POLITEKNIK UNGKU OMAR

ARTIFICIAL INTELLIGENCE IN VEHICLE COUNTING AND CLASSIFICATION (AI-VEC) FOR TRAFFIC DATA COLLECTION

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(01BCT21F3006)

CIVIL ENGINEERING DEPARTMENT

SESSION II 2023/2024

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A project report submitted in partial fulfilment of the requirements for the award of the Bachelor's of Civil Engineering Technology with Honours.

CIVIL ENGINEERING DEPARTMENT

SESSION II 2023/2024

DECLARATION OF ORIGINAL AND OWNERSHIP

TITLE: ARTIFICIAL INTELLIGENCE IN VEHICLE COUNTING AND CLASSIFICATION (AI-VEC) FOR TRAFFIC DATA COLLECTION

SESSION: SESSION II 2023/2024

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In front of me, DR. AZUIN BINTI RAMLI	) ………………………
as project supervisor on date:	)

APPRECIATION

In the name of Allah SWT, most gracious, most merciful, peace and blessing be upon prophet Muhammad SAW, his family and his friend selected. Firstly, I want to offer my deepest gratitude must be towards Allah because of His grace and His guidance; I am able to complete this “Artificial Intelligence In Vehicle Counting And Classification (AI-VEC) For Traffic Data Collection” report.

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ABSTRACT

Traffic data collection plays a crucial role in transportation planning and management, yet traditional methods often suffer from limitations in accuracy, efficiency, and scalability. This study addresses these challenges by developing an innovative approach that harnesses the power of artificial intelligence (AI) for vehicle counting. The main objectives of this research are to identify the limitations of existing traffic data collection methods, develop an AI-based software solution, and evaluate its performance in enhancing traffic data collection. Through a comprehensive review of literature and analysis of current methodologies, this study identifies common shortcomings such as manual counting errors and reliance on stationary sensors. To address these issues, an AI-based software solution using OpenCV-Python is developed, utilizing deep learning algorithms for automated vehicle counting in recorded traffic video. An evaluation is conducted based on responses gathered through qualitative research administered to users to evaluate the performance of the AI software. The findings of this research underscore the transformative potential of AI in optimizing traffic data collection processes, offering a reliable and scalable solution for transportation planners and urban developers. An accuracy test comparing manual counts with AI-VEC results demonstrated a high level of precision, with minor discrepancies primarily in light vehicle counts. The study concludes with recommendations for further research and implementation, emphasizing the importance of continued exploration and refinement of AI-based approaches in traffic data collection.

ABSTRAK

Pengumpulan data trafik memainkan peranan penting dalam perancangan dan pengurusan pengangkutan, namun kaedah tradisional sering mengalami kekurangan dari segi ketepatan, kecekapan, dan kebolehkembangan. Kajian ini menangani cabaran-cabaran ini dengan membangunkan pendekatan inovatif yang memanfaatkan kuasa kecerdasan buatan (AI) untuk pengiraan kenderaan. Objektif utama penyelidikan ini adalah untuk mengenal pasti kekurangan kaedah pengumpulan data trafik sedia ada, membangunkan penyelesaian perisian berasaskan AI, dan menilai prestasinya dalam meningkatkan pengumpulan data trafik. Melalui tinjauan menyeluruh terhadap literatur dan analisis metodologi semasa, kajian ini mengenal pasti kelemahan biasa seperti kesilapan pengiraan manual dan kebergantungan pada sensor pegun. Untuk mengatasi masalah ini, penyelesaian perisian berasaskan AI menggunakan OpenCV-Python dibangunkan, dengan menggunakan algoritma pembelajaran mendalam untuk pengiraan kenderaan secara automatik dalam video trafik yang direkodkan. Penilaian dilakukan berdasarkan respons yang dikumpulkan melalui penyelidikan kualitatif yang diberikan kepada pengguna untuk menilai prestasi perisian AI tersebut. Penemuan kajian ini menekankan potensi transformasi AI dalam mengoptimumkan proses pengumpulan data trafik, menawarkan penyelesaian yang boleh dipercayai dan berskala untuk perancang pengangkutan dan pemaju bandar. Ujian ketepatan yang membandingkan pengiraan manual dengan keputusan AI-VEC menunjukkan tahap ketepatan yang tinggi, dengan perbezaan kecil terutamanya dalam pengiraan kenderaan ringan. Kajian ini diakhiri dengan cadangan untuk penyelidikan dan pelaksanaan lanjut, menekankan kepentingan penerokaan berterusan dan penambahbaikan pendekatan berasaskan AI dalam pengumpulan data trafik.

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LIST OF ABBREVIATION

IR 4.0	Industrial Revolution 4.0
AI	Artificial Intelligent
CNN	Convolutional Neural Network
ML	Machine Learning
VSCode	Visual Studio Code
OpenCV	Open Computer Vision
AI-VEC	Articial Intelligent in Vehicle Counting and Classification

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

In today's fast-paced world, traffic congestion has become a widespread issue affecting urban areas and highways alike. The increasing number of vehicles on the road, coupled with inadequate infrastructure and urban planning, has led to severe traffic congestion in many cities (Sun et al., 2021). This congestion not only results in wasted time and fuel for commuters but also contributes to air pollution and overall decreased quality of life. As a result, there is a growing need for innovative solutions to alleviate traffic congestion and improve mobility for all road users (Afrin & Yodo, 2020). Traffic engineers are working tirelessly to tackle this issue by implementing advanced technologies and innovative strategies. The goal is to find sustainable solutions that can effectively reduce congestion, improve traffic flow, and enhance the overall transportation system. With the integration of machine learning and data analysis, traffic engineers are leveraging insights to optimize traffic signal timings, develop dynamic routing algorithms, and implement intelligent transportation systems (Kumar & Raubal, 2021). These efforts are aimed at creating safer, more efficient, and environmentally friendly transportation networks for urban communities and highways. Through ongoing research and collaboration, traffic engineers are committed to shaping the future of transportation and addressing the challenges posed by growing urbanization and increasing vehicle populations (Han & Zhang, 2021).

Traffic engineering is a crucial field that encompasses the design and management of traffic systems to ensure efficient and safe transportation of people and goods. It plays a vital role in urban and rural settings, aiming to optimize the flow of traffic while minimizing congestion and improving safety (Zhou, 2021). The evolution of traffic engineering has been driven by advancements in technology, urbanization, and the increasing complexity of transportation networks. As such, the importance of traffic engineering in modern society cannot be overstated. Traffic engineering is a multifaceted discipline that draws from various fields such as civil engineering, urban planning, and transportation management. One of the key aspects of traffic engineering is the use of advanced technologies, including intelligent transportation systems, traffic simulation models, and real-time traffic monitoring. These technologies allow traffic engineers to analyze and optimize traffic flow, manage intersections, and implement adaptive traffic signal control systems (Sarrab et al., 2020).

Traffic engineering involves a range of tasks and responsibilities aimed at ensuring the smooth and safe movement of vehicles and pedestrians. One of the main tasks is to analyze traffic patterns and volumes to identify areas of congestion and potential safety hazards. This involves collecting and analyzing data from various sources such as traffic cameras, sensors, and historical records. Once data has been collected and analyzed, traffic engineers use this information to design and implement traffic management solutions. This can include the design of road networks, traffic signal timings, and signage to improve traffic flow and reduce congestion. Additionally, they develop and implement transportation policies and regulations to ensure the safe and efficient use of transportation infrastructure (Saha, 2019).

In recent years, technology has significantly influenced the field of traffic engineering. Advanced tools such as machine learning algorithms and predictive analytics are now being employed to forecast traffic patterns and optimize traffic flow (Boukerche & Wang, 2020). Machine learning models can analyze large volumes of historical traffic data to identify trends and make accurate predictions about future traffic conditions. This allows traffic engineers to proactively implement solutions to alleviate congestion and improve traffic management.

Furthermore, real-time traffic monitoring systems, including advanced sensors and cameras, have revolutionized the way traffic engineers collect and analyze data. These systems provide up-to-the-minute information on traffic conditions, allowing for immediate responses to incidents and congestion. Additionally, the integration of traffic simulation models into the design process enables engineers to evaluate the impact of new infrastructure projects or traffic management strategies before they are implemented, ensuring their effectiveness and safety (K, 2019). The use of technology in traffic engineering work continues to evolve, with the integration of connected vehicle technologies, smart traffic lights, and autonomous vehicles on the horizon.

These advancements hold the potential to further enhance the efficiency and safety of transportation systems, showcasing the critical role of technology in shaping the future of traffic engineering (Shubho et al., 2021).

Therefore, this project will focus on implementing Artificial Intelligence (AI) in traffic data collection through historical video recordings. AI, also known for its advanced real-time object detection capabilities, is renowned for its speed and accuracy. By incorporating AI into traffic data collection, the efficiency and accuracy of vehicle counting and detecting vehicle movements will be significantly improved. The use of AI will enable the processing of historical video data to identify and track vehicles with high precision. This will provide valuable insights into traffic flow, congestion hotspots, and safety concerns, empowering traffic engineers to make data-driven decisions for optimizing road networks and traffic management systems (Dewantoro et al., 2020).

1.2 PROBLEM STATEMENT

Traditional data collection methods used in traffic engineering work, such as traffic surveys and traffic impact assessments, often involve manual data collection techniques that are time-consuming, labor-intensive, and prone to errors. These methods typically rely on human observers manually recording vehicle counts, speed, movement patterns at various intersections and road segments (Paľo et al., 2019). This manual approach to data collection can lead to inconsistencies in data accuracy and reliability, making it challenging for traffic engineers to make informed decisions regarding road network optimization and traffic management strategies.

Firstly, traditional traffic data collection methods are notorious for their time-consuming nature. These techniques require human observers to be stationed at various points along roads or intersections for extended periods. This time commitment is not only demanding on the personnel but also necessitates meticulous planning and scheduling to ensure comprehensive coverage of data collection points. In practice, this means allocating resources, defining shifts, and ensuring that data is collected continuously over days, weeks, or even months (Aljamal et al., 2020). Consequently, the time constraints associated with manual data collection can limit the frequency at which data can be gathered, potentially overlooking crucial short-term fluctuations in traffic conditions. Additionally, the time investment may not align with the need for real-time data analysis and immediate traffic management responses (Mai-Tan et al., 2020).

Furthermore, the labour-intensive nature of manual data collection is another significant challenge. To execute these methods, traffic engineers often need to recruit and train field staff specifically for data collection purposes. This recruitment process involves searching for suitable candidates, conducting training sessions, and managing personnel schedules. Moreover, it entails the provision of equipment and tools necessary for data recording. This extensive human resource management and equipment procurement add to the overall operational expenses of traffic data collection efforts. Furthermore, the physical presence of observers on roadways can disrupt traffic flow, especially in congested urban areas, potentially leading to skewed data or safety hazards (Wardrop et. al., 2023)

Moreover, human observers who are responsible for recording vehicle counts, speed measurements, and movement patterns are susceptible to various sources of errors. Factors such as observer fatigue, distraction, or subjectivity can introduce inaccuracies in the collected data. Fatigue, especially during extended data collection periods, can cause lapses in attention and data recording, leading to gaps or inconsistencies in the dataset. Distractions, such as adverse weather conditions or unexpected events, can divert an observer's focus from the task at hand, further compromising data accuracy (Johnstone et al., 2018). Additionally, the subjectivity of human judgment can result in variations in data collection methodologies among different observers, potentially introducing bias or inconsistencies in the dataset. These errors can hinder the reliability and integrity of the collected traffic data, making it challenging to draw precise conclusions or implement effective traffic management strategies based on such data (Alsanabani et al., 2020).

To address these challenges and optimize traffic data collection, the implementation of machine learning techniques presents a promising solution. By leveraging the capabilities of Artificial Intelligent (AI), a state-of-the-art object detection system, we can revolutionize the process of traffic data collection and analysis. This advanced approach will not only enhance the efficiency and accuracy of vehicle counting and movement detection but also address the time-consuming, labor-intensive, and error-prone nature of manual data collection techniques.

1.3 OBJECTIVE

The main aim of this project is to develop a user-friendly software that focus for traffic data collection, specifically catering to the design phase of construction within the field of Traffic Engineering. The goal is to provide the company with an easily accessible software, emphasizing convenience for workers involved in traffic engineering projects related to roads, data input, and data analysis. This application aims to facilitate anytime, anywhere access, enabling workers to efficiently input, manage, and analyze traffic-related data. The key objectives include creating an intuitive interface, implementing Artificial-Intelligent(AI) for object detection, enabling automated data collection, and supporting offline usage for traffic data analyzing. The software aims to be a valuable tool for enhancing the efficiency of traffic data collection method in Traffic Engineering field by achieving these objectives:

I. To identify the limitations of the existing methods for traffic data collection.

II. To develop an Artificial Intelligent based solution for traffic data collection.

III. To evaluate the effectiveness of software in enhancing traffic data collection method.

1.4 SCOPE OF STUDY

The scope of study for this final year project will took place at the Prima Reka Konsultan office located at Jalan Ampang Baru 6a. This project is focused on four lane two-way roads. 2 road is taken as observation for study purpose. The first road is at Jalan Panglima Bukit Gantang Wahab, Ipoh and the second road is at Jalan Taiping, Kuala Kangsar. Figures below shows scope of study for this project.

Figure 1.1: Prima Reka Konsultan Office

Figure 1.2: Jalan Panglima Bukit Gantang Wahab, Ipoh

Figure 1.3: Jalan Taiping, Kuala Kangsar

1.5 SIGNIFICANT OF STUDY

The company faces significant challenges in managing large-scale projects due to delays in work caused by constraints related to both time and labor. The current method of collecting traffic data relies on manual counting, which contributes to project delays, especially when dealing with extensive projects that demand more time and workforce than available. To address this issue, this final-year project aims to introduce an innovative software that can greatly benefit the company's project management processes. This application boasts a range of features that can be accessed by all workers regardless of their location and the time, enabling them to input data conveniently and efficiently. By doing so, this technology promises to save valuable time and mitigate the risk of project delays.

