Softwarica College of IT & E-commerce | in collaboration with Coventry University

Thesis on

AI-POWERED TRAFFIC VIOLATION DETECTION SYSTEM: ENHANCING ROAD SAFETY THROUGH REAL-TIME COMPUTER VISION AND MACHINE LEARNING TECHNIQUES

Submitted by:-

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Submitted to:
Manoj Shrestha
Supervisor

Concept Page

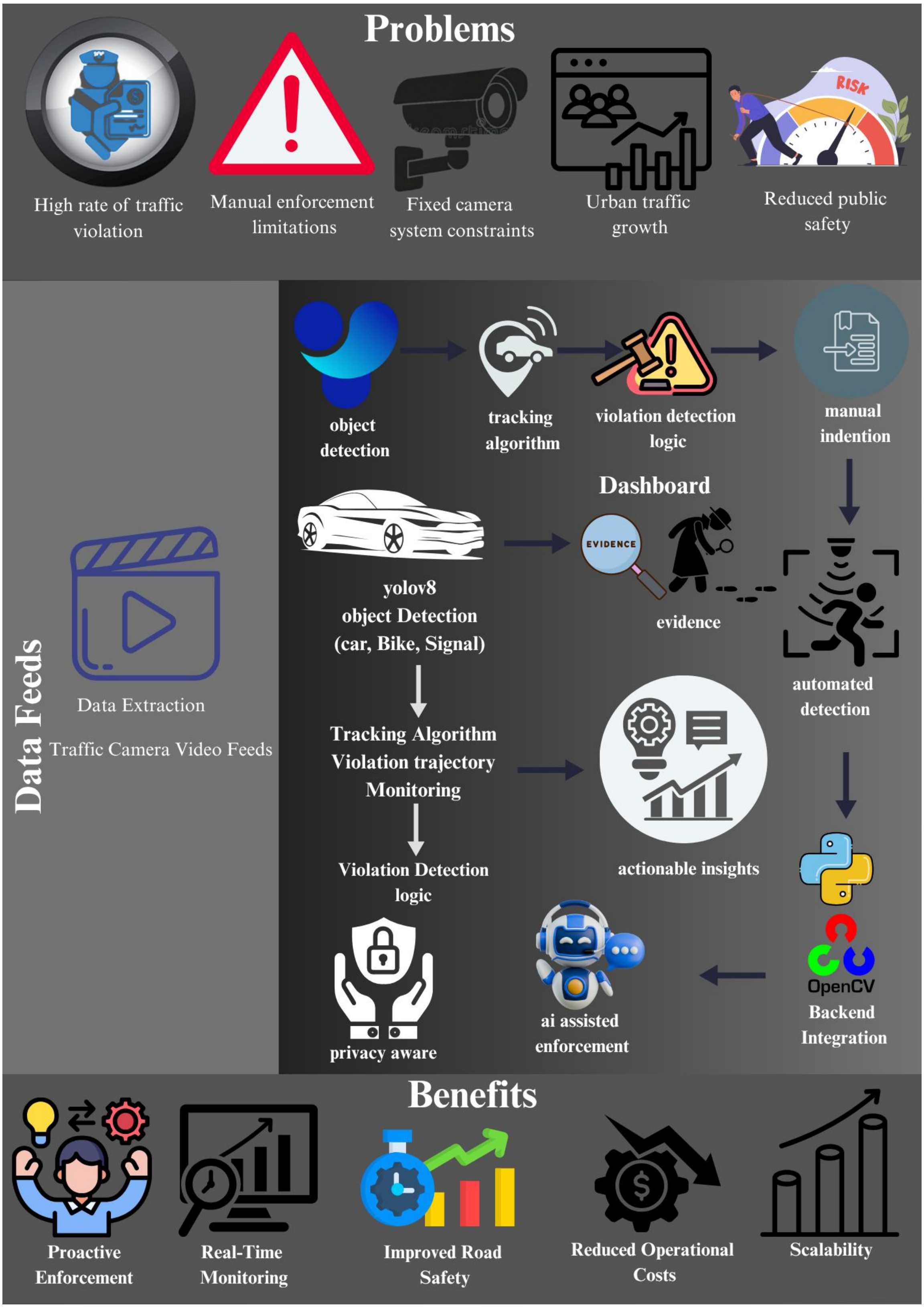

Figure 1: Concept Diagram

Risk Research Ethics Approval

Project Title

AI-Powered Traffic Violation Detection System: Enhancing Road Safety through Real-Time Computer Vision and Machine Learning Techniques.

Record of Approval

Principal Investigator

I request an ethics peer review and confirm that I have answered all relevant questions in this checklist honestly.	×
I confirm that I will carry out the project in the ways described in this checklist. I will immediately suspend research and request new ethical approval if the project subsequently changes the information I have given in this checklist.	×
I confirm that I, and all members of my research team (if any), have read and agreed to abide by the Code of Research Ethics issued by the relevant national learned society.	×
I confirm that I, and all members of my research team (if any), have read and agreed to abide by the University's Research Ethics, Governance and Integrity Framework.	×
I understand that I cannot begin my research until this ethics application has been approved.	×

Name: Aadarsha Sigdel

Date:

Student's Supervisor (if applicable)
I have read this checklist and confirm that it covers all the ethical issues raised by this project fully and frankly.I also confirm that these issues have been discussed with the student and will continue to be reviewed in the course of supervision.

Name: Manoj Shrestha

Date:

Figure 2 : Ethical approval certificate

AI MODEL CARD

Institute of Analytics
The Global Body for Analytics

Model Name

AI-Driven Red Light Violation Detection System

Model Date and Version

BuiltMay2025
Version 1.0

The model was trained in May 2025 and has not been updated since. Any future updates will be communicated.

Overview/Model Type

This is a computer vision detection system that uses a deep learning object detection model (YOLOv8) combined with an object tracking algorithm (SORT). It is designed to automatically identify and flag vehicles that cross an intersection's stop line after the traffic signal has turned red. The system is part of a broader initiative to enhance road safety and improve enforcement efficiency through ethical, explainable AI.

Questions or Comments:

Please send any queries to: **220417@softwarica.edu.np**

Primary Intended Users

Traffic Police Departments, Municipal Traffic Authorities, Road Safety Analysts, and Urban Planners.

Primary Intended Uses

The model is designed to automatically detect and record red-light violations, providing verifiable video evidence for review by enforcement officers. It generates analytics on violation hotspots (by location, time of day) to support