hz frame rate allows for the monitoring of fast thermal processes, even including a line-scan function. The spot finder IR camera has an optical resolution of 382 x 288 pixels and comes with an extensive ready-to-use package including a versatile image processing software.

Figure 4- 1 IR camera Xi 400

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Based on the results of [56], we collected front-view photos of vehicles focusing on the different engine heat signatures. However, the performance was not as expected, and there were significant instances where vehicles were misclassified as EVs. We speculate that the following reasons may have contributed to this issue:

(1) Newness of the vehicle

We observed that the engine of the old-generation car heats up very obviously, compared to the new-generation car which does not heat up significantly. It can be attributed to the advancement of vehicle manufacturing process, aerodynamic design and engine technology. The vehicle's ability to dissipate heat has been emphasized and the efficiency of the engine has been improved. The advancement of car body materials and aerodynamic design may also be the reasons. Figure 4- 2 shown the different of two kind of car, the left rectangle one is hot and old while right rectangle one is cold and new respectively.

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Figure 4- 2 Example of Thermal image of New car and Old car

(2) Vehicle operating conditions

We observed that vehicles exit the highway exhibit less noticeable heat, whereas vehicles operating at low speeds, such as those in parking lots or idling by the roadside exhibit more pronounced heat signatures. This can be attributed to the fact that the primary cooling mechanism of vehicles is air cooling generated by the airflow. Higher speeds indicate better cooling efficiency as the airflow increases. On the other hand, stationary vehicles have poorer cooling efficiency due to the lack of airflow. Figure 4-3 shown that all the cars are cold but only the right car is an EV.

Figure 4- 3 Example of Thermal Image of Vehicle operating condition

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(3) Cold car

We observed that the heat generation of cold started vehicles is not significant. The engine temperature in this case follows a linear increase over time. Cold car might be observed near the parking lot and resident neighborhood due to the long-term parking. Cold-started vehicles are also a major contributor to pollution[76][77]. Figure 4- 4 shown a cold car, while its tire also didn't heat up by the friction to the ground. We can speculate that this vehicle has recently been started or is in the early stages of operation.

Figure 4- 4 Example of Thermal Image of Cold Car

These factors pose significant challenges in accurately determining engine temperature. It makes the judgment of engine temperature not as simple as "hot" or "cold". This means conventional vehicles may not exhibit clear thermal characteristics due to those factors. Also, EVs may experience overheating due to factors like solar.

After numerous attempts, we have identified a thermal feature that allows us to make more accurate judgments, namely the exhaust pipe. We found that the temperature of the exhaust pipe exhibits clear thermal characteristics within the first 20

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seconds after starting the vehicle. Additionally, there are no restrictions imposed by car manufacturers on this aspect, as the purpose of the exhaust pipe is to dissipate waste heat. Any impact on the efficiency of the exhaust pipe would only result in reduced vehicle efficiency. Figure 4- 5 Figure 4- 6 shown the example of EVs and Cars in the rear view.

Figure 4- 5 Example of Thermal Image of EV

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Figure 4- 6 Example of Thermal Image of Car

For EMs, we have also adopted the same strategy. Since EMs do not have an exhaust pipe, we can easily classify them based on their thermal characteristics as either hot or not hot. Figure 4- 7 Figure 4- 8 shown the example of EMs and Motor in the rear view.

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Figure 4- 7 Example of Thermal Image of EM

Figure 4- 8 Example of Thermal Image of Motor

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From this point on, our model's objective is defined as classifying EVs and EMs from the thermal imaging vehicle flow observed from the rear. Thus, we collected EM and EV image around the campus of National Taiwan University. We have prepared 1431images with EMs and 2003 images with EVs. In order to provide more details, the images include both front-view and rear-view perspectives. Details of samples are shown in Table 4- 1Table 4- 2Figure 4- 5Figure 4- 6 Figure 4- 7 Figure 4- 8.