The significance of this study lies in its potential to revolutionize traffic data collection in traffic engineering projects. By improving the model detection accuracy and inference speed through algorithm improvement, and deploying it to edge computing devices such as on-board cameras or electronic monitoring, the study aims to create a more efficient and accurate system for collecting real-time traffic data. Through developing a user-friendly software that leverages Intelligent Transportation Systems and modern technology, this research endeavour aims to overcome limitations inherent in traditional manual traffic data collection methods. It seeks to enhance the efficiency of traffic engineering practices by providing capabilities for collecting and analyzing data related to traffic conditions. The potential success of this study and subsequent deployment of the software could offer valuable insights for industries looking to transition from manual practices to technology-driven approaches in traffic engineering and construction project management. Ultimately, this effort aims to make significant contributions toward advancing traffic engineering and improving construction project management practices.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION TO TRAFFIC DATA COLLECTION

Traffic data collection is a critical aspect of urban planning and traffic management, providing valuable insights into traffic patterns, congestion levels, and transportation infrastructure utilization. While traditional methods have been essential, they are limited by inefficiencies, errors, and deviations in data collection processes (Liu, 2023). However, technological advancements have led to the development of innovative methods for traffic data collection, including wireless sensor networks (WSN) (Wang et al., 2020), machine learning, the Internet of Things (IoT) (Zantalis et al., 2019), computer vision techniques (Buch et al., 2011), and intelligent transportation systems (Zhou & Feng, 2016).

Accurate traffic data is crucial for urban planners to make informed decisions regarding road network design, traffic flow optimization, and infrastructure development. Advanced data collection methods enable real-time traffic information gathering, essential for improving traffic management strategies and enhancing overall transportation efficiency. Traffic data also helps identify critical road segments for speed prediction and traffic estimation (Ru et al., 2020), as well as assess alternative paths during road disruptions (Pucci et al., 2021).

Furthermore, traffic data is not only valuable for urban planning but also for intelligent transportation systems (ITS). Traffic prediction models based on spatio-temporal data significantly enhance transportation system efficiency (Yuan & Li, 2021). Integrating traffic data with machine learning and artificial intelligence technologies facilitates the development of interactive urban traffic pattern exploration tools, utilizing extensive GPS trajectories for in-depth analysis (Wang et al., 2020).

In conclusion, the collection and analysis of traffic data are fundamental in modern urban planning and traffic management. By utilizing innovative technologies and methodologies for data collection, urban planners and transportation authorities can make data-driven decisions to enhance traffic flow, reduce congestion, and improve urban mobility.

2.2 LIMITATION IN CONVENTIONAL METHOD FOR TRAFFIC DATA COLLECTION

Traffic data collection is an essential aspect of transportation planning and management. In the realm of transportation planning and management, the limitations of conventional traffic data collection methods have long been acknowledged (Yang et al., 2023). While manual traffic counts and loop detectors have provided valuable insights, their inability to capture real-time data has been a significant constraint. This constraint becomes especially apparent when considering the dynamic nature of traffic flow, influenced by various factors such as events and weather conditions (Nasim et al., 2023).

One of the major limitations of conventional traffic data collection methods is the potential for inaccurate data collection. Traditional methods such as manual traffic counts or simple video recording can be prone to human error or limitations in technology, leading to inaccuracies in the data collected. These limitations can include miscounting vehicles, misclassifying vehicle types, or missing certain periods of high traffic volume. This can result in flawed analysis and decision-making, as the collected data does not accurately reflect the true traffic conditions. This also can lead to incomplete and outdated information, hindering the ability to make informed decisions about transportation systems (Qi, 2020).

Conventional methods for traffic data collection have limitations in terms of accuracy, comprehensiveness, and real-time monitoring.These methods rely on manual observations or static sensors, which can result in limited coverage and outdated information . This can lead to incomplete and inaccurate data, hindering the ability to effectively analyze and manage traffic flow. In addition, conventional methods often require significant resources and time to collect data, making them costly and inefficient. Conventional methods for traffic data collection have long been the foundation of transportation planning and management. While these methods have provided valuable insights, they do have limitations that can impede their effectiveness (Nasim et al., 2023).

Moreover, the time and cost-intensive nature of conventional traffic data collection methods can be a significant drawback. Manual traffic counts and labour-intensive processes require significant resources and time, making them costly and inefficient. Not only do these methods require trained personnel to manually collect and analyze data, but they also necessitate the installation and maintenance of physical infrastructure such as loop detectors or pneumatic tubes, which can be expensive to implement and maintain (Song et al., 2019). As a result, the coverage and frequency of data collection may be limited, leading to incomplete or outdated information. Overall, conventional methods for traffic data collection are limited in terms of accuracy, comprehensiveness, real-time monitoring, and cost-effectiveness (Lee et al., 2016).

Therefore, there is a need for alternative methods, such as AI-based traffic management systems, that can overcome these limitations and provide more accurate, comprehensive, and real-time data on traffic conditions. These alternative methods can leverage advanced technologies like artificial intelligence, machine learning, and big data analytics to collect and analyze traffic data in a more efficient and timely manner. This can lead to more accurate traffic flow predictions, better allocation of resources, and improved decision-making for transportation systems (Rinchi et al., 2024).

2.3 EVOLUTION OF MACHINE LEARNING IN TRAFFIC ANALYSIS

The advancement of machine learning in traffic analysis has significantly transformed the field by offering sophisticated tools and methods for processing and interpreting large volumes of traffic data. The history of machine learning applications in traffic data collection demonstrates a shift from traditional methods to more efficient and precise models. Initially, port-based, data packet inspection, and classical machine learning methods were commonly used but encountered challenges with the rise of encrypted traffic and the dynamic nature of internet traffic Rezaei & Liu (2019).

A comparative evaluation of different machine learning models utilized in traffic analysis highlights the diversity and efficacy of these approaches. For example, deep learning principles have been employed to forecast the evolution patterns of congestion in large-scale transportation networks, enabling the implementation of proactive congestion mitigation strategies (Ma et al., 2015). Additionally, machine learning techniques like deep reinforcement learning algorithms have been utilized to enhance the accuracy of network traffic prediction (Balamurugan et al., 2022). Furthermore, the integration of machine learning classifiers based on multilayer perceptrons (MLP) has shown potential in heterogeneous traffic and anomaly detection (Guezzaz et al., 2021).

Moreover, the adoption of federated learning for internet traffic classification has emerged as a decentralized machine learning approach, ensuring data privacy and security while effectively categorizing traffic types (Mun & Lee, 2020). Machine learning algorithms have also played a crucial role in intelligent data analysis within the Internet of Things (IoT) ecosystem, aiding in the development of symmetric applications and managing vast amounts of data generated by IoT devices (Alsharif et al., 2020).

In conclusion, the evolution of machine learning in traffic analysis has greatly enhanced the efficiency and accuracy of traffic data collection and interpretation. By leveraging various machine learning models and techniques, researchers and professionals can derive valuable insights from traffic data, forecast congestion patterns, improve network traffic classification, and optimize traffic flow in urban settings.

2.4 ARTIFICIAL INTELLIGENT (AI) OVERVIEW

Artificial Intelligence (AI) refers to the intelligence demonstrated by machines, enabling them to perform tasks that typically require human intelligence, such as learning, problem-solving, and decision-making (Laakkonen, 2021). AI has evolved significantly over the years, with current cutting-edge research focusing on physics-aware AI, which combines physical models with machine learning to capture correct physical behavior (Zubatiuk & Isayev, 2021). This development has led to the emergence of new technologies and applications across various fields (Xie, 2023).

The integration of AI into today's world has transformed society in numerous ways compared to before. AI has become a commonly used term and concept in global discussions, contributing significantly to the progress of digital society and human civilization (Gams & Gjoreski, 2021). The era of AI is considered the evolution of traditional analytics, known as analytics 4.0, particularly in the context of business analytics (Gómez-Caicedo et al., 2022). Moreover, AI has the potential to bring about transformative changes through the concept of Transformative AI (TAI), which can impact various aspects of life and society (Bova et al., 2021).

In the realm of industry, AI, along with technologies like 3D printing and robotics, is driving the emergence of Industry 4.0, which promises to revolutionize manufacturing processes and economies (Setiyo et al., 2021). The application of AI in fields such as healthcare, education, and e-commerce has led to significant advancements and improvements in service delivery and efficiency (Xie, 2023). Additionally, AI has the potential to influence economic resources allocation and firm performance positively (Li, 2022).

However, the widespread adoption of AI also presents challenges and risks, particularly in areas such as criminal law, where issues related to errors in AI creation, illegal access, and autonomous decision-making by AI systems may arise (Лопашенко, 2022). Furthermore, the impact of AI on the economy and society is a subject of ongoing research, aiming to provide insights for policymakers, businesses, and individuals to navigate the challenges and opportunities presented by AI (Han et al., 2020).

In conclusion, Artificial Intelligence has become a transformative force in today's world, revolutionizing industries, enhancing efficiency, and presenting both opportunities and challenges across various sectors. As AI continues to advance, understanding its implications and harnessing its potential responsibly will be crucial for shaping a future were AI benefits society positively.

2.5 MACHINE LEARNING IN OBJECT DETECTION AND RECOGNITION

Machine learning is a fundamental component in object detection and recognition, facilitating automated systems in identifying and categorizing objects within images or videos. The process involves training models to recognize distinctive patterns and features of various objects, which includes preprocessing data, extracting relevant features, training the model with labeled data, and assessing its performance based on accuracy and efficiency Miao et al. (2017). Object detection and recognition are fundamental tasks in computer vision that involve identifying and locating objects of interest within images or video frames. Machine learning plays a crucial role in advancing these tasks by providing algorithms and models capable of automatically learning patterns and features from data. General principles underlying object detection and recognition in machine learning involve the following:

i. **Feature Extraction**

Feature extraction is the process of identifying relevant patterns or characteristics within images that distinguish different objects. Traditional methods involved handcrafted features such as edges, corners, or textures. However, with the advent of deep learning, features are learned automatically through convolutional neural networks (CNNs). CNNs employ multiple layers of convolutions to extract hierarchical representations of input images, capturing both low-level and high-level features essential for object detection and recognition.

ii. **Object Localization**

Object localization refers to determining the spatial extent or location of objects within images. In object detection, this involves predicting bounding boxes that tightly enclose objects of interest. Localization is typically achieved by regressing coordinates or offsets relative to predefined anchor boxes or reference points. Convolutional neural networks are trained to simultaneously predict bounding box coordinates and confidence scores indicating the presence of objects within these boxes.

iii. **Classification**

Classification entails assigning labels or categories to detected objects based on their features and characteristics. In the context of object detection, classification involves determining the class or category of each detected object within bounding boxes. This is typically accomplished using softmax activation functions and multi-class classification techniques. Machine learning models are trained on labeled datasets to recognize and classify objects into predefined categories such as cars, pedestrians, traffic signs, etc.

iv. **Post-processing**

Post-processing steps are applied to refine object detection results and improve accuracy. This includes techniques such as non-maximum suppression (NMS) to eliminate redundant or overlapping bounding boxes, thresholding to filter out detections with low confidence scores, and clustering to group closely located detections into coherent object instances.

Feature extraction plays a critical role in object detection, where deep learning models autonomously identify relevant patterns and features from images using convolutional neural networks (CNNs) Liu et al. (2019). Object localization involves predicting bounding boxes around objects by regressing coordinates relative to anchor boxes, while classification assigns labels to detected objects using softmax activation functions (Singh et al., 2022). Post-processing techniques such as non-maximum suppression refine detection results by eliminating redundant boxes and filtering out low-confidence detections (Hoi et al., 2015).

In the realm of traffic analysis, machine learning algorithms analyze video feeds from traffic cameras to detect, track, and classify vehicles. Convolutional neural networks trained on annotated vehicle images learn discriminative features for precise detection and classification (Opromolla et al., 2019). Real-time vehicle detection systems implemented at intersections and highways monitor traffic conditions, enforce regulations, and improve road safety (Jakubec et al., 2023).

2.6 CASE STUDIES AND APPLICATIONS

2.6.1 Case Study 1: Implementation Of AI In Traffic Management: Need, Current Techniques And Challenges (Nasim et al., 2023).

The case study within the research paper "Implementation of AI in Traffic Management: Need, Current Techniques and Challenges" investigates the application of artificial intelligence as a solution for traffic management challenges in major cities, particularly focusing on alleviating traffic congestion.

Traffic congestion has become a crucial challenge in metropolitan areas, leading to increased air and noise pollution, stress, reduced productivity, and excessive energy consumption. The surge in vehicle ownership has outmatched the available road capacity, triggering these issues.

The study aims to explore the necessity for AI in traffic management, examine the AI techniques that have been developed thus far, and recognize the common barriers that obstruct the wide-scale implementation of AI in this domain.

The study reviews various models and systems put forward by global researchers aiming to tackle traffic congestion through AI, examining different techniques and their effectiveness while highlighting where improvements and further research are needed.

Despite significant research and development of AI applications in traffic systems, such as neural networks for traffic flow prediction and deep learning models for demands like ride-sharing, the practical, widespread deployment of AI solutions in traffic management is still limited. The study outlines the success of specific methods, the need for further integration of AI technology in traffic management, and the persistent challenges that must be addressed to improve traffic conditions in urban areas.

