

**TRAJECTORY PREDICTION AND NEAR MISS
DETECTION USING SOCIAL DISTANCING
MONITORING AND DISTANCE BASED
PROXIMAL INDICATORS**

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DETECTION USING SOCIAL DISTANCING
MONITORING AND DISTANCE BASED PROXIMAL
INDICATORS**

by

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LIST OF ABBREVIATIONS

AdaLEA	Adaptive Loss for Early Anticipation
ADE	Average Displacement Error
ANN	artificial neural networks
ANOVA	Analysis of variance
AR	Augmented reality
BN	Batch Normalization
C3	CSPDarknet53
CAT	Contextual Attention Transformer
CBS	Convolution-BN-SiLU
CCTV	Closed-circuit television
CMC	Convolutional- Multi-scale Processing-Convolutional
Concat	Concatenation
Conv	Convolutional layers
ConvNet /CNN	Convolutional Neural Network
CPU	Central Processing Unit
CSPDarknet53	Cross Stage Partial Darknet-53
CUDA	Compute Unified Device Architecture
DA	Domain Adaptation
DBO	dung beetle optimizer
DN	Distance-Neighbours
DNN	Deep neural network
DSS	Difference between Space Distance and Stopping Distance
DWCONV	Depth Wise Convolution
E-ELAN	Extended Efficient Layer Aggregation Network
EfficientNet	Efficient Convolutional Neural Network
ELAN-H	Hierarchical fusion is improved by Extended Efficient Layer Aggregation Network
ER	event recorders
Fast RCNN	Fast Region-Based Convolutional Neural Network

Faster RCNN	Faster Region-Based Convolutional Neural Network
Faster-BRCNN	Faster-RCNN based data equalizing strategy
FDE	Final Displacement Error
FPN	feature pyramid network
FPNs	Feature Pyramid Networks
GAP	Global Average Pooling
GDS	Geriatric Depression Scale
GELU	Gaussian Error Linear Unit
GIS	Geographical Information Systems
GPU	Graphics Processing Unit
HOG	Histogram of Gradient
HQV	High quality video
ID	number
IoT	Internet of Things
IoU	Intersection over Union
IPM	Inverse Perspective Mapping
JKR	Jabatan Kerja Raya
KF	Kalman Filter
LN	Layer Normalization
LQV	Low quality video
Max	Maximum
MBPP	Majlis Bandaraya Pulau Pinang
MCDM	multi-criteria decision making
Min	Minimum
MP	Multi-scale Processing
MRBLSTM	Modified ReLU-based Bidirectional Long Short-Term Memory
MSB	Between-Group Mean Square
MSW	Within-Group Mean Square
NB	Negative binomial
NMS	non-maximum suppression

PAN	Path Aggregation Network
PDPA	Personal Data Protection Act
PICUD	Potential Index for Collision with Urgent Deceleration
POL 37	Police record data 37
PSD	Proportion of Stopping Distance
QRNN	Quasi- recurrent neural network
RAM	Random Access Memory
RCNN	Region-Based Convolutional Neural Network
RELR	Rare event logistic regression
REP	Residual Encoding Pooling
ReLU	Rectified linear unit
ResNet152	Residual Network with 152 layers
RFRC	Random Forest Regression Classifier
RM	Rancangan Malaysia
RoI pooling	Region of Interest pooling
RPN	Region Proposal Network
SDGs	Sustainable Development Goals
SEM	Structural Equation Model
Sig.	Significance
SiLU	Sigmoid Linear Unit
SMEs	Small- and medium-sized enterprises
SPP	Spatial Pyramid Pooling
SPP	Spatial Pyramid Pooling
SPPCSPC	Spatial Pyramid Pooling with Contextual Spatial Pyramid Convolution
SPP-NET	Spatial Pyramid Pooling Network
SSB	Between-Group Sum of Squares
SSD	Single-shot detector
SST	Total Sum of Squares
SSW	Within-Group Sum of Squares
Std. Dev.	Standard Deviation

SVM	Support Vector Machine
TLR	Traditional logistic Regression
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
UAV	Unmanned Aerial Vehicle
UD	Unsafe Density
USM	Universiti Sains Malaysia
V2I	vehicle-to-infrastructure
V2V	vehicle-to-vehicle
V2X	vehicle-to-everything
Vgg16	Visual Geometry Group 16-layer network
VR	Virtual reality
YOLO	You Only Look One
YOLOv3-tiny	You Only Look One version 3-tiny
YOLOv4-tiny	You Only Look One version 4-tiny
YOLOv5	You Only Look One version 5
YOLOv5l	You Only Look One version 5 large
YOLOv5m	You Only Look One version 5 medium
YOLOv5n	You Only Look One version 5 nano
YOLOv5s	You Only Look Once version 5 small
YOLOv5x	You Only Look One version 5 extra large
YOLOv7	You Only Look One version 7
YOLOv7+CNeB	You Only Look One version 7 with ConvNeXt Block
YOLOv7+G3HN	You Only Look One version 7 with <i>gn</i> Conv3 with HorNet

RAMALAN TRAJEKTORI DAN PENGESANAN NYARIS KEMALANGAN MENGUNAKAN PEMANTAUAN JARAK SOSIAL DAN PENUNJUK PROKSIMAL BERASASKAN JARAK