Table 4- 1 Training data detail of EV and Car

Type	EV		Car	
Total Images#	2003			
Labels#	1872		7943	
View	Front	Rear	Front	Rear
Images#	1490	513	1490	513

Table 4- 2 Training data detail of EM Motor

Type	EM		Motor	
Images#	1431			
Labels#	923		8547	
View	Front	Rear	Front	Rear
Vehicles#	408	1023	408	1023

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4.2 Trace model and vehicle counting model Performance Evaluation and Validation

In this chapter, we aim to validate the performance of the model in classifying vehicles in a traffic flow. For this purpose, we selected a specific scene and recorded the traffic flow, and the ground truth of vehicles in the flow was manually calculated by human observers.

In order to minimize the issue of vehicles obstructing each other, we chose to observe the traffic flow from a pedestrian overpass near campus which located at No. 92, Sec. 4, Roosevelt Rd., Taipei City, Taiwan, as Figure 4- 9 shown.

Figure 4- 9 Site for Model evaluation

We collected data for two different time periods, namely from 15:30 to 16:30 in the afternoon on June 2, 2023 and from 20:50 to 21:30 in the evening on June 6, 2023. The chosen time periods include both the afternoon and evening to showcase the

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performance of the model during both daytime and nighttime conditions. The result is shown at Table 4- 3 Table 4- 4

Table 4- 3 Result of model evaluation on June 2

	bus	car	EM	EV	motor	truck
Ground truth	101	891	98	10	1103	75
Model	87	895	102	7	1095	77
Model/Ground truth	0.86	1.01	1.04	0.7	0.99	1.03

Table 4- 4 Result of model evaluation on June 6

	bus	car	EM	EV	motor	truck
Ground truth	74	478	136	7	1070	16
Model	80	482	132	5	1066	14
Model/ground truth	1.08	1.01	0.97	0.71	0.99	0.88

Moreover, this model performance evaluation also applied to our on-road site data. We selected Sec. 3, Keelung Rd., Taipei City, Taiwan as our on-road measurement location. Figure 4- 10 shown the site.

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Figure 4- 10 Site for Pollution Emission

We collected data for two different time periods, namely from 22:20 to 23:20 in the evening on June 7, 2023, and from 15:30 to 16:30 in the afternoon on June 13, 2023.

shown the result.

Table 4- 5 Result of model evaluation on June 7

	bus	car	EM	EV	motor	truck
Ground truth	42	401	175	13	1843	17
Model	44	414	173	13	1847	14
Model/ground truth	0.96	0.97	1.01	1	0.99	1.21

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4.3 Analysis of Pollution Emission Contributions by Vehicle Types

Multilinear regression was applied in this section. Feature selection was also applied. Figure 4- 11 Figure 4- 12 shows the results. The symbol '- 'in the Table indicates that this variable is not significant, and the lower the value of the P-value, the more significant it is considered. These pollutants can be broadly categorized into two types.

(1) Particles Pollutants

Particles pollutants, such as CPN and PM_1, are also considered non-exhaust emissions. Non-exhaust emissions (e.g., brake, tire wear) may become the main source of PM on the road. Also, these pollutants are influenced by the power generation methods. Research [10] shown that vehicles powered by clean energy sources can significantly reduce particles emissions. On the other hand, the greater the proportion of coal in the generation mix, the more negative impacts EVs may have on air quality. However, we expected that EM and EV should have significant to these pollutants as the previous research indicated. The variables Car, T and RH are significant to CPN. The variables Bus, Car, Motor, T, RH and P are significant to PM_1.