2.6.2 Case Study 2: Vision-Based Vehicle Detection And Counting System Using Deep Learning In Highway Scenes (Song et al., 2019).

The background of the study "Vision-based vehicle detection and counting system using deep learning in highway scenes" (Song et al., 2019) is grounded in the necessity for intelligent traffic management on highways. The paper identifies the challenge of vehicle detection due to the varying sizes of vehicles, especially tiny, distant objects, and the complexity of traffic camera scenes.

The main objective of the study is to propose and validate a vision-based vehicle detection and counting system using deep learning techniques to improve accuracy and effectiveness in highway management.

The methodological approach involves a novel dataset published with annotated instances for deep learning, a new segmentation method to differentiate between remote and proximal areas of the highway, and the application of the YOLOv3 network for vehicle detection. Additionally, vehicle trajectories are captured using the ORB algorithm to determine driving direction and vehicle count.

Key findings from the research demonstrate that their proposed segmentation method enhances detection accuracy, particularly for small vehicles, and the overall system is effective at judging the driving direction and counting vehicles, supporting its practical significance for highway scene management and control (Song et al., 2019).

2.6.3 Case Study 3: Detection and Classification Of Vehicles For Traffic Video Analytics (Arinaldi et al., 2018)

The background of the study "Detection and classification of vehicles for traffic video analytics" involves the application of automated surveillance and monitoring systems to reduce the need for human labor for vision-based tasks, which can instead be performed by automated systems. These computer vision systems are particularly applied to public areas like roads, airports, and retail spaces. The study highlights the importance of these systems for monitoring and analyzing road traffic, especially at highways and intersections. This monitoring is crucial for real-time traffic management that can adapt quickly to changes in traffic flow and conditions. The study points out that such systems are valuable for policymakers and regulators who need to gather traffic statistics automatically.

The study's objective is to devise a computer vision-based system that can automatically provide reliable statistics for traffic analysis, including vehicle counting, vehicle type classification, vehicle speed estimation from video, and lane usage monitoring. Such a system aims to assist in effective traffic management by providing timely data to authorities, enabling them to promptly address traffic situations, which could enhance overall traffic flow and safety.

In terms of methods, the study selects and implements two models to achieve its objectives. The first model is a combination of a Gaussian Mixture Model and a Support Vector Machine; the second model utilizes Faster R-CNN, a deep learning network recognized for its object detection capabilities in images. The efficacy of both models is evaluated, particularly their performance in scenarios involving static or overlapping vehicles and in nighttime conditions, where visibility is reduced.

The study's main findings reveal that the Faster R-CNN significantly outperforms the MoG model for vehicle detection, especially under challenging conditions such as vehicles that are static, overlapping, or during nighttime. Furthermore, Faster R-CNN also surpasses the SVM method in the task of classifying the types of vehicles based on their appearances, suggesting its superiority as a method for traffic video analysis in the contexts tested.

2.7 CHALLENGES AND LIMITATIONS

Implementing machine learning algorithms for traffic data collection poses several challenges that need to be addressed to ensure effective and reliable performance in real-world applications. One significant challenge is the variability and complexity of traffic environments, which can include diverse scenarios such as different weather conditions, lighting conditions, and road geometries. Machine learning models trained on limited datasets may struggle to generalize to unseen conditions, leading to reduced accuracy and reliability in object detection and recognition. Addressing this challenge requires the collection of comprehensive and diverse datasets that adequately represent the full range of traffic scenarios encountered in practice.

Another challenge is the need for real-time processing and low-latency inference, particularly in applications such as traffic monitoring and autonomous driving, where timely decision-making is critical. While modern machine learning algorithms offer impressive speed and efficiency, achieving real-time performance on resource-constrained devices or processing high-resolution video streams can still be challenging. Optimizing model architectures, implementing hardware acceleration, and deploying distributed processing systems are strategies to mitigate latency and ensure timely data collection and analysis.

Data annotation and labelling represent another significant challenge in implementing machine learning algorithms for traffic data collection. Annotated datasets are essential for training supervised machine learning models, but manually annotating large-scale traffic datasets can be labour-intensive and error-prone. Moreover, ensuring the accuracy and consistency of annotations across different annotators and datasets is a non-trivial task. Leveraging semi-automated annotation tools, crowdsourcing platforms, and transfer learning techniques can help streamline the data annotation process and improve the quality of annotated datasets.

Additionally, privacy and ethical considerations pose challenges in deploying machine learning algorithms for traffic data collection, particularly in surveillance and monitoring applications. Balancing the need for data collection with individual privacy rights and data protection regulations requires careful consideration and adherence to ethical guidelines and legal frameworks. Implementing anonymization techniques, data minimization practices, and ensuring transparent data usage policies are essential steps to address privacy concerns and build trust among stakeholders.

While Artificial Intelligent and similar state-of-the-art object detection algorithms offer impressive performance and versatility, they also have limitations that need to be considered. One limitation is the trade-off between accuracy and speed, where increasing the speed of inference may lead to a reduction in detection accuracy, particularly for small or occluded objects. Balancing these trade-offs requires careful optimization of model architectures, hyperparameters, and inference strategies to achieve the desired performance characteristics.

Another limitation is the susceptibility of machine learning models to adversarial attacks, where carefully crafted input perturbations can cause the model to make incorrect predictions. Adversarial robustness is particularly crucial in safety-critical applications such as autonomous driving, where adversaries may attempt to manipulate traffic signals or road signs to cause accidents. Enhancing the robustness of machine learning models to adversarial attacks through techniques such as adversarial training, robust optimization, and model ensembling is an active area of research.

In conclusion, while machine learning algorithms offer significant promise for traffic data collection, addressing challenges such as variability in traffic environments, real-time processing requirements, data annotation complexities, and privacy concerns is essential to realize their full potential in improving traffic management, safety, and efficiency. Moreover, understanding the limitations of current technologies and actively researching solutions to address these limitations are critical steps towards building more robust and reliable traffic data collection systems.

2.8 FUTURE DIRECTIONS AND POTENTIAL IMPROVEMENTS

The field of traffic data collection and analysis is poised for significant advancements in the coming years, driven by ongoing research efforts and technological innovations. One key direction for future research is the development of more robust and adaptable machine learning algorithms tailored specifically for traffic surveillance and monitoring. As traffic environments continue to evolve in complexity, algorithms need to become more resilient to varying conditions, such as changes in lighting, weather, and traffic density. Advanced techniques in deep learning, reinforcement learning, and unsupervised learning hold promise for enhancing the accuracy, efficiency, and adaptability of traffic data collection systems.

Furthermore, there is growing interest in integrating machine learning algorithms with emerging technologies such as the Internet of Things (IoT) and smart city infrastructure to create more interconnected and intelligent transportation systems. IoT devices such as traffic sensors, cameras, and connected vehicles generate vast amounts of data that can be leveraged to improve traffic management, optimize routing, and enhance safety. Machine learning algorithms can analyze this data in real-time, uncovering valuable insights and enabling proactive interventions to mitigate congestion, accidents, and other traffic-related issues.

Moreover, the proliferation of smart city initiatives presents opportunities for synergistic collaborations between machine learning, urban planning, and transportation engineering disciplines. By integrating traffic data collection systems with smart city infrastructure such as adaptive traffic signal control systems, smart parking solutions, and public transit networks, cities can create more efficient, sustainable, and livable urban environments. Machine learning algorithms can play a central role in optimizing the operation of these systems, dynamically adjusting traffic signals, rerouting vehicles, and allocating resources based on real-time traffic conditions and demand patterns.

Another promising avenue for future research is the development of multi-modal traffic data collection systems capable of capturing and analyzing diverse types of transportation modes, including pedestrians, cyclists, and public transit vehicles. By incorporating data from multiple sources, such as surveillance cameras, GPS trackers, and mobile devices, these systems can provide a holistic view of urban mobility patterns and support integrated transportation planning and management strategies. Machine learning algorithms can fuse and analyze this multi-modal data, identifying synergies, conflicts, and opportunities for improving multi-modal connectivity and accessibility in urban areas.

In conclusion, the future of traffic data collection and analysis lies in advancing machine learning algorithms, integrating with IoT and smart city infrastructure, and embracing multi-modal approaches to urban mobility. By harnessing the power of data-driven insights and innovative technologies, cities can address the complex challenges of modern transportation systems and pave the way for more sustainable, resilient, and equitable urban futures. Continued collaboration between researchers, practitioners, policymakers, and industry stakeholders is essential to realizing this vision and unlocking the full potential of data-driven transportation solutions.

2.9 CONCLUSION

In conclusion, the literature on traffic data collection and management underscores the critical role of machine learning, particularly algorithms like Artificial Intelligent (AI), in addressing the challenges and complexities of modern transportation systems. Key findings from the literature highlight the versatility and efficiency of machine learning algorithms in object detection, recognition, and traffic analysis, offering real-time insights into traffic flow, congestion patterns, and safety hazards. By leveraging advanced deep learning techniques and large-scale datasets, researchers and practitioners have made significant strides in enhancing the accuracy, speed, and scalability of traffic data collection systems, paving the way for more informed decision-making and proactive interventions in traffic management.

Reflecting on the impact of machine learning, particularly AI, on traffic data collection and management, it is evident that these technologies have revolutionized the field, enabling unprecedented levels of automation, efficiency, and accuracy. AI, with its state-of-the-art object detection capabilities and real-time performance, has become a cornerstone of traffic surveillance, monitoring, and analysis systems, empowering transportation authorities with actionable insights to improve traffic flow, safety, and efficiency on road networks. Its integration with other technologies such as IoT and smart city infrastructure holds promise for creating more interconnected and intelligent transportation systems, ushering in a new era of data-driven urban mobility solutions.

Looking ahead, continued research and innovation in machine learning, coupled with advancements in hardware and data infrastructure, are expected to further propel the field of traffic data collection and management. Future developments may focus on enhancing the robustness and adaptability of machine learning algorithms to diverse traffic environments, integrating multi-modal data sources for comprehensive urban mobility analysis, and leveraging emerging technologies for real-time decision support and intervention. By embracing these opportunities and addressing the remaining challenges, stakeholders can harness the full potential of machine learning to create safer, more efficient, and sustainable transportation systems for the cities of tomorrow.

CHAPTER 3

METHODOLOGY

3.1 INTRODUCTION

The methodology and process for developing the system will be explained in this chapter. In addition, this chapter will set out the methods used to find the problem and the appropriate system will be used in this project from the start to the end of the project. This method is used to achieve the objectives of the project that will achieve a perfect result. It will explain the method adopted by this research. Besides, this chapter will mention every component involved in conducting this research from population, population frame and sampling techniques used for the interview. This chapter provides a detail explanation of the selected mode of analysis used and data collection method.

The observation would be made by implementation while working on a task to determine the effectiveness of the website. A process path that will be implemented for this project and will be applied to the work environment on site will be attached to this chapter. The observation will be carried out when working on the mission by the implementation knowing the feasibility of the applications. Also seen in this chapter is concept simulation. The viability of using primary and secondary sources is to add value to the project. The source had studies completed. Furthermore, the strategies to be used will also be clarified entirely based on the problems available as well as the option of suitable systems when employed and when chosen suitable inside the platform to apply. This is focused on current work, based on all attainable work, references such as records, interviews, interactions and other variables. Subsequent in this chapter will be attached the process path that will be implemented for this project and will be applied to the work environment on site.

3.2 RESEARCH DESIGN

Design research is the framework of research methods and techniques chosen by a researcher. The design allows researcher to hone in on research methods that are suitable for the subject matter and set up researcher studies up for success. This method is very important for planning any observation. Steps from implementation should be monitored to identify the problems that will arise during implementation. Changes need to be made if there is a critical issue that is a major cause of failure in the implementation of the work. Next, control measures need to be taken to maintain a steady flow.

Generally, design research means a structure to plan and execute particular research. Design research is the crucial part of the research as it includes all the four important considerations; the conceptual framework, the identification of whom and what to study on and the tools and procedures to be used for collecting and analyzing data. The purpose of the design research is to discuss and explains method used by researcher in provide a plan of study that permits accurate assessment in conducting the AI-VeC. Figure _ below shows flowchart of research framework for this project.

From the figure 3.1 below, the start phase marks the inception of the research project, setting the stage for all subsequent activities. This phase involves assembling the research team, defining the project scope, and outlining the initial objectives. Key administrative tasks, such as securing funding, establishing timelines, and setting up collaborative tools, are also handled during this phase. It sets the foundation for a structured and systematic approach to the research and development process.

In this literature review phase, a comprehensive review of existing literature is conducted to gather insights into the current state of AI in vehicle counting and classification. This includes reviewing academic papers, industry reports, and existing technologies to understand what has already been accomplished. Identifying gaps and limitations in the current research helps in shaping the project's direction. The literature review also provides a theoretical framework and informs the methodology for developing the AI solution.