ABSTRAK

Walaupun terdapat usaha untuk menambahbaikkkan keselamatan jalan raya, kemalangan masih berlaku disebabkan oleh bukti yang tidak mencukupi dari laporan manual polis, algoritma pengesanan yang tidak dioptimumkan, dan keterbatasan teknikal dalam pemprosesan video masa nyata dan pemodelan. Kajian ini memberi tumpuan kepada pengesanan dan penjejakan kenderaan dalam sistem pemantauan dan menganalisis kejadian nyaris kemalangan (black spot dan blind spot), dengan secara khusus meneliti pengaruh kualiti video terhadap prestasi pengesanan menggunakan model pengesan lanjutan (YOLOv3-tiny, YOLOv4-tiny, YOLOv5, YOLOv7, YOLOv7+G3HN, YOLOv7+CNeB, dan Faster RCNN). Eksperimen ini menggunakan kaedah pengesanan kenderaan dan ramalan trajektori melalui sistem pemantauan. Pengesanan nyaris kemalangan dijalankan menggunakan dua pendekatan: pemerhatian manual (Pemantauan Penjarakan Sosial dan Pandangan Mata Burung) dan pengiraan automatik (menggunakan penunjuk DN, PICUD, dan PSD). Kaedah statistik, termasuk statistik deskriptif, korelasi Pearson, dan ANOVA sehalu, digunakan untuk membandingkan set data yang diperoleh daripada penunjuk-penunjuk ini. Kajian ini menyimpulkan bahawa YOLOv7+CNeB berkesan untuk pengesanan kenderaan dan analisis nyaris kemalangan apabila kualiti video dipertimbangkan dalam reka bentuk dan pelaksanaan sistem. YOLOv7+CNeB dengan ketara mengurangkan masa yang diperlukan untuk mengumpul bukti dari jalan tertentu, menyediakan laporan visual, dan menangani keterbatasan teknikal dalam algoritma

semasa. Penyelidikan masa depan harus meneroka faktor tambahan yang menyumbang kepada kejadian nyaris kemalangan, seperti persekitaran jalan, perubahan lorong, dan tingkah laku pemandu.

TRAJECTORY PREDICTION AND NEAR MISS DETECTION USING SOCIAL DISTANCING MONITORING AND DISTANCE BASED PROXIMAL INDICATORS

ABSTRACT

Despite efforts to improve road safety, accidents persist due to insufficient evidence from manual police reporting, non-optimized detection algorithms, and technical limitations in real-time video processing and modelling. This study focuses on detecting and tracking vehicles within a monitoring system and analysing near-miss incidents (black spot and blind spot), specifically examining the influence of video quality on detection performance using advanced model detectors (YOLOv3-tiny, YOLOv4-tiny, YOLOv5, YOLOv7, YOLOv7+G3HN, YOLOv7+CNeB, and Faster RCNN). The experiment employed methods for vehicle detection and trajectory prediction through the monitoring system. Near-miss detection was conducted using two approaches: manual observation (Social Distancing Monitoring and Bird's Eye View) and automatic calculation (using DN, PICUD, and PSD indicators). Statistical methods, including descriptive statistics, Pearson correlation, and one-way ANOVA, were applied to compare datasets obtained from these indicators. The study concludes that YOLOv7+CNeB is effective for vehicle detection and near-miss analysis when video quality is considered in system design and implementation. YOLOv7+CNeB significantly reduces the time required to collect evidence from specific roads, provides visual reports, and addresses technical limitations in current algorithms. Future research should explore additional factors contributing to near-miss events, such as road environment, lane changes, and driver behaviour.

CHAPTER 1

INTRODUCTION

1.1 Background Study

Pulau Pinang has introduced several measures to improve traffic safety and encourage sustainability, such as installing closed-circuit television (CCTV) systems on the mainland and island. Road safety is enhanced by the use of these CCTV systems, which are essential for observing traffic flow, detecting incidents, and enforcing traffic regulations. This Penang 2030's vision of creating a "Family-Focused, Green and Smart State" by improving traffic safety through smart surveillance technologies like CCTV and AI-based monitoring systems. By implementing predictive algorithms to identify near-miss events and optimize traffic flow, this research supports Penang's goals in digital governance, sustainability, and smart city transformation under Pillar A (Enhancing liveability) and Pillar B (Increasing household income).

The state government of Pulau Pinang emphasizes the implementation of smart solutions and green technology in urban planning and development as part of the Penang 2030 vision for a Green and Smart City. Policies such as the Green Economy Policy for Industry (2020), Public Transit Oriented Transportation (2020), Renewable Energy Policy (2030), and Green Public Procurement (2030) reflect this commitment. The higher authorities of Pulau Pinang aim to optimize traffic management, reduce congestion, and improve overall road safety by employing technologies including the Internet of Things (IoT) and data analytics. Additionally, an eco-friendly and sustainable transport system

is facilitated by initiatives designed to reduce carbon emissions and increase energy efficiency.

Moreover, the transport and traffic safety-related Sustainable Development Goals (SDGs) are in alignment with Pulau Pinang's policy. Pulau Pinang intends to construct comprehensive plans that solve issues with road safety and improve the development of sustainable cities by giving these objectives top priority. This involves implementing initiatives to upgrade public transit, develop infrastructure, and establish laws in place that support environmentally friendly methods of transportation involving walking and cycling.