(2) Gaseous Pollutants

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Gaseous pollutants include NOx, NO, O^3, CO, CO_2, NMHC and CH4. We expected that EM and EV should have no significant to these pollutants. Because these pollutants were generated by burning gasoline in the engine which EM and EV don't have. But not all of them are so sensitive to the vehicle. For example, O^3 is formed through the reaction of compounds in the air with sunlight and heat. Although some of these compounds may be emitted by vehicles, the influence of temperature and heat cannot be disregarded. This is consistent with the fact that O^3 concentration tends to be highest around 14:00 to 16:00, when sunlight is strongest and temperatures are highest. The variables Motor, WS, T, EM_ratio and Motor_ratio are significant to NOx. The variables Car, EV, Motor, WS, T, EM_ratio, Motor_ratio and Electrify_ratio are significant to NO. The variables T and RH are significant to O^3. The variables Bus, Car and Motor are significant to CO. The variables EM, Motor, P and EM_ratio are significant to CO_2. The variables EV, Motor, EM_ratio and Electrify_ratio are significant to NMHC. The variables EM, Motor, Truck and P are significant to CH4.

From the traffic flow variables perspective, EM is significant to CO_2 and CH4, EV is significant to NO and NMHC. Car is significant to NOx, NMHC. Motor is significant to NO, PM_1. Bus is significant to CO and PM_1. Truck is significant to CH4. EV_ratio doesn't show any significant. EM_ratio is significant to NOx, NO, CO_2 and NMHC. Motor_ratio is significant to NOx and NO. Electrify_ratio is significant to NO and

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NMHC.

	NOx		NO		O^3		CO		CO_2	
	coef	P-value	coef	P-value	coef	P-value	coef	P-value	coef	P-value
Bus	-	-	-	-	-	-	-0.031	0.05	-	-
Car	-	-	-0.194	0.026	-	-	-0.005	0.039	-	-
EM	-	-	-	-	-	-	-	-	-3.189	0.016
EV	-	-	-3.23	0.029	-	-	-	-	-	-
Motor	0.060	0.045	0.138	0.001	-	-	0.004	0.002	0.344	0.002
Truck	-	-	-	-	-	-	-	-	-	-
WS	-11.0585	0.005	-5.429	0.014	-	-	-	-	-	-
T	16.34	0.002	2.88	0.05	-22.018	0.005	-	-	-	-
RH	-	-	-	-	-4.03	0.006	-	-	-	-
P	-	-	-	-	-	-	-	-	5.653	0.0001
EV_ratio	-	-	-	-	-	-	-	-	-	-
EM_ratio	-541.44	0.048	-543.943	0.025	-	-	-	-	1113.54	0.005
Motor_ratio	689.96	0.045	-101.408	0.018	-	-	-	-	-	-
Electrify_ratio	-	-	816.55	0.015	-	-	-	-	-	-
Adj R-squared	0.661		0.888		0.953		0.834		0.97	

Figure 4- 11 Result of analysis of Pollution Emission of NOx, NO, O^3, CO, CO_2

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	NMHC		CH4		PM_1		CPN	
	coef	P-value	coef	P-value	coef	P-value	coef	P-value
Bus	-	-	-	-	-0.058	0.01	-	-
Car	-	-	-	-	-0.018	0.014	-0.041	0.003
EM	-	-	0.006	0.021	-	-	-	-
EV	0.041	0.002	-	-	-	-	-	-
Motor	0.001	0.045	-0.001	0.001	0.004	0.01	-	-
Truck	-	-	0.007	0.001	-	-	-	-
WS	-	-	-	-	-	-	-	-
T	-	-	-	-	1.382	0.003	2.939	0.003
RH	-	-	-	-	0.62	0.0001	1.167	0.0001
P	-	-	-0.031	0.0001	-1.03	0.0001	-	-
EV_ratio	-	-	-	-	-	-	-	-
EM_ratio	3.72	0.01	-	-	-	-	-	-
Motor_ratio	-	-	-	-	-	-	-	-
Electrify_ratio	-5.938	0.001	-	-	-	-	-	-
Adj R-squared	0.551		0.988		0.971		0.997	

Figure 4- 12 Result of analysis of Pollution Emission of NMHC, CH4, PM_1, CPN

5 Conclusion

In this chapter, we first summarize our finding regarding to our study. Second, we listed the limitations to our study. Final is our future work.