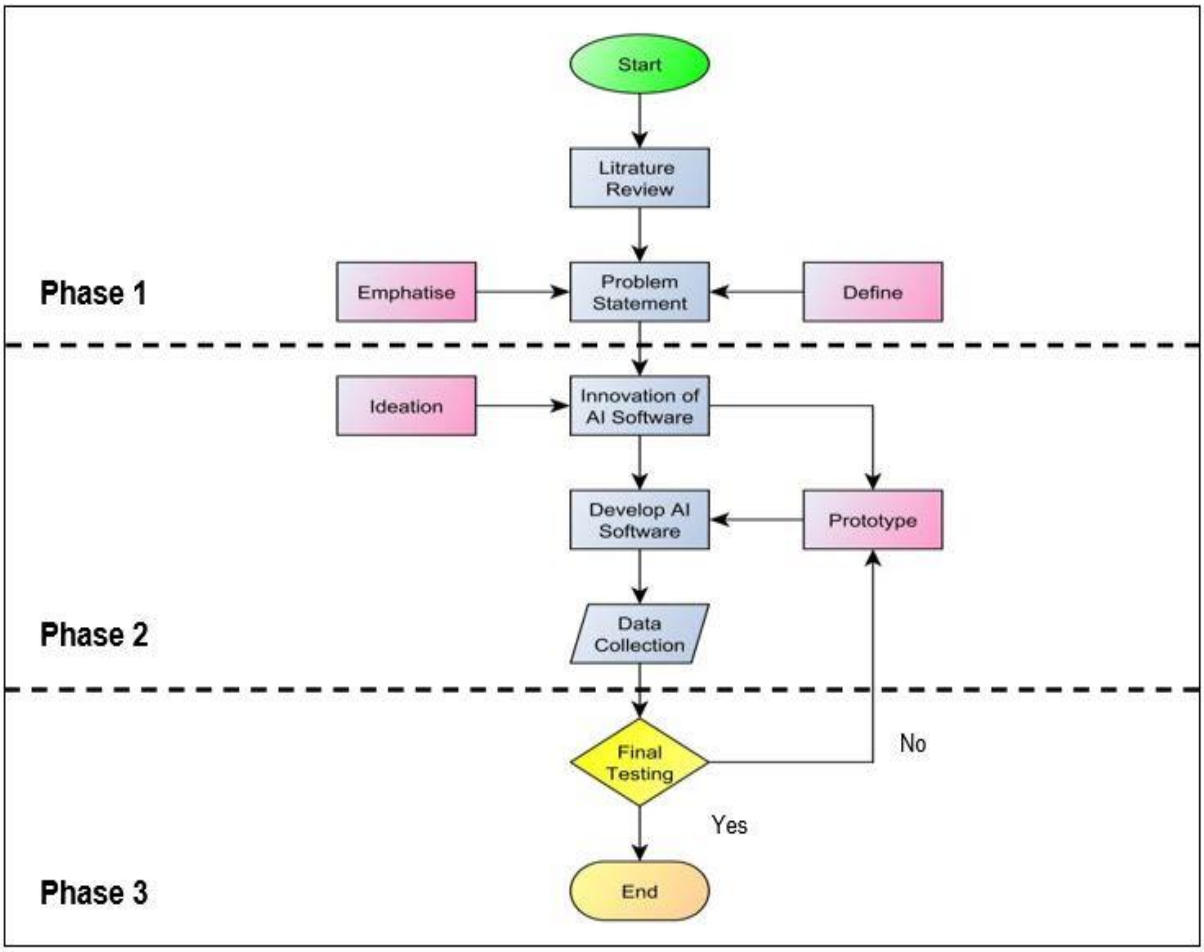

Figure 3.1: Flowchart of Research Framework

From the problem statement stage, defining the problem statement is a critical step where the specific issues and challenges the research aims to address are clearly articulated. This involves understanding the requirements for vehicle counting and classification in traffic data collection, such as accuracy, real-time processing, and adaptability to different traffic conditions. A well-defined problem statement ensures that the research stays focused and relevant, addressing real-world needs effectively. In this step, the focus is on understanding the perspectives and needs of stakeholders, such as traffic management authorities, urban planners, and policymakers. Engaging with stakeholders through interviews, surveys, and workshops helps to gather insights into their challenges and expectations. This ensures that the AI solution being developed is aligned with the practical requirements and can provide actionable insights for traffic management. The define phase involves clearly articulating the objectives, scope, and constraints of the project. This includes setting specific goals, determining the boundaries of the research, and identifying any limitations or constraints. This step ensures that all team members have a shared understanding of the project's aims and what is expected from the research. It serves as a reference point for evaluating progress and making decisions throughout the project.

Ideation is the creative process of generating potential solutions for the problem at hand. During this phase, the team brainstorms various approaches and technologies that could be employed in the AI software. This involves exploring different algorithms, data processing techniques, and machine learning models. The goal is to generate a wide range of ideas and then narrow down to the most promising ones that could effectively address the defined problem. This phase focuses on developing innovative concepts and methodologies for the AI software. It involves designing and refining algorithms and models that can accurately count and classify vehicles. The innovation phase is characterized by experimentation and iteration, where different models are tested and optimized. The aim is to create a robust and effective AI solution that leverages state-of-the-art technologies. Creating a prototype involves developing a preliminary version of the AI software to test and validate the concepts. Prototyping allows the team to experiment with the design and functionality of the software in a controlled environment. It helps in identifying any issues, such as inaccuracies or inefficiencies, and making necessary adjustments before proceeding to full-scale development. The feedback from the prototype phase is crucial for refining the final product.

In this developing phase, the final version of the AI software is developed based on the validated prototype. This involves detailed coding, integration of various components, and rigorous testing to ensure the software meets the defined requirements. The development phase is iterative, with continuous testing and refinement to enhance performance and reliability. The result is a fully functional AI solution ready for deployment.

Once the AI software is developed, it is deployed in real-world scenarios to collect traffic data. This phase involves setting up the software in various traffic conditions to gather comprehensive data for analysis. The collected data is used to test the software's performance in real-time and to further refine its accuracy and efficiency. Data collection is a crucial step for validating the practical applicability of the AI solution.

Final testing involves thorough validation of the AI software to ensure it performs accurately and reliably in counting and classifying vehicles. This step includes extensive testing against various test cases and scenarios to check for any edge cases or unexpected behaviours. The goal is to ensure the software is robust and can handle different traffic conditions effectively. Successful final testing signifies that the software is ready for deployment.

The end phase marks the conclusion of the research project after the successful testing and validation of the AI software. The final product is now ready for deployment and use in traffic data collection. This phase includes documenting the research findings, preparing user manuals, and planning for any future updates or maintenance. The project is considered complete when the AI solution is effectively implemented and operational in the intended environment. Each of these steps is essential for the systematic development and implementation of AI software for vehicle counting and classification in traffic data collection, ensuring a thorough and methodical approach to solving real-world traffic management challenges.

3.3 PROTOTYPE DEVELOPMENT

The software prototype development is important to make sure the process is smoothly created and run. To develop a smooth prototype software system, need a systematic system to guide all the work process. Prototype software development is the process of creating or altering systems, along with the processes, practices, models, and methodologies used to develop (Blanchard, 2010). Figure _ below shows flowchart of software prototype development.

From the figure 3.2 below, the start phase marks the beginning of the software development process. This phase involves setting up the project infrastructure, gathering requirements, and defining the initial objectives. Key activities include outlining the project plan, and establishing timelines and milestones. This foundational step ensures that the project is well-organized and that all team members are aligned with the project goals and expectations.

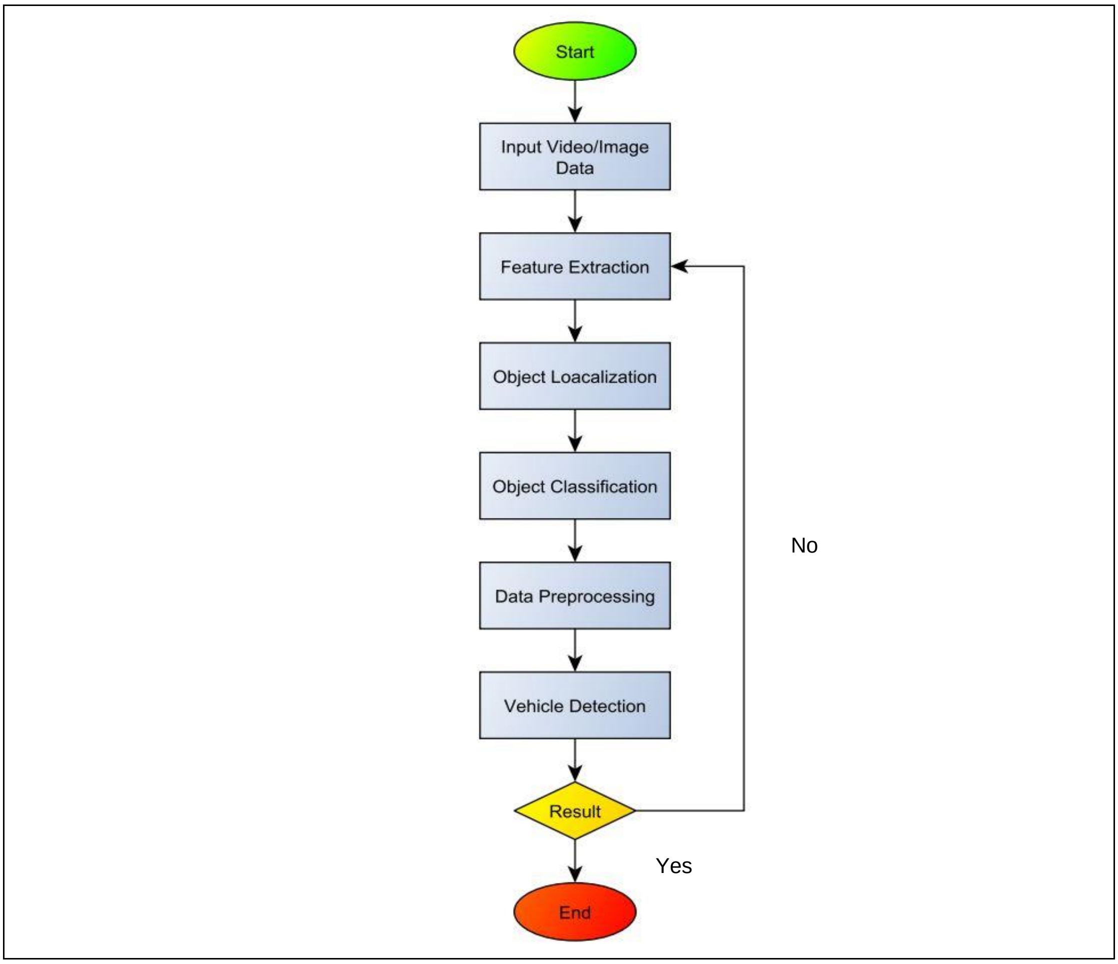

Figure 3.2: Flowchart of Prototype Software Development

In this second step, the system receives video or image data as input. This data is typically captured from traffic cameras or other imaging devices positioned to monitor traffic flow at various locations. The input data serves as the raw material for the AI algorithms. The quality and resolution of the video or images are crucial, as they directly impact the accuracy of subsequent processing steps. The data may also include metadata such as timestamps and camera positions, which can aid in analysis.

Feature extraction is a critical step where the system processes the input data to extract relevant visual characteristics. Features could include edges, textures, shapes, colours, and patterns that help in identifying and distinguishing different objects within the video or images. Advanced techniques like convolutional neural networks (CNNs) are often employed to automatically learn and extract these features. The extracted features form the basis for object detection and classification in later stages.

In the object localization step, the system identifies and locates objects within the input data. This involves determining the position and boundaries of potential vehicles in each frame of the video or image. Techniques such as bounding boxes or segmentation masks are used to highlight areas where vehicles are likely to be present. Object localization is essential for isolating vehicles from the background and other non-relevant elements, allowing the system to focus on specific regions of interest for further analysis.

Once objects are localized, the system classifies them into different categories, such as cars, trucks, buses, motorcycles, etc. This step utilizes machine learning algorithms and models that have been trained on labeled datasets to recognize and differentiate between various types of vehicles. Techniques such as deep learning, particularly CNNs, are commonly used for this purpose. Accurate classification is crucial for understanding the composition of traffic and making informed decisions based on vehicle types.

Data pre-processing involves cleaning and preparing the data for further analysis. This step may include tasks such as noise reduction, normalization, and data transformation. Noise reduction aims to remove any irrelevant or misleading data points, while normalization ensures that the data is in a consistent format. Transformation may involve resizing images or converting them into different colour spaces. Pre-processing is vital for enhancing the quality of the data and improving the performance of detection algorithms.

In the vehicle detection step, the system applies detection algorithms to identify and count vehicles in the pre-processed data. This involves analyzing the classified objects and confirming their presence as vehicles. Detection algorithms may use techniques such as background subtraction, optical flow, or deep learning models like YOLO (You Only Look Once) or Faster R-CNN. The system may also track the movement of vehicles across multiple frames in a video to ensure accurate counting and avoid duplicate detections.

The result step is where the system generates the final outcomes, which include the count and classification of vehicles detected in the input data. These results are typically presented in a format that is easy to interpret, such as tables, charts, or visual overlays on the original video/images. The results can be used for various applications, including traffic analysis, reporting, and decision-making. They provide valuable insights into traffic patterns, vehicle types, and congestion levels, aiding in effective traffic management.

The end phase marks the conclusion of the software development process. After generating the final results, the project undergoes a review to ensure all objectives have been met and the system performs as expected. Documentation is finalized, and the software is prepared for deployment. This phase may also include post-development activities such as user training, maintenance planning, and setting up support systems. The project is considered complete once the software is operational and delivering the intended benefits. Each of these steps is essential for developing a robust AI system capable of accurately detecting and classifying vehicles in traffic data, thereby enabling effective monitoring and management of traffic flow.

3.4 PROTOTYPE WORKFLOW

Creating a prototype for the AI-VEC (Artificial Intelligence in Vehicle Counting and Classification) system involves several key steps to ensure the preliminary version of the software is functional and can be used effectively. The prototype working process for AI-VEC ensures a systematic approach to guide user on how to run the prototype software from scratch. Figure 3.3 below shows flowchart of prototype software workflow process.

From the figure 3.3 below, the start phase marks the beginning of the process. This is where you prepare to run the AI-VEC prototype, ensuring you have all necessary files and software ready. Confirm that Visual Studio Code (VSCode) is installed on your computer and that you have the required Python environment and dependencies configured.