The measures of the state for safer and greener roads are also greatly aided by Pulau Pinang's small- and medium-sized enterprises (SMEs) industrialization. SMEs can encourage these initiatives by integrating sustainable practices into their organization's operations. Examples of such activities involve reducing trash production, introducing energy-efficient technology, and encouraging eco-friendly transportation options for their employees. By implementing sustainable industrialization techniques, SMEs assist Pulau Pinang achieve its environmental goals while simultaneously rendering communities safer and more habitable for locals.

The long-term objective of the transportation system in Pulau Pinang is to improve the quality of life for its citizens by focusing on safety, sustainability, and innovation. To achieve these goals, the state government is working with many stakeholders, including SMEs, and implementing legislative initiatives and technical improvements. Therefore, Pulau Pinang state government is implementing of "A Family-focused Green and Smart State that Inspires the Nation" where the ultimate objective is to promote environmental

sustainability and improve the living standards of people and countries. This initiative also aligns with the Sustainable Development Goals (SDGs) that can be applied under the Penang 2030 projects (United Nations, 2016).

1.2 Problem Statement

The accidents reported in Penang usually involve manual procedures such as POL 37 data in police record data. Accidents in Penang were documented in manual reports that had to be referred to the police station. Typically, accident reports are written by hand also known as manual reports, which results in incomplete evidence and data and makes it difficult to effectively analyse and make decisions (Lim *et al.*, 2022). The Rancangan Malaysia (RMK) which is the Malaysia's national development plan, promotes evidence-based urban planning and smart infrastructure; however, when road safety issues are addressed manually under RMK using traditional methods for road repairs and safety analysis, it often results in higher costs and inefficiencies due to significant labour, resource demands, and time consumption.

On the other hands, the research on vehicle transport analysis using feature selection and parameter selection is limited in Penang. Even with the widespread use of CCTV surveillance, there are still insufficient advanced monitoring techniques or systems to make efficient use of the recorded data for real-time observation and forecasting. Furthermore, the development of reliable monitoring and prediction systems suffers from the prevailing usage of videos for insurance claims. The current limitations, such as the 45-day automatic deletion period after which video footage is stored by MBPP, limit the

amount of historical data that can be accessed for research and analysis. Processing a lot of video data in real-time continues to be restricted by technological restrictions such as RAM shortages. Authorities thus face budgetary difficulties as a result of the high expense of video storage. The differences in video footage quality, from low to high quality, are one of the difficulties faced. The accuracy of the predictive models is affected by noise and distortions introduced by low-quality footage. While the approaches exist to make use of the available video data, the limitations created by low-quality footage need to lead to the development of effective algorithms that can analyse noise images and generate precise predictions. The variability in video quality, particularly with low-resolution footage, poses a significant challenge for accurate traffic analysis, as critical details such as vehicle positions may be missed. These issues underscore the need for solutions that can enhance video clarity, manage video storage, and optimize real-time processing to ensure effective traffic safety monitoring.

Pulau Pinang state government promoted “Penang 2030” to build a smart city where the ultimate objective is to prevent and reduce the number of fatalities in road accidents. Although the implementation of many regulations, the incidence of accidents in Pulau Pinang continues to persist without reduction (Lim *et al.*, 2023). Even while detection models like RCNN, CNN, and YOLO are available, the issue is that they are general and not optimized for particular roadways in Penang. Penang’s unique road characteristics, such as narrow streets, complex intersections, and diverse traffic patterns, create challenges for these generic models, which may not capture local nuances. Moreover, these models often demand substantial computational resources, making real-time processing and forecasting of traffic difficult, particularly in systems with limited

hardware capacity. The inability to efficiently process video data in real-time, combined with the computational limitations, hinders the potential for accurate traffic safety monitoring. Besides that, incorporating research findings into traffic management systems is challenging, as it involves more than advanced detection methods and requires clear guidelines for effective implementation. Without practical frameworks to apply these insights, optimizing traffic flow, reducing accidents, and improving road safety within existing infrastructures remains difficult. In addition, a thorough investigation is necessary to create preventative methods that are specifically targeted at issues such as changing road conditions and rear vehicle behaviours during lane shifts. Moreover, the existing algorithms for object recognition and data collection from CCTV videos are incomplete. They also require powerful processors and do not capture data about vehicles on specific roads, which could assist in traffic management and accident prevention.

Near-miss events are leading indicators of potential accidents and offer a critical opportunity for proactive intervention in traffic safety management. According to the safety triangle theory, for every major accident, there are typically 300 near misses and 29 minor injuries, emphasizing their predictive value (Karakaya et al., 2020). Despite their importance, near-miss events are frequently overlooked in both manual reporting systems and current detection models. Drivers rarely report these incidents unless fatalities occur, and many prefer to avoid involvement altogether. Consequently, such events often go unrecorded, especially in congested traffic conditions, where they silently contribute to accidents and fatalities without triggering preventive measures.