5.1 Contribution

In this section, we summarize the results regarding our objective, which can be divided into the following categories: EV and EM classifier, analysis of Pollution Emission Contributions by Vehicle Types

5.1.1 EV and EM classifier

Based on our validation of the model's performance, we can conclude that thermal

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imaging demonstrates excellent object recognition capabilities. We have proposed a classification method based on thermal features to differentiate between EM and EV, which are often difficult to distinguish on the road. Although the recognition of EVs is not yet perfect, we attribute this to the limited number of EV fleets in Taiwan, and primarily concentrated on a single vehicle brand, Tesla which cause our training data lack of variety of EV. This limitation results in some uncertainty when encountering EVs from other manufacturers. However, in our model performance test, the performance of EM and EV are 100.7% and 87%. The performance of bus, car, motor, truck are 91.7%, 101.3%, 99.9% and 98.9%, respectively. Our model still shows it's great ability to distinguish EVs and EMs from traffic flow. The performance here means the total vehicle count by model divided by the real-world vehicle count. That is not the meaning of "accuracy" or "precision" in statistic.

With the increasing trend of EVs in the future, the growing presence of EVs on the roads may allow for the collection of a more comprehensive training dataset, thereby enhancing the performance of the model. The insights derived from this research could potentially offer valuable references for future researchers.

5.1.2 Analysis of Pollution Emission Contributions

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by Vehicle Types

In analysis of pollution emission, we mainly focus on the impact causes by EVs and EMs. For those gaseous pollutants, EM and EV shows no significant to NOx, O^3, CO, which meets our expectations. The increase or decrease in the number of electric vehicles will not affect any of them. Electric Vehicle did not emit any of them on the road. However, EV is significant to NO and NMHC, EM is significant to CO_2 and NMHC, which is out of our expectation. But our own created variables, such as EM_ratio, Motor_ratio, and Electrify_ratio, have shown significant associations with these four pollutants. We speculate that the reason behind this is due to the limited capacity of the road. As the number of EVs and EMs increases, it reducing the number of Car and Motor. This can be inferred from the contributions of Electrify_ratio and EM_ratio. Similarly, Car and Motor can also compete with each other, resulting in the contribution of Motor_ratio.

For Particles Pollutants, both EM and EV shows insignificant to CPN and PM_1. Our own created variables also show insignificant to CPN and PM_1. However, temperature and humidity show a significant correlation. We speculate that Particles pollutants may be more influenced by weather conditions, making the impact of vehicle emissions less evident and difficult to capture accurately. This hypothesis could be

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addressed with further data collection.

In conclusion, despite the relatively small dataset, we were able to deduce conclusions similar to those found in the literature. Our results confirm the pollution variations caused by electric vehicles.

5.2 Limitation

Due to the low resolution of the thermal camera, there are often misjudgments in recognizing vehicles in the video due to external interference at each frame. Fortunately, the StrongSORT algorithm can address such issues. However, we have also observed that it has significant difficulties in correctly identifying stationary vehicles. Therefore, the application of our research work should not be used in areas where there are stationary vehicles, for example, in front of traffic lights. This limitation is due to the insufficient recognition capabilities of the model. Also, we found that weather condition and low temperature cause blur in each frame. We speculate that replacing the thermal imaging camera with a higher quality one can solve this problem.

5.3 Future work

We have observed that electric buses also exhibit similar thermal characteristics,

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with their engines and exhaust pipes positioned at the rear of the vehicle, making it a potential distinguishing feature for classification. Although this study did not consider electric buses due to their absence at the study location, future research could aim to develop a tool capable of identifying all types of vehicles on the road. Such a tool could provide valuable data for the development of smart cities and their transportation systems.

For the emission analysis part, We should collect more information to prove our inference.

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