Secondly. launch Visual Studio Code (VSCode), which serves as the integrated development environment (IDE) for this project. VSCode provides a robust platform for writing, running, and debugging Python code, and it offers features like syntax highlighting, code completion, and integrated terminal support.

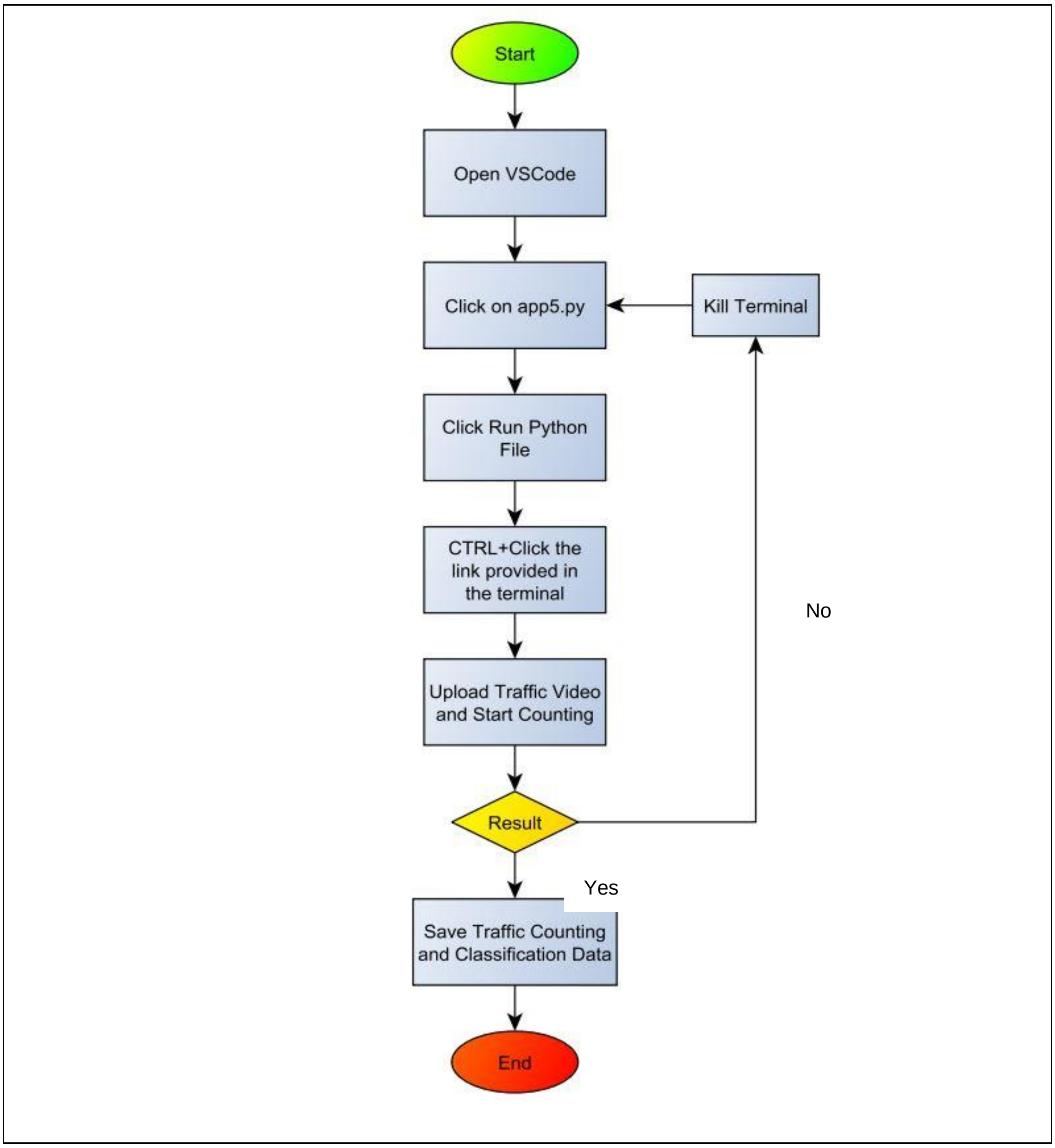

Figure 3.3: Flowchart of Prototype Working Process

Thirdly, in VSCode, open the specific Python script named `app5.py`. This script contains the core code for the AI-VEC prototype. Navigate through the file explorer on the left sidebar of VSCode to locate `app5.py` within your project directory and click to open it in the editor window.

Fourth step, to execute the `app5.py` script, click on the "Run Python File" button, which is typically found at the top right corner of the editor or by right-clicking the script and selecting "Run Python File in Terminal." This action initiates the script, starting the processes defined in your code, including loading necessary libraries, setting up the application server, and preparing for data input.

In the fifth step, after the script starts running, the terminal in VSCode will display an output that includes a link to the web interface or application. This link is typically a local server address such as `http://127.0.0.1:5000`. Hold the `CTRL` key (or `CMD` key on Mac) and click on this link to open it in your default web browser. This interface allows you to interact with the AI-VEC prototype.

For the sixth step within the web-based interface, you will find an option to upload a traffic video. Click the “Upload” button, select the traffic video file from your computer, and upload it. Once the video is uploaded, the AI-VEC system will automatically start processing the video to detect, count, and classify vehicles. The system leverages pre-trained AI models to analyze the video frames and extract relevant traffic data.

In the seventh step, as the system processes the video, it will generate results in real-time or after processing is complete. These results typically include the count and classification of vehicles detected in the video. The results are displayed on the web interface, often with visual overlays on the video showing detected objects and their classifications.

In the eighth step, after reviewing the results, you have the option to save the traffic counting and classification data. This step is crucial for documenting the analysis and for future reference or reporting. The result interface will be saved as an image file.PNG in the document location. Once you have saved the results, you can stop the execution of the `app5.py` script by killing the terminal in VSCode. Another option in the 9th step can be used if the prototype software cannot be open or run. To do this, click on the trash can icon or use the `Ctrl+C` command in the terminal to terminate the running process. This action ensures that all processes are cleanly shut down and no resources are left hanging. To repeat the counting process again, users need to start form the second steps.

Lastly, the end phase signifies the conclusion of the process. This final step involves closing any remaining open files in VSCode and ensuring that all data has been properly saved and backed up. The process is now complete, and you have successfully run the AI-VEC prototype from start to finish, generating valuable traffic data for further analysis. Each of these steps is integral to the successful operation of the AI-VEC prototype, ensuring a systematic approach from launching the development environment to processing video data and saving the results.

3.5 MATERIAL USED

The development of the AI-based vehicle counting and classification system (AI-VEC) utilized several essential materials and tools to ensure effective and efficient creation. Table 3.1 below show maerial and tools used to develop the AI-VEC software.

Table 3.1: Material and Tools Used

NO	Material/Tools	Function
1.	Computer/Laptop 	Used in developing the AI software prototype and access.
2.	Internet 	To link the computer and internet connection while develop and exploring for sources.
3.	Visual Studio Code	An open-source code editor for writing and editing code of programming language.
4.	OpenCV-Python	Provides access to a wide range of computer vision algorithms and tools. Speciality in object detection and classification.

Firstly, a computer or laptop served as the primary platform for developing the AI software prototype. This hardware was fundamental in accessing and utilizing various software and online resources required throughout the development process. Internet connectivity played a crucial role by linking the development computer to a vast array of online resources. This connection facilitated the exploration of sources, downloading necessary libraries, and accessing remote databases, which were vital for the software's development and testing phases. Visual Studio Code was employed as the code editor for writing and editing the program's code. As an open-source tool, it provided a robust and versatile environment for programming in different languages, making it an indispensable part of the software development workflow Lastly, OpenCV-Python was utilized to integrate advanced computer vision capabilities into the AI-VEC system. This tool provided access to a comprehensive suite of algorithms and tools for object detection and classification, which are central to the system's functionality in accurately identifying and counting various vehicle types. Together, these materials and tools created a strong foundation for developing a sophisticated and reliable AI-driven traffic monitoring system.

3.6 DATA COLLECTION AND ANALYSIS

Data collection and analysis methods include techniques for gathering and interpreting information for research and decision-making (Creswell & Creswell, 2017). Primary methods involve direct data collection through surveys, interviews, and experiments (Saunders, Lewis, & Thornhill, 2019), while secondary methods use existing data from databases and reports (Johnston, 2017). Quantitative analysis uses statistical techniques for numerical data to identify patterns and trends (Field, 2018), whereas qualitative analysis interprets non-numerical data through thematic, content, and narrative analysis (Braun & Clarke, 2006). Mixed-methods research combines both approaches for a comprehensive understanding (Creswell & Plano Clark, 2018). Effective data collection and analysis require careful planning to ensure accuracy, reliability, and validity (Bhattacherjee, 2012).

3.6.1 Qualitative Data Collection Method

For the AI-VeC (Artificial Intelligence in Vehicle Counting and Classification) research, qualitative research methods were employed to delve into the multifaceted aspects of vehicle counting and classification from various perspectives. Qualitative research is well-suited for exploring nuanced dimensions such as the physiological, psychological, and cultural aspects involved in the process. By focusing on qualitative analysis, the study aimed to capture rich, detailed insights primarily from the viewpoint of stakeholders involved in traffic data collection and management. This approach enabled the researchers to observe and understand the emotions, thoughts, and attitudes of individuals involved in the development and implementation of AI technologies for vehicle counting and classification.

In this qualitative research endeavour, methods such as interviews with traffic engineers, engineers, and traffic draughtman were utilized to gather first-hand accounts and experiences related to the implementation of AI-VeC systems. These interviews provided qualitative data that illuminated individual perspectives on the challenges, benefits, and socio-cultural implications of using AI in traffic management. The qualitative research method chosen for this study aligns closely with the definitive status study approach. This methodological choice facilitated a systematic and in-depth exploration of the phenomenon within its specific context, considering factors such as time, place, and individual perspectives. Following established qualitative research stages outlined by Denzin and Lincoln (2008), the study involved defining the scope of the research, identifying relevant cases for investigation, rigorously analyzing qualitative data sets, deriving meaningful findings, providing insightful interpretations, and effectively communicating the results.

Ultimately, by employing qualitative research methods in the AI-VeC study, researchers were able to uncover nuanced insights that quantitative methods alone might not capture. This approach not only enriched understanding of the technological and human dimensions of AI-VeC systems but also provided valuable insights into how these technologies are perceived, utilized, and integrated into real-world traffic management practices.

3.6.2 Thematic Data Analysis

Thematic analysis is a qualitative research method used to identify and interpret patterns, or themes, within qualitative data. In the context of the AI-VeC (Artificial Intelligence in Vehicle Counting and Classification) research, thematic analysis was crucial for systematically organizing and making sense of the diverse qualitative data collected. The process began with immersion in the data through thorough reading and familiarization with interview transcripts, documents, and observational notes.

Researchers then proceeded to generate initial codes, which involved systematically labeling and categorizing segments of data based on their content and relevance to the research questions. These codes were derived directly from the data and served as building blocks for identifying broader themes.

The next step in thematic analysis was the iterative process of searching for themes across the coded data. Themes emerged as patterns of meaning that recurred throughout the data set, capturing important aspects of participants' experiences, perceptions, and attitudes towards AI-driven vehicle counting and classification. Researchers paid attention to both explicit and implicit meanings within the data, ensuring that themes reflected the depth and complexity of the participants' responses. Once potential themes were identified, they were reviewed, refined, and defined with clear descriptions that encapsulated their essence. This process involved examining how themes related to each other and contributed to a comprehensive understanding of the research topic. Themes were supported by illustrative quotations or examples from the data, demonstrating their relevance and grounding them in participants' voices.

In the final stages of thematic analysis, researchers synthesized the findings into a coherent narrative. They contextualized the themes within existing literature and theoretical frameworks relevant to AI technologies in traffic management, providing insights into the practical implications and theoretical contributions of the study. Thematic analysis thus enabled a nuanced exploration of the multifaceted dimensions of AI-VeC systems, highlighting both the technical challenges and the socio-cultural factors influencing their implementation and adoption.

3.6.3 Accuracy Test

An Accuracy Test is conducted by performing a detailed comparison between traffic data obtained through manual counting and the data collected using AI-VEC software. This process involves manually counting the number of vehicles in a specific area over a given period, and then comparing these results with the data automatically recorded by traffic counting software. The purpose of this test is to assess the precision and reliability of the software in accurately capturing traffic volumes, ensuring that the automated system provides data that closely matches human observations.