Environmental factors such as blind spots, black spots, poor visibility, and adverse weather, which combined with driver behaviours like sudden lane changes or distracted driving are common causes of near misses. However, existing detection systems often fail to capture these events due to limitations in camera positioning, resolution, and adaptability to varying road or lighting conditions. This shortfall hinders accurate traffic safety assessments and leads to under-informed, reactive policies rather than preventive strategies. By effectively detecting and analysing near-miss events, traffic authorities can implement timely interventions that mitigate risk and prevent more serious incidents from occurring.

The lack of automation and scalability in current manual methods, like Social Distancing Monitoring and Bird's Eye View, further exacerbates the issue, leaving authorities unable to efficiently detect and address near-miss events in real time. This gap in reporting and detection leads to wasted resources and delays in addressing road safety problems. These road issues not only cause air and noise pollution but also increase the death rate in Pulau Pinang. Due to algorithm limitations, the experiment videos cannot be too long, and there are no algorithms capable of real-time computation for live videos. Moreover, research on vehicle transport analysis in Penang is limited, particularly in areas such as feature selection, parameter selection, and the forecasting of blind spots, black spots, and lane changes. Statistical methods, such as the analysis of DN, PICUD and PSD indicators through descriptive statistics, Pearson correlation, and one-way ANOVA, are essential to identify correlations and improve detection models. The correlations can enhance predictive modelling and allowing for better anticipation of near miss events and more effective implementation of traffic safety measures.

1.3 Objectives

From the problem statement in section 1.2, the objectives of this study are as follows:

- a) To determine and identify all possible factors (vehicle size, shape, colour, speed, camera resolution and environment factors) and parameters contributing to road accidents in Penang, including optimization of advance detection models.
- b) To classify and optimize the times by implementing an advanced monitoring approach using an object detection algorithm to enhance the effectiveness of low- and high-quality video footage of CCTV surveillance.
- c) To detect, measure and perform the accuracy of the near misses (blind spot and black spot) between vehicles in CCTV videos to capture near-miss events for better analysis and decision-making in road safety initiatives using Distance-Neighbours (DN), Potential Index for Collision with Urgent Deceleration (PICUD) and Proportion of Stopping Distance (PSD).

1.3.1 Research Questions

In order to guide the investigation, the following research questions (RQs) were formulated. These questions aim to address the RQs.

Research Questions:

- RQ1: What are the most significant features and parameters influencing accurate vehicle detection under varying video quality?
- RQ2: How do high- and low-quality videos affect the accuracy of near-miss detection?

- RQ3: Can indicators like DN (Distance to Nearest object), PICUD (Proximal Indicator of Critical Unsafe Distance), and PSD (Projected Safety Distance) reliably predict near-miss events?

1.3.2 Hypotheses

Based on the above research questions and the underlying theoretical framework, the following hypotheses are proposed. These hypotheses are shown as below:

- Hypotheses 1: Advanced object detection models yield higher accuracy in vehicle and near-miss detection than traditional models.
- Hypotheses 2: Low-quality CCTV video significantly reduces detection precision.
- Hypotheses 3: The integration of statistical indicators (DN, PICUD, PSD) enhances near-miss prediction accuracy.

1.4 Limitation of study

MBPP is responsible for urban planning, infrastructure, and traffic management in Penang, using tools like CCTV to monitor road conditions and enhance public safety. While CCTV footage provides valuable data for identifying traffic issues, it raises privacy concerns, necessitating the use of data anonymization techniques and adherence to regulations like the Personal Data Protection Act (PDPA) to protect individuals' privacy. Ethical approval is required to ensure compliance with privacy guidelines, and transparency in data collection and usage must be maintained to ensure the data serves solely for traffic safety analysis, contributing responsibly to the Penang 2030 project. The Penang Government provides CCTV footage from specific roads in Penang for vehicle and near-miss detection, which located at Lebuhraya Tun Dr. Lim Chong Eu (highway) and Jalan Sungai Dua near USM (urban road), monitored between 6:30 p.m. and 7:00 p.m. The dataset limited to specific roads and timeframes in Penang, provides valuable

insights into local traffic behavior and near-miss events but does not capture diverse scenarios such as extreme weather or varying lighting conditions. To address these limitations, the algorithms are designed to be adaptable, allowing them to be applied to similar limited datasets in other regions. The use of preprocessing techniques, such as noise reduction and resolution enhancement, ensures that the models can handle variability in video quality, making the findings applicable to broader traffic dynamics in different areas. These areas being an industrial hub and school zone respectively, presents a high likelihood of near-miss incidents. However, the study solely focuses on car detection to simplify data analysis, excluding other vehicle types. This study focused on specific roads in Penang to provide a detailed analysis of traffic patterns and near-miss incidents, but its findings may have limited applicability to other regions with different traffic dynamics. Future research can expand the methods to include broader datasets, vehicle types, and pedestrian data, supporting the Penang 2030 project by adapting the models to new road networks and future traffic complexities.

By focusing on car detection, the study addresses a significant portion of traffic, aligns with specific research objectives such as reducing car-related accidents or optimizing traffic flow, and serves as an initial step towards developing more comprehensive multi-vehicle detection systems. Experimentation involves YOLOv3-tiny, YOLOv4-tiny, YOLOv5 (YOLOv5s), YOLOv7, YOLOv7+G3HN, YOLOv7+CNeB and Faster RCNN models, specifically trained and tested for car detection in high-and low-quality video. The models were chosen because of their well-documented performance, existence of pre-trained versions, efficient architectures, community support, and comparability that make them suitable for the car detection experiment in

the study. Due to computational and algorithmic limitations, the tested video duration is restricted to 3 minutes (Abid et al., 2020). In the previous study, the experimental video only utilized an 80-second duration in vehicle detection. The high-quality video was captured from the black spot location, while the low-quality video was recorded due to blind spot identification. The specific factors included were selected due to their comprehensive influence on the accuracy and effectiveness of vehicle detection. The elements ranged from size, colour, shape, speed, camera resolution, and environmental factors, which are necessary for understanding and optimizing vehicle detection algorithms. Trajectory prediction is type of forecasting which can predict the movement of cars to prevent accidents and calculate near miss incidents. Manual calculation of accidents and near-miss events is challenging due to the absence of recorded near-miss incidents in manual reports. Although YOLOv3-tiny, YOLOv4-tiny, YOLOv5, YOLOv7, YOLOv7+G3HN, YOLOv7+CNeB and Faster RCNN models are employed, limitations persist in accurately predicting and preventing future near misses. Therefore, Distance-Neighbours (DN), Potential Index for Collision with Urgent Deceleration (PICUD) and Proportion of Stopping Distance (PSD) are utilized to address the challenges associated with calculating near misses through the monitoring system.

This study makes the assumption that the dataset is normally distributed, even if the data may may deviate from normality. Apparently, this contention stands from the robustness of parametric statistical methods like t-tests and ANOVA, which would also remain valid even when an assumption regarding normality is violated, provided the sample size is sufficiently large and the deviations from normality are not so extreme (e.g. no heavy skewness or excessive kurtosis). This assumption allows the study to utilize

simple, efficient, and interpretable well-known statistical techniques while avoiding complex nonparametric methods that would require extra work in computation. However, that limitation is recognized since it could impair the results if the dataset deviates sharply from normality. To reduce this risk, visual checks and tests for normality have been carried out to make sure that the data are not too skewed or heavy-tailed.

1.5 Significance of study

This study is significant in identifying key visual parameters that influence detection accuracy in vehicle surveillance systems. These parameters are essential for optimizing vehicle detection algorithms, particularly in the context of Malaysia's national development plans such as the Rancangan Malaysia (RMK), which prioritize evidence-based urban planning and cost-efficient smart infrastructure. By replacing traditional handwritten traffic reports with automated vehicle detection using short-duration with duration of 3-minute CCTV footage, the study enhances the accuracy, objectivity, and timeliness of road condition monitoring. This also contributes to smarter traffic data collection practices while conserving storage and improving data retrieval efficiency.

The enhancing the accuracy of vehicle detection under both high- and low-quality video conditions directly supports Penang2030's vision for digital governance and real-time urban monitoring. By optimizing detection models for scenarios involving limited hardware capabilities or compressed storage formats, this study allows local authorities to reduce false detections, improve system responsiveness, and make better use of existing infrastructure. Furthermore, advanced detection architectures are employed to perform vehicle detection, trajectory prediction, and incident identification, enabling

proactive traffic management even in suboptimal video conditions. This work ensures that smart surveillance systems remain reliable despite technical limitations in resolution or lighting.

By introducing and evaluating statistical indicators such as DN PICUD, and PSD, this study enables the quantification of near-miss events for data-driven traffic safety analysis. These indicators offer a more objective and scalable alternative to traditional, underreported near-miss documentation. Through automated calculation and integration into deep learning-based detection models, the study supports the early identification of traffic hazards, enabling the implementation of early warning systems or roadway design interventions. These contributions align with the potential to significantly reduce near-miss incidents and accidents, thereby improving overall road safety in Penang.

1.6 Organizations of the Chapters

The thesis is structured into five distinct segments. Each segment serves a specific purpose, systematically addressing different aspects of the research topic to provide a comprehensive analysis and discussion.

The first chapter introduces the study's background and motivation, outlining its objectives and goals. It discusses the encountered limitations and challenges, emphasizing their impact on the research. The chapter also defines the study's scope, detailing its focus areas and boundaries, while underscoring the study's significance and potential contributions to the field.

The second chapter comprises a comprehensive literature review that examines various aspects: manual reports, traditional methods for scaling parameters, techniques for vehicle detection and feature selection, applications of advanced statistical methods in real-life environments, and the near misses. This review aims to bridge the gap between current research findings and established methodologies, providing insights into how these elements contribute to enhancing understanding and methodologies in the field.

Chapter 3 delves into the methodologies employed to investigate the research objectives. This includes the utilization of YOLOv3-tiny, YOLOv4-tiny, YOLOv5, YOLOv7, YOLOv7+G3HN, YOLOv7+CNeB, and Faster RCNN for tasks such as car detection, near-miss detection, and forecasting traffic flow. The chapter details how each of these models is applied to analyse and interpret data related to these aspects, aiming to provide comprehensive insights into their effectiveness and applications in the study.

Chapter 4 presents the comprehensive results of this research, encompassing the detection and tracking of vehicles, prediction of their movements, monitoring and computation of near-miss incidents, and comparative analysis of the indicators derived from these findings, which are subsequently used to formulate traffic predictions. The chapter meticulously details the methodologies employed and the outcomes obtained, offering a thorough examination of each aspect to elucidate their implications and contribute to the broader understanding in the field.