3.7 Gantt Chart

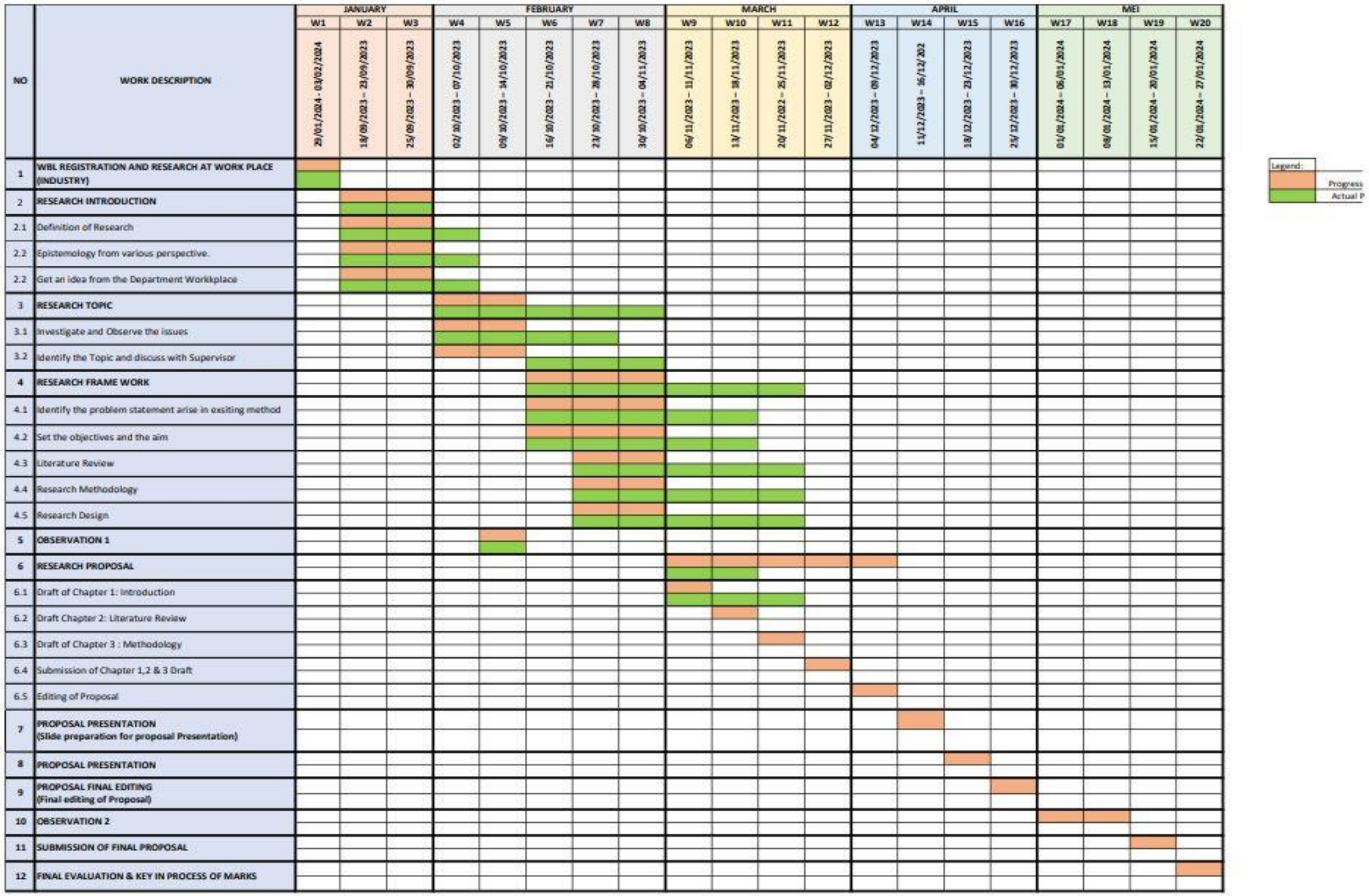

Figure 3.4: Gantt Chart Pre-Project

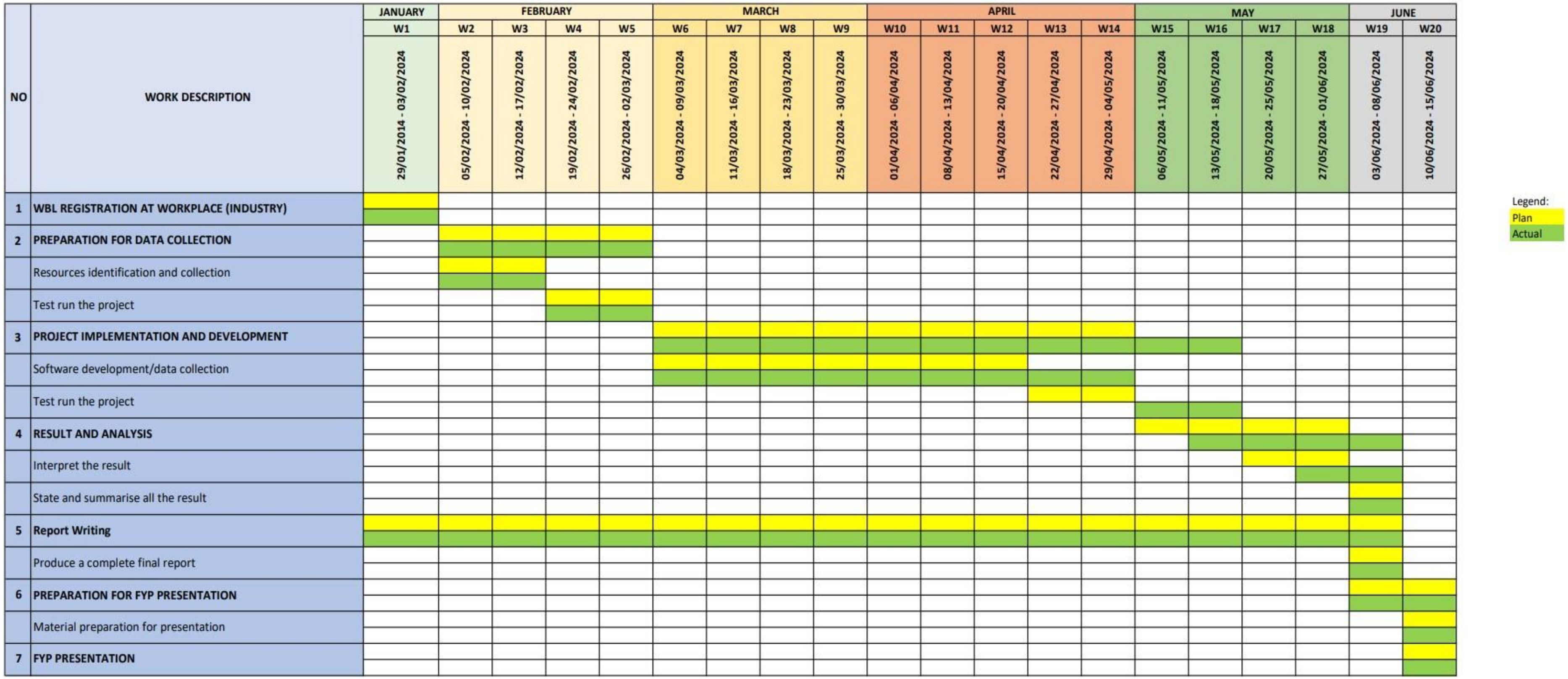

Figure 3.5: Gantt Chart Final Year Project

CHAPTER 4

RESEARCH FINDING

4.1 INTRODUCTION

In this chapter, the expected result from the project has been carried out were explained. The finding of the project was being showed according to the following objectives:

I. To identify the limitations of the existing methods for traffic data collection.
II. To develop an Artificial Intelligent software for traffic data collection.
III. To evaluate the software performance in enhancing traffic data collection methods.

4.2 IDENTIFY THE LIMITATIONS OF THE EXISTING METHODS

To identify the limitation of the existing methods for traffic data collection, a few methods is applied such as observation, personal experience, and research. In table 4.1 below shows finding obtained from the method use.

From my observation, one significant limitation of existing traffic data collection methods is the labour-intensive nature of manual vehicle counting. Workers spend considerable time counting vehicles, leading to inefficiencies and increased labour costs. The process is not only time-consuming but also prone to human error, which can compromise the accuracy of the collected data. Manual counting, often conducted at specific intervals, cannot provide continuous monitoring, resulting in gaps and outdated information that do not accurately reflect traffic conditions.

Table 4.1: Limitation of existing methods

Observation	**Personal Experience**	**Research**
Labour-intensive nature of manual vehicle counting.	Consumes a substantial amount of time	Budget constraints
Workers spend considerable time counting vehicles.	Inefficient work performance	Prone to errors and deviations
Inefficiencies and increased labour costs	Lead to loss focus and decreased accuracy over time	In-road sensors for data collection can be costly
Prone to human error		

From my personal experience, the manual counting of vehicles consumes a substantial amount of time and is highly inefficient. The repetitive nature of the task can lead to fatigue and decreased accuracy over time. Additionally, manual methods lack the scalability needed to monitor large and complex traffic networks effectively. The need for continuous human presence to gather data makes this method unsustainable for long-term traffic management analysis.

From my research finding, limitations of conventional methods for traffic data collection include budget constraints often limit the adoption of more advanced data collection methods, leading to a reliance on statistical analysis despite its inherent limitations (Pucci et al., 2021). Traditional methods such as manual statistics and random sampling are not only inefficient but also prone to errors and deviations when collecting network traffic data (Liu, 2023).

Moreover, conventional methods may struggle with missing data, requiring imputation techniques that may introduce uncertainties (Cheong et al., 2023). The use of in-road sensors for data collection can be costly, prompting a shift towards mobile data like GPS reports, although challenges remain in ensuring comprehensive coverage (Chao et al., 2019).

In summary, the limitations of conventional traffic data collection methods encompass issues related to data granularity, budget constraints, inefficiencies, errors, missing data, and inadequate coverage of essential parameters like speed and location.

4.3 Develop an Artificial Intelligent Software using OpenCV - Python

The figure 4.1 below shows the completed AI-VEC interface, displaying uploaded traffic video and classification results. The left panel features is a table summarizing vehicle counts by class (cars, vans, trucks, buses, motorcycles) and direction (up and down), while the right panel shows a video feed with vehicles crossing detection lines. The integration of data visualization and recorded video enhances the system's usability and effectiveness in traffic data collection method.

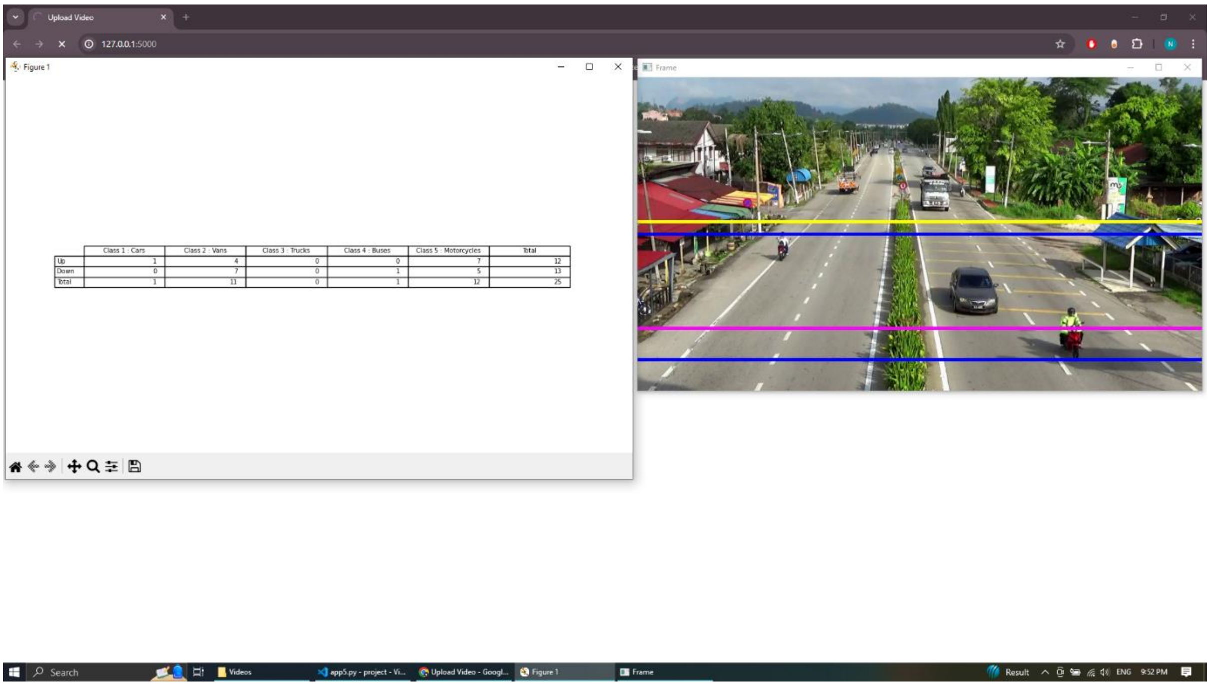

Figure 4.1: AI-VEC Interface

4.4 EVALUATE THE EFFECTIVENESS OF AI-VEC SOFTWARE

Once software has been developed and tested, it is time to evaluate the effectiveness of AI-VEC software. The evaluation result is obtained from the open-ended interview questions conducted on five traffic expertise. This overarching theme encompasses the system’s performance, comparative effectiveness, and potential enhancements from the perspective of users. Table 4.2 below shows demographic table of respondent.

Table 4.2: Respondent Demographic

ID code of expertise	Age	Position	Education	Experience
E1	57	Director	PhD	34
E2	48	Draughtman	Diploma	24
E3	39	Traffic Supervisor	Diploma	14
E4	28	Traffic Engineer	Degree	3
E5	27	Site Engineer	Degree	2

4.4.1 Thematic Analysis

The thematic analysis of user feedback on the traffic counting software reveals a comprehensive understanding of its performance, accuracy, and comparative effectiveness. Users commend the software for significantly enhancing their work efficiency and delivering impressive results in vehicle counting and classification, with many highlighting its reliability and accuracy compared to manual methods. The software's efficiency and time-saving capabilities position it as a superior alternative to conventional traffic counting methods, which are often prone to errors and labor-intensive. While users appreciate the advantages of reduced labor costs and ease of use, they also identify limitations, such as its inability to analyze vehicles at junctions and classify heavy vehicles by axle.

Suggestions for improvement focus on enhancing the classification of heavy vehicles to support road design and integrating the software into existing workflows to replace older methods like Automatic Traffic Count (ATC). Overall, the feedback underscores the software's effectiveness and user satisfaction, alongside a clear path for future enhancements to better meet user needs and expectations. In this analysis, three themes “system performance”, “comparative effectiveness”, and “potential enhancement” were defined in the table 4.3 below.

Table 4.3: Thematic analysis table

Main Theme	**Sub-Theme**	**Indicative Quote**
System Performance	User's experience	"*The software really helps in enhancing my work for traffic counting as it also shows an outstanding result in counting and classifying*." (E4)
	System's accuracy	"*The system accuracy is reliable when we compare the data with manual and software counting*." (E1) "*The accuracy of vehicle detection for this software is reliable when the result that we obtained from manual count is almost the same as software count*." (E4)
Comparative Effectiveness	Comparison between conventional method	"*After we have seen the software performance, this AI-VEC is way much better compared with conventional method*." (E5) *"Conventional upon rely on time consuming and sometime could drag to lost focus while counting meanwhile this software is user-friendly and save more time.*" (E2)
	Advantages	"*In terms of advantages, I see that this software saves more time and makes work easier."* (E5) "*AI-VeC reduces the need for human observers to be physically present at multiple locations, lowering labour costs."* (E5)
	Disadvantages	"*The disadvantages of this software are that it can't count and analyse vehicles at junction.*" (E5) "*The software can't categorize vehicle according to its axle for heavy vehicles*." (E3)
Potential Enhancement	System improvement	"*Improvement is needed especially when classifying heavy vehicle. Try to categorize them according to the vehicle axle as it will help in road design*". (E1)
	Potential to integrate into existing workflows.	"*I would love to integrate this software to my future workspace as I believe it can help me in improving my work efficiency in time*". (E4) "*I will use this software to replace the Automatic Traffic Count (ATC) methods if it can categorize the heavy vehicle according to its axle*". (E3)

System Performance

User’s Experience:

Users find the software beneficial for traffic counting, enhancing their work efficiency and providing impressive results in counting and classifying vehicles. One user highlighted that the software "really helps in enhancing my work for traffic counting as it also shows an outstanding result in counting and classifying." This indicates a positive user experience and satisfaction with the software's performance.

System’s Accuracy:

The accuracy of the system is consistently praised when compared to manual counting methods. Users trust the system's reliability, as it produces results similar to manual counts. Quotes such as "The system accuracy is reliable when we compare the data with manual and software counting" and "The accuracy of vehicle detection for this software is reliable when the result that we obtained from manual count is almost the same as software count" underscore the system’s dependable accuracy.

Comparative Effectiveness

Comparison Between Conventional Method:

The software is considered superior to conventional methods, which are often time-consuming and prone to errors. Users appreciate the software's efficiency and time-saving capabilities. For instance, a user noted, "After we have seen the software performance, this AI-VBC is way much better compared with conventional method," and another mentioned, "Conventional upon rely on time consuming and sometime could drag to lost focus while counting meanwhile this software is user-friendly and save more time."

Advantages:

The software offers significant advantages, including time savings and reduced need for human presence, thus lowering labor costs. Users emphasized that "this software saves more time and makes work easier" and that "AI-VeC reduces the need for human observers to be physically present at multiple locations, lowering labour costs."

Disadvantages:

Despite its benefits, the software has some limitations, particularly in its inability to count and analyze vehicles at junctions and classify vehicles by axle for heavy vehicles. Users expressed concerns, stating, "The disadvantages of this software are that it can't count and analyze vehicles at junction" and "The software can't categorize vehicle according to its axle for heavy vehicles."

Potential Enhancement

System Improvement:

Users suggested improvements, especially in classifying heavy vehicles according to their axle, which would aid in road design. One user recommended, "Improvement is needed especially when classifying heavy vehicle. Try to categorize them according to the vehicle axle as it will help in road design."

Potential to Integrate into Existing Workflows:

There is a strong desire to integrate the software into existing workflows to enhance efficiency. Users believe it can significantly improve work processes and replace older methods like Automatic Traffic Count (ATC). A user expressed, "I would love to integrate this software to my future workspace as I believe it can help me in improving my work efficiency in time," and another noted, "I will use this software to replace the Automatic Traffic Count (ATC) methods if it can categorize the vehicle according to its axle."

4.4.2 Data Accuracy Test

An Accuracy Test is conducted by performing a detailed comparison between traffic data obtained through manual counting and the data collected using AI-VEC software. This process involves five comparisons by manually counting the number of vehicles in a specific area over a given period, and then comparing these results with the data automatically recorded by AI-VEC software. The purpose of this test is to assess the precision and reliability of the software in accurately capturing traffic volumes, ensuring that the automated system provides data that closely matches human observations. Table 4.4 below shows comparison data for accuracy test.

Table 4.4: Comparison Data for Accuracy Test

Comparison 1				
Class of vehicle	**Up**		**Down**	
	Manual	**Software**	**Manual**	**Software**
Class 1: Car	267	270	298	299
Class 2: Light Vehicle	23	22	12	13
Class 3: Heavy Vehicle	6	6	2	2
Class 4: Buses	3	3	4	4
Class 5: Motorcycle	87	86	89	85
Comparison 2				
Class of vehicle	**Up**		**Down**	
	Manual	**Software**	**Manual**	**Software**
Class 1: Car	265	265	291	294
Class 2: Light Vehicle	26	25	17	25
Class 3: Heavy Vehicle	2	2	1	1
Class 4: Buses	3	3	3	3
Class 5: Motorcycle	61	60	84	82
Comparison 3				
Class of vehicle	**Up**		**Down**	
	Manual	**Software**	**Manual**	**Software**
Class 1: Car	257	260	263	262
Class 2: Light Vehicle	33	31	14	15
Class 3: Heavy Vehicle	2	2	3	2
Class 4: Buses	1	1	2	2
Class 5: Motorcycle	63	62	82	80
Comparison 4				
Class of vehicle	**Up**		**Down**	
	Manual	**Software**	**Manual**	**Software**
Class 1: Car	225	220	237	231
Class 2: Light Vehicle	21	22	15	15
Class 3: Heavy Vehicle	3	3	2	2
Class 4: Buses	2	3	1	1
Class 5: Motorcycle	43	44	51	51
Comparison 5				
Class of vehicle	**Up**		**Down**	
	Manual	**Software**	**Manual**	**Software**
Class 1: Car	216	217	232	232
Class 2: Light Vehicle	22	23	19	19
Class 3: Heavy Vehicle	2	2	3	3
Class 4: Buses	1	1	1	1
Class 5: Motorcycle	41	42	47	44

From the table 4.4, it can be seen the range of differences between manual and software counting is 8. This means that the greatest discrepancy observed between the manual and software counts was 8 vehicles, which occurred for light vehicles in the downward direction in Comparison 2. This discrepancy highlights potential areas for improvement in the software, particularly in accurately counting light and vehicles in specific directions or scenarios. However, overall, the software demonstrates a high level of accuracy, closely aligning with manual counts (Alsanabani et al., 2020). The accuracy test showed that AI-VEC demonstrated a high level of precision, closely aligning with manual vehicle counts, with the greatest discrepancy being only eight vehicles, highlighting its overall reliability despite minor differences in specific scenarios.

CHAPTER 5

CONCLUSION

5.1 INTRODUCTION

Based on the data analyses in the previous chapter, this section summarizes the findings, conclusions, and suggestions. The efficiency of using the AI-Vehicle Counting (AIVEC) system to digitalize traffic monitoring at various locations was assessed by determining how well some of the study's objectives were met. In this chapter, the researcher should provide recommendations to upgrade the system to enhance its functionality and performance in future projects. It is also one of the processes after the project has been carried out, requiring careful consideration of what recommendations will be produced during the course of the project. The AI-Vehicle Counting (AIVEC) system functions as a digital traffic monitoring tool. This system collects and analyzes video data to accurately count and classify vehicles, easing the workload of traffic analysts and improving efficiency. Additionally, AIVEC can be used for real-time traffic updates, enabling better traffic management. This system is user-friendly and economical, reducing the need for manual counting and paper-based records while being accessible from any device with internet connectivity. The data results and user feedback prove that the AIVEC system is significantly better compared to traditional manual methods, aligning with the advancements of the Fourth Industrial Revolution (IR 4.0) in the transportation sector.

5.2 DISCUSSION

The thematic analysis of user feedback on the AI-Vehicle Counting (AI-VEC) system reveals key insights into its performance and effectiveness. Users praised AI-VEC for enhancing workflow by providing accurate and reliable traffic counting and classification, significantly reducing the workload associated with manual counting. The system's accuracy closely matches manual counts, bolstering confidence in its ability to replace traditional methods. Compared to conventional methods, AI-VEC is superior, being user-friendly, time-saving, and less prone to errors. Its main advantages include saving time, reducing the need for physical presence at multiple locations, and lowering labor costs, thereby increasing overall efficiency and productivity. However, users noted some limitations, such as difficulty in counting vehicles at junctions and categorizing vehicles based on axle for heavy vehicles. Users suggested refining classification algorithms, particularly for heavy vehicles, to improve system performance and enhance its applicability in road design and traffic management. There is also a strong desire to integrate AI-VEC into existing workflows, as users believe it aligns with the goals of Innovation Revolution 4.0 (IR 4.0), significantly improving work efficiency and replacing traditional traffic counting methods.

From the analysis of accuracy test, it is evident that the range of differences between manual and software counting is relatively minimal, with the greatest observed discrepancy being 8 vehicles. This maximum discrepancy occurred for light vehicles in the downward direction in Comparison 2. Such a discrepancy indicates specific areas where the AI-Vehicle Counting (AI-VEC) software could be enhanced, particularly in accurately counting light vehicles in certain directions or scenarios. Despite this, the overall performance of the AI-VEC software is commendable, demonstrating a high level of accuracy and reliability. The software's counts closely align with manual counts, showcasing its precision and effectiveness in most cases. These findings suggest that while the AI-VEC system performs well overall, targeted improvements could further enhance its accuracy in specific contexts. This high level of precision, with only minor differences in specific scenarios, underscores the software's potential as a reliable tool for traffic counting and classification, supporting its broader adoption and integration into existing workflows.

5.3 CONCLUSION

In conclusion, this research has successfully achieved its objectives in developing an effective traffic counting system through the AI-Vehicle Counting (AI-VEC) software. The software has demonstrated substantial improvements in work efficiency and accuracy, showing a close alignment with manual counts. This close alignment is critical as it validates the system's reliability and builds user confidence in its capacity to replace traditional methods. The AI-VEC software's ability to streamline traffic counting tasks allows users to reallocate their efforts to more critical, higher-value activities, thereby enhancing overall productivity.

While the software's performance is commendable, the research also identified minor areas for improvement. One such area is the classification of heavy vehicles by axle. Accurate classification based on axle weight is essential for applications in road design and traffic management, where specific vehicle characteristics impact infrastructure planning and maintenance. Another area requiring attention is the counting of vehicles at junctions. Junctions pose unique challenges due to their complexity and the confluence of multiple traffic streams, which can complicate accurate vehicle detection and counting.

Despite these areas for refinement, the overall effectiveness of the AI-VEC system is highly validated through the qualitative research method employed. Users have reported significant benefits, including reduced manual labor, lower operational costs, and enhanced accuracy. These benefits align well with the goals of Innovation Revolution 4.0 (IR 4.0), which emphasizes the integration of advanced technologies to improve efficiency and productivity in various sectors, including transportation and construction.

The successful integration of the AI-VEC software into existing workflows highlights its potential to replace conventional traffic counting methods comprehensively. Traditional methods, often reliant on manual counting, are time-consuming and prone to human error. In contrast, AI-VEC offers a user-friendly, automated solution that reduces these inefficiencies. The positive reception from users indicates a strong potential for broader adoption, which could revolutionize traffic management processes by providing more accurate data, facilitating better decision-making, and ultimately leading to more efficient traffic flow and infrastructure planning.

Overall, this research underscores the transformative potential of AI-VEC in traffic management. By addressing the identified areas for improvement, the software can become an even more powerful tool for urban planners, traffic engineers, and policymakers. Its ability to enhance accuracy, efficiency, and integration into existing systems marks a significant step forward in the digitalization of traffic management, paving the way for smarter, more responsive transportation systems.

5.4 RECOMMENDATION

Based on the thematic analysis and comparison data accuracy, several recommendations for future improvements of the AI-Vehicle Counting (AI-VEC) system can be made. Enhancing the system's performance and accuracy is paramount, particularly in distinguishing and counting specific vehicle classes such as light and heavy vehicles. This can be achieved by refining the classification algorithms and integrating advanced machine learning techniques, which can improve the system's ability to accurately categorize vehicles based on detailed characteristics like axle count. Additionally, addressing the system's current limitations, such as its difficulty in counting vehicles at complex junctions, will be crucial. Implementing sophisticated algorithms that can handle the intricacies of junctions and other complex traffic scenarios will enhance overall accuracy and reliability.

The integration of more advanced computer vision techniques and deep learning models can help in reducing the discrepancies observed between manual and software counts, as highlighted in studies by Sun et al. (2020) and Chen et al. (2021). These improvements will not only enhance the precision of vehicle counting but also ensure the system's adaptability to various traffic conditions and scenarios, thereby increasing its robustness and usability in different environments.

User feedback has indicated that while the AI-VEC system already significantly enhances traffic monitoring efficiency, there is potential for further refinement to maximize its effectiveness and user satisfaction. Users have suggested that improvements in handling diverse traffic conditions and specific vehicle categorizations will make the system more reliable and user-friendly. Therefore, continuous engagement with users to gather feedback and understand their needs will be essential for iterative development and refinement of the system.

In summary, future software improvements for AI-VEC should focus on enhancing vehicle classification accuracy, particularly for light and heavy vehicles, improving performance at junctions, and integrating advanced algorithms to handle various traffic scenarios effectively. These enhancements will ensure the system's reliability and efficiency, making it a more powerful tool for traffic monitoring and management, ultimately leading to higher user satisfaction and broader adoption.

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APPENDICES

CODING FOR AI-VEC

```
from flask import Flask, render_template, request, redirect, url_for
import os
import cv2
import numpy as np
import time
import vehicles
import matplotlib.pyplot as plt

app = Flask(__name__)
app.config["UPLOAD_FOLDER"] = "vehicle-counting/Programs/uploads"
# Folder to store uploaded videos
app.config["ALLOWED_EXTENSIONS"] = {"mp4", "avi"}  # Allowed
video formats
app.config['MAX_CONTENT_LENGTH'] = 1000 * 1024 * 1024  # for
example, 16 megabytes



# Function to check file extension
def allowed_file(filename):
    return (
        "." in filename
        and filename.rsplit(".", 1)[1].lower() in
app.config["ALLOWED_EXTENSIONS"]
    )
```

```
@app.route("/", methods=["GET", "POST"])
def upload_video():
    if request.method == "POST":
        file = request.files["file"]
        if file and allowed_file(file.filename):
            filename = file.filename
            filepath = os.path.join(app.config["UPLOAD_FOLDER"], filename)
            file.save(filepath)
            return redirect(url_for("process_video", filename=filename))
    return render_template("upload.html")


@app.route("/process/<filename>")
def process_video(filename):
    filepath = os.path.join(app.config["UPLOAD_FOLDER"], filename)
    cap = cv2.VideoCapture(filepath)
    fgbg = cv2.createBackgroundSubtractorMOG2(
        detectShadows=False, history=200, varThreshold=90
    )
    kernalOp = np.ones((3, 3), np.uint8)
    kernalOp2 = np.ones((5, 5), np.uint8)
    kernalCl = np.ones((11, 11), np.uint8)
    font = cv2.FONT_HERSHEY_SIMPLEX
    cars = []
    max_p_age = 5
    pid = 1
    cnt_up = 0
    cnt_down = 0
    line_up = 400
    line_down = 250
    up_limit = 230
    down_limit = int(4.5 * (500 / 5))
```

```
print("VEHICLE DETECTION,CLASSIFICATION AND COUNTING")

# Initialize matplotlib figure and axes

fig, ax = plt.subplots(figsize=(10, 6))

if cap.isOpened() == False:
    print("Error opening video stream or file")

car_count_up = 0
truck_count_up = 0
bike_count_up = 0
bus_count_up = 0
van_count_up = 0

car_count_down = 0
truck_count_down = 0
bike_count_down = 0
bus_count_down = 0
van_count_down = 0

while cap.isOpened():
    ret, frame = cap.read()
    frame = cv2.resize(frame, (900, 500))
    for i in cars:
        i.age_one()
    fgmask = fgbg.apply(frame)

    if ret == True:
        ret, imBin = cv2.threshold(fgmask, 200, 255, cv2.THRESH_BINARY)
        mask = cv2.morphologyEx(imBin, cv2.MORPH_OPEN, kernalOp)  #
Opening :E->D
```

```
        mask = cv2.morphologyEx(mask, cv2.MORPH_CLOSE, kernalCl)  #
Closing :D->E

        (contours0, hierarchy) = cv2.findContours(
            mask, cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_NONE
        )  # Contour Extraction
        for cnt in contours0:
            area = cv2.contourArea(cnt)

            if area > 300:
                m = cv2.moments(cnt)
                cx = int(m["m10"] / m["m00"])
                cy = int(m["m01"] / m["m00"])
                x, y, w, h = cv2.boundingRect(cnt)

                # Calculate the aspect ratio of the bounding rectangle
                aspect_ratio = float(w)/h

                if aspect_ratio > 2:  # Buses
                    vehicle_type = "Bus"
                    # print(vehicle_type, aspect_ratio)
                elif aspect_ratio > 1.7:  # Coaches
                    vehicle_type = "Truck"
                    # print(vehicle_type, aspect_ratio)
                elif aspect_ratio > 1.3:  # Vans
                    vehicle_type = "Van"
                    # print(vehicle_type, aspect_ratio)
                # elif aspect_ratio > 1.2:  # SUVs
                #     vehicle_type = "SUV"
                    # print(vehicle_type, aspect_ratio)
                elif aspect_ratio > 1.1:  # Cars
                    vehicle_type = "Car"
                    # print(vehicle_type, aspect_ratio)
```

```
                elif aspect_ratio > 0.8:  # Motorcycles
                    vehicle_type = "Motorcycle"
                    # print(vehicle_type, aspect_ratio)
                else:  # Bikes
                    vehicle_type = "Bike"
                    # print(vehicle_type, aspect_ratio)



                new = True
                if cy in range(up_limit, down_limit):
                    for i in cars:
                        if abs(x - i.getX()) <= w and abs(y - i.getY()) <= h:
                            new = False
                            i.updateCoords(cx, cy)

                            if i.going_UP(line_down, line_up) == True:
                                cnt_up += 1
                                if vehicle_type == "Truck":
                                    truck_count_up += 1
                                elif vehicle_type == "Bus":
                                    bus_count_up += 1
                                elif vehicle_type == "Van":
                                    van_count_up += 1
                                elif vehicle_type == "Car":
                                    car_count_up += 1
                                else:
                                    bike_count_up += 1
                                img = cv2.rectangle(frame, (x, y), (x + w, y + h), (0, 255,
0), 2)
                                cv2.imwrite("./detected_vehicles/vehicleUP" +
str(cnt_up) + ".png", img[y:y + h - 1, x:x + w])
                                print(vehicle_type, aspect_ratio)
```

```
                elif i.going_DOWN(line_down, line_up) == True:
                    cnt_down += 1
                    if vehicle_type == "Truck":
                        truck_count_down += 1
                    elif vehicle_type == "Bus":
                        bus_count_down += 1
                    elif vehicle_type == "Van":
                        van_count_down += 1
                    elif vehicle_type == "Car":
                        car_count_down += 1
                    else:
                        bike_count_down += 1
                    img = cv2.rectangle(frame, (x, y), (x + w, y + h), (0, 255,
0), 2)
                    cv2.imwrite("./detected_vehicles/vehicleDOWN" +
str(cnt_down) + ".png", img[y:y + h - 1, x:x + w])
                    print(vehicle_type, aspect_ratio)



                break
            if new == True:
                p = vehicles.Car(pid, cx, cy, max_p_age)
                cars.append(p)
                pid + 1

        # str_up = "UP: " + str(cnt_up) + " (Bikes: " + str(bike_count) + ",
Cars: " + str(car_count) + ", Vans: " + str(van_count) + ", Buses: " +
str(bus_count) + ", Trucks: " + str(truck_count) + ")"
        # str_down = "DOWN: " + str(cnt_down) + " (Bikes: " +
str(bike_count) + ", Cars: " + str(car_count) + ", Vans: " + str(van_count) +
", Buses: " + str(bus_count) + ", Trucks: " + str(truck_count) + ")"

        frame = cv2.line(
```

```
        frame, (0, line_up), (900, line_up), (255, 0, 255), 3, 8
    )
    frame = cv2.line(
        frame, (0, up_limit), (900, up_limit), (0, 255, 255), 3, 8
    )
    frame = cv2.line(
        frame, (0, down_limit), (900, down_limit), (255, 0, 0), 3, 8
    )
    frame = cv2.line(
        frame, (0, line_down), (900, line_down), (255, 0, 0), 3, 8
    )

    # cv2.putText(frame, str_up, (10, 40), font, 0.5, (0, 0, 255), 2,
cv2.LINE_AA)
    # cv2.putText(
    #     frame, str_down, (10, 90), font, 0.5, (255, 0, 0), 2, cv2.LINE_AA
    # )

    ax.clear()
    ax.axis('off')
    ax.table(cellText=[[car_count_up, van_count_up, truck_count_up,
bus_count_up, bike_count_up, cnt_up],
            [car_count_down, van_count_down, truck_count_down,
bus_count_down, bike_count_down, cnt_down],
            [car_count_up + car_count_down, van_count_up +
van_count_down, truck_count_up + truck_count_down, bus_count_up +
bus_count_down, bike_count_up + bike_count_down, cnt_down+cnt_up]],
        colLabels=['Class 1 : Cars', 'Class 2 : Vans', 'Class 3 : Trucks', 'Class
4 : Buses', 'Class 5 : Motorcycles', "Total"],
        rowLabels=['Up', 'Down', 'Total'],
        loc='center')
    plt.draw()
    plt.pause(0.0001)
```

```
            cv2.imshow("Frame", frame)

            if cv2.waitKey(1) & 0xFF == ord("q"):
                break

        else:
            break

    cap.release()
    cv2.destroyAllWindows()


if __name__ == "__main__":
    app.run(debug=True)
```

INTERVIEW FORM

KEMENTERIAN PENGAJIAN TINGGI

POLITEKNIK UNGKU OMAR
Jalan Raja Musa Mahadi
31400 Ipoh
PERAK, MALAYSIA

Visi : Menjadi institusi TVET premier yang diterajui industri.
Misi : Menghasilkan graduan yang holistik, kompeten dalam teknologi dan berdaya keusahawanan.
Slogan : dreamBIG@PUO

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Laman Web : www.puo.edu.my
Facebook : POLITEKNIK UNGKU OMAR (PUO)

Department of Civil Engineering
Final Year Project (BCT80318)

Interview Form

I am inviting Mr/Mrs to participate in this research by completing the following survey. This survey is part of my project for course BCT80318: Final Year Project. Objective of this study aims to evaluate effectiveness of Artificial Intelligence in Vehicle Counting and Classification (AI-VeC) for Traffic Data Collection.

Name of Student: MUHAMMAD NAZRUL BIN ZAILANI

Student ID: 01BCT21F3006

Course Code: BCT80318

Project Title: **Artificial Intelligence in Vehicle Counting and Classification (AI-VeC) for Traffic Data Collection**

Name of Supervisor: DR. AZUIN BINTI RAMLI

INTERVIEWEE NAME	
AGE	
POSITION	
YEARS OF EXPERIENCE	

SIGN/COP	

Supervisor's Signature: **Approved By:**

_____________________ _____________________

1 – STRONGLY DISAGREE, 2 – DISAGREE, 3 – NEUTRAL, 4 – AGREE, 5 – STRONGLY AGREE

QUESTION	1	2	3	4	5
Using the Artificial Intelligence in Vehicle Counting (AI-VeC) enables me to collect traffic data more quickly.					
The Artificial Intelligence in Vehicle Counting (AI-VeC) improve the accuracy in vehicle counting.					
Using the Artificial Intelligence in Vehicle Counting (AI-VeC) enhances the efficiency of traffic data collection.					
Using the Artificial Intelligence in Vehicle Counting (AI-VeC) makes it easier to manage traffic data.					
I find the Artificial Intelligence in Vehicle Counting (AI-VeC) useful for traffic data collection.					
I find the Artificial Intelligence in Vehicle Counting (AI-VeC) is easy to use.					
Learning how to use the Artificial Intelligence in Vehicle Counting (AI-VeC) is easy for me.					
My interaction when using the Artificial Intelligence in Vehicle Counting (AI-VeC) is clear and understandable.					
I find the Artificial Intelligence in Vehicle Counting (AI-VeC) to be flexible to interact with.					
It would be easy for me to become skilful when using the Artificial Intelligence in Vehicle Counting (AI-VeC).					
I completely satisfied in using the Artificial Intelligence in Vehicle Counting (AI-VeC).					
I feel very confident when using the Artificial Intelligence in Vehicle Counting (AI-VeC).					
I believe using the Artificial Intelligence in Vehicle Counting (AI-VeC) is a good idea.					
I generally favour the use of Artificial Intelligence in Vehicle Counting (AI-VeC) for collecting data.					
I can accomplish the task quickly by using the Artificial Intelligence in Vehicle Counting (AI-VeC).					
I intend to use the Artificial Intelligence in Vehicle Counting (AI-VeC) in the future					

I intend to use the Artificial Intelligence in Vehicle Counting (AI-VeC) for my work.					
I intend to use the Artificial Intelligence in Vehicle Counting (AI-VeC) frequently.					
I am eager to use Artificial Intelligence in Vehicle Counting (AI-VeC) for traffic data collection.					
I am committed to integrating Artificial Intelligence in Vehicle Counting (AI-VeC) into my regular traffic data collection processes.					

INTERVIEW QUESTION

1. Can you describe yourexperience using the AI-VEC system for vehicle counting and classification? How reliable did you find the system in accurately identifying and categorizing different types of vehicles?
   Bolehkah anda menerangkan pengalaman anda menggunakan sistem AI-VEC untuk pengiraan dan pengelasan kenderaan? Sejauh manakah anda mendapati sistem ini boleh dipercayai dalam mengenal pasti dan mengkategorikan pelbagai jenis kenderaan dengan tepat?

2. In your opinion, how does the AI-VeC system compare with traditional methods of vehicle counting and classification (e.g., manual counting, video-based systems)? What are the key advantages or disadvantages you observed?
   Pada pendapat anda, bagaimanakah sistem AI-VeC dibandingkan dengan kaedah pengiraan dan pengelasan kenderaan tradisional (cth., pengiraan manual, sistem berasaskan video)? Apakah kelebihan atau kekurangan utama yang anda perhatikan?

3. What suggestions do you have for potential improvements or enhancements to make the system even more effective for traffic data collection? Additionally, how likely are you to application this product into your workspace or existing workflows in the future?
   Apakah cadangan yang anda ada untuk penambahbaikan atau peningkatan yang berpotensi untuk menjadikan sistem lebih berkesan untuk pengumpulan data trafik? Selain itu, sejauh manakah anda akan mengaplikasikan produk ini ke dalam ruang kerja anda atau aliran kerja sedia ada pada masa hadapan?