Chapter 5 concludes the research by thoroughly examining the findings and providing recommendations aimed at improving traffic conditions in Penang, Malaysia. The chapter synthesizes the study's outcomes, offering insightful analysis and proposing

strategic measures based on the research findings to address current challenges and optimize traffic management practices in the region.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The aims and scope of the study indicated in Chapter 1 show the importance of monitoring system in vehicle detection and near miss algorithms to reduce the near miss events and accidents. Section 2.2 will concentrate on the manual reports or collecting manual report data. The traditional method collects blackspot, blind spot and other environment parameter are discussed in Section 2.3. Section 2.4 describes the vehicle detection and feature selection. Section 2.5 will concentrate on the advance statistical software application. Section 2.6 of the previous research explores near miss events. Section 2.7 reviews the summary from Section 2.2 through Section 2.6.

2.2 Manual reports

The main concern in the transportation issue is regarding the accuracy, recent (real-time based) and reliable data. Currently, there are too much dependent on observing manual data compared to auto calculating real-time data (Lim *et al.*, 2022). The baseline data, POL 37 which is a police report are the only manual confidential data that will be used by most of the insurances companies to do claims to theirs's clients. However, the data did not use to understand the road condition due to not solely enough information because of the inaccurate and missing data.

According to the research of Costela & Castro-Torres, (2020), uses manual reports to supplement automated data collection for enhanced accuracy and reliability. Despite their limitations, such as being time-consuming and potentially incomplete, manual reports provide valuable contextual insights and detailed observations that can improve the comprehensiveness of the data and support the development of more robust predictive models.

Perdana & Umbul, (2020) uses manual reports to evaluate epidemiological surveillance of transport equipment as a strategy for preventing quarantinable and pandemic potential diseases. Despite the limitations of manual reports, such as being time-consuming and prone to errors, their use provides detailed and context-specific data that enhance the accuracy and reliability of surveillance and prevention strategies.

Zhao *et al.*, (2022) utilizes manual reports for event extraction in aviation accident analysis, implementing attention-based multi-label classification. Although manual reports can be labour-intensive and susceptible to human error, they provide detailed and context-rich data that significantly improve the accuracy and comprehensiveness of automated classification models.

Chen *et al.*, (2023) uses manual reports to assess the quality of raw data in vessel operations. Despite limitations such as being time-consuming and prone to human error, manual reports provide detailed and accurate context that enhances the overall data quality assessment process.

In the study of Yin *et al.*, (2023), the researchers utilize manual reports to supply detailed annotations and contextual data, enhancing the training and accuracy of deep

learning models for automatic image caption generation. Although manual reports can be labour-intensive and prone to human error, they significantly improve data quality, leading to better model performance and capturing insights that automated methods alone might miss.

In summary, manual traffic reporting has long been a standard practice, but it is fraught with significant limitations that undermine its reliability and utility for comprehensive traffic analysis. manual reports typically document basic information such as the number of drivers involved, victims, the time and location of the accident, and the sequence of events leading to the accident. However, these reports are often error-prone, incomplete, and inconsistent, primarily due to human subjectivity and resource constraints. Critical data, such as accidents details and near-miss incidents, are frequently omitted, resulting in gaps that hinder a thorough understanding of road safety challenges. This lack of detailed and accurate data limits the ability to identify risky patterns or trends, thereby reducing the effectiveness of safety interventions and predictive modelling.

Table 2.1 Manual reports

No.	Research	Source of data	Study area	Details of manual report				Remark
				Time and location	Environment condition	Object details	Human factors	
1	Costela & Castro-Torres, (2020)	Simulated driving data	Simulated driving environments	✓			✓	Spain
2	Perdana & Umbul, (2020)	Government report, field survey	Port of Surabaya, Tanjung Perak Port	✓		✓		Indonesia
3	Wanjura, (2021)	Field survey, sensor data	Cotton module feeders in agricultural settings	✓	✓	✓	✓	USA
4	Ahmad, A., et al., (2022)	Government report, field survey	Hydrocarbon pipeline systems	✓		✓	✓	UAE
5	Chen & Lam, (2022)	Field survey, operational data	Tugboat operations	✓	✓	✓		Singapore
6	Zhao, X., et al., (2022)	Aviation accident reports	Aviation industry	✓	✓	✓	✓	USA

Table 2.1 cont.

No.	Research	Source of data	Study area	Details of manual report				Remark
				Time and location	Environment condition	Object details	Human factors	
7	Daanen, et al., (2023)	Traffic database, field survey	US roadways	✓	✓	✓	✓	USA
8	Chen, G., et al., (2023)	Field survey, operational data	Vessel operations	✓		✓	✓	China
9	Yin, X., et al., (2023)	Traffic database, image datasets	Rail transportation systems	✓	✓	✓		China

Table 2.1 demonstrates that the majority of researchers have substantiated that manual reports are time-consuming and prone to human error. These reports have often failed to convincingly establish the factors contributing to road accidents, often attributing accidents to driver behaviours without sufficient evidence. Therefore, addressing these gaps necessitates a shift towards automated, data-driven approaches that leverage real-time analytics and advanced detection technologies to ensure consistency, accuracy, and completeness in traffic monitoring and reporting. For example, integrating manual reports with visual documentation such as CCTV videos are necessary to provide robust evidence. The use of CCTV footage in traffic analysis raises ethical concerns about privacy, as it can capture personal data such as license plates and faces, which could infringe on privacy rights if not properly safeguarded. To mitigate these risks, techniques like data anonymization, along with compliance to frameworks like Malaysia's Personal Data Protection Act (PDPA), are essential to ensure the responsible use of such footage.

2.3 Type of parameter scaled (Traditional method)

Traditionally, parameter scaling during blackspot, blind spot, and other environmental evaluations was based on manual collecting information and basic statistical calculations. These approaches usually involve identifying factors like traffic volume, road structure, visibility conditions, and accident records. The parameters are then scaled using empirical data and local traffic limitations. Despite their methodical approach, traditional approaches frequently face limitations in capturing dynamic environmental elements, demanding the use of modern data analytics and real-time

monitoring technology for thorough analysis and predictive modelling. This static nature of traditional methods limits their applicability in real-time scenarios, reducing the accuracy and adaptability of models for predicting traffic incidents. To address this gap, the study emphasizes the importance of integrating dynamic, real-time analytics, which can process continuously evolving data to capture nuanced traffic behaviours. Such advancements would enhance the scalability and precision of traffic management systems, allowing for more proactive and effective interventions in response to immediate traffic conditions.

2.3.1 Blackspot

A black spot is a location on a road where there is a concentrated history of traffic accidents. The reasons for these accidents can vary widely, including sharp curves or straight stretches that hinder visibility of oncoming traffic, obscured intersections along high-speed roads, and inadequate or obscured warning signs at certain intersections. These factors contribute to the higher incidence of accidents at these spots, highlighting the need for enhanced safety measures and improved road design to mitigate such risks effectively.

Karamanlis, I., Nikiforiadis, *et al.*, (2023) utilizes black spot analysis to identify high-risk locations on roads. The method involves analyzing historical data of road traffic accidents to pinpoint areas with a concentrated occurrence of incidents. The advantages of this approach include targeted interventions and improvements in road safety measures at identified black spots, potentially reducing accident rates. However, limitations may include reliance on historical data that may not capture current traffic patterns or emerging

risks, necessitating regular updates and supplementary real-time monitoring for comprehensive safety improvements.

Jima & Sipos, (2023) utilizes density estimation methods to pinpoint blackspot locations within road networks, particularly at intersections. By employing remote sensing and spatial analysis techniques, the research examines traffic crash scenes to identify areas with high accident densities. This approach offers the advantage of accurately identifying critical road segments for targeted safety improvements, potentially decreasing accident frequencies and enhancing overall road safety. However, challenges include the complexity of analysing remote sensing data and integrating spatial information from diverse sources, which may limit the comprehensive identification and mitigation of blackspots.

Karamanlis, Kokkalis, et al., (2023) employs both classical and modern approaches to identify road accident black spots. Classical methods likely involve statistical analysis of historical accident data, while modern approaches include advanced data analytics and geographical information systems (GIS). The advantages of this dual approach include comprehensive analysis and potentially more accurate identification of high-risk areas, leading to targeted safety improvements. However, limitations include the complexity and resource intensity of modern techniques, as well as the need for robust data integration and ongoing updates to maintain effectiveness in identifying and mitigating black spots.

Hussein *et al.*, (2023) utilizes an assessment method to identify road accident black spots in the state of Perak, Malaysia. The specific approach used to spot these black spots involves analysing accident data, conducting site assessments, and possibly utilizing

geographical information systems (GIS) for spatial analysis. The advantages include targeted countermeasures to improve safety at identified high-risk locations, potentially reducing accidents and enhancing overall road safety. Limitations include challenges in data accuracy, resource availability for comprehensive assessments, and the need for ongoing monitoring and evaluation of implemented measures to ensure effectiveness.

Sulistiyono et al., (2024) utilizes a method focused on improving road safety at blackspots along the tourist road access to Mount Bromo in East Java. The specific approach used to identify these blackspots is not detailed in the summary provided. Typically, methods involve analyzing accident data, conducting field surveys, or employing geographical information systems (GIS) for spatial analysis. The advantages likely include targeted interventions to enhance safety in high-risk areas, potentially reducing accidents and improving overall road conditions. Limitations involve challenges in data collection, accuracy of accident data, and implementation of safety measures in remote or tourist-heavy areas.

In this study, the identification of blackspots is paramount due to their significant contribution to accidents on the roads. Identifying these blackspots is crucial for implementing effective safety measures and reducing the frequency of accidents in the studied area.

Table 2.2 Blackspot

No.	Research	Application data		Cause of blackspot	Method	Type of transportation involved		
		Image process	Empirical data			Vehicles	Motorcycles/ Bicycles	Pedestrians
1	Bisht & Tiwari (2020)		✓	Environment condition, Lane change, Driver behaviour	Black Spots Focused Policies	✓		
2	Goyal et al. (2020)		✓	Road conditions, traffic volume	Blackspot Identification	✓		
3	Yuan et al. (2020)		✓	Urban road conditions	Firefly Clustering Algorithm and Geographic Information System (GIS)	✓		
4	Hartatik et al. (2021)		✓	Road traffic crashes	Blackspot Analysis	✓		
5	Hamid (2021)		✓	Day and night time	Geographic Information System Database	✓		
6	Khamankar et al. (2021)		✓	Road conditions, traffic volume	Blackspot Identification	✓		
7	Singh & Katiyar (2021)		✓	Urban road network issues	Geographical Information System (GIS)	✓		
8	Aziz & Ram (2022)		✓	Global methodologies	Meta-analysis of Black Spots Identification	✓		

Table 2.2 cont.

No.	Research	Application data		Cause of blackspot	Method	Type of transportation involved		
		Image process	Empirical data			Vehicles	Motorcycles/ Bicycles	Pedestrians
9	Baranyai & Sipos (2022)		✓	Road conditions, traffic volume	Kernel Density Estimation	✓		
10	Novriani (2022)		✓	Road conditions, traffic volume	Accident Equivalent Key and Black Spot Key Analysis	✓		
11	Ochieng et al. (2022)		✓	Road conditions, traffic volume	RFID-based Localization Based Services Framework	✓		
12	Yadav & Chaturvedi (2022)		✓	State highway issues	Road Safety Audit	✓		
13	Yadav et al. (2022)		✓	Highway conditions	Safe System Approach	✓		
14	Noor Azmi & Sarif (2023)		✓	Federal route conditions	Geographic Information System Database	✓		
15	Kulheriya et al. (2024)		✓	Road conditions, traffic volume	Black Spot Investigation	✓		
16	Karamanlis, I., Nikiforiadis, et al. (2023)		✓	Environment condition, Lane change, Driver behaviour	Black Spot Analysis	✓		

Table 2.2 cont.

No.	Research	Application data		Cause of blackspot	Method	Type of transportation involved		
		Image process	Empirical data			Vehicles	Motorcycles/ Bicycles	Pedestrians
17	Jima & Sipos (2023)		✓	Intersection-related crashes	Density Estimation	✓		
18	Karamanlis, I., Kokkalis, et al. (2023)		✓	Environment condition, Lane change, Driver behaviour	Classical and Modern Approaches for Identifying Black Spots	✓		
19	Sulistyono et al. (2024)		✓	Tourist road access	Blackspot Analysis on Mount Bromo Tourist Road Access	✓		
20	Hussein et al. (2023)		✓	Environment condition, Lane change, Driver behaviour	Black Spot Identification and Countermeasures	✓		

Table 2.2 summarizes previous research that primarily focuses on connecting blackspots with accidents but does not extend this correlation to include near-miss incidents. Next, the data quality and completeness due to inconsistent data collection, underreporting, and lack of detailed accident information. Spatial and temporal resolution issues arise from aggregating data over large areas and long periods, obscuring specific trends and patterns. Manual data collection and analysis processes introduce time-consuming tasks and potential human errors. Additionally, these methods often fail to leverage advanced technologies like Geographic Information System (GIS), machine learning, and real-time data analytics, which could enhance their accuracy and effectiveness. However, blackspots play a crucial role in near-miss incidents, which are significant as they can lead to severe injuries in traffic situations. Therefore, understanding the relationship between blackspots and near-miss incidents is essential for comprehensive road safety strategies.

2.3.2 Blind spot

A blind spot refers to the area around a moving vehicle where neither the rearview nor side mirrors provide visibility. This blind area poses a significant risk, especially when drivers are changing lanes or maneuvering in traffic, increasing the likelihood of collisions, obstacles, and accidents that can result in severe injuries or even fatalities. Monitoring the blind spot requires drivers to swiftly turn their heads to check this critical zone before making any maneuvers, such as lane changes. However, some drivers may overlook this essential check, focusing solely on their immediate surroundings rather than the broader road ahead, potentially leading to accidents, injuries, or tragic loss of life.

Hajare et al., (2023) utilizes a vehicle safety system designed for identifying blind spots and navigating hilly areas. The systems may utilize sensors, cameras, or radar technologies to monitor blind spots around the vehicle. The advantages likely include improved driver awareness and enhanced safety through real-time monitoring and alerts. Limitations involve cost, technological complexity, and potential challenges in adverse weather conditions or rugged terrain affecting sensor performance.

Suresh et al., (2023) uses a non-linear intelligent fuzzy decision-making system to estimate blind spots. This approach capitalizes on the strengths of fuzzy logic and non-linear modeling to enhance the accuracy of blind spot identification, particularly in scenarios where relationships between variables are complex and uncertain. However, the method's complexity and computational requirements are potential challenges that need to be considered in its application.

Kim et al., (2023) employs a Blind Spot Detection Radar System to enhance safe driving in smart vehicles. This method leverages radar technology's strengths in accurate and long-range detection of objects within blind spots, contributing significantly to driver awareness and overall vehicle safety. The considerations such as cost and limitations related to radar's sensitivity to certain materials are important factors in its implementation and effectiveness.

Mukhopadhyay et al., (2024) employs an edge-based blind spot avoidance and speed monitoring system tailored for emergency vehicles. This method leverages edge computing advantages such as real-time processing and reduced latency to enhance the safety and efficiency of emergency responses. However, challenges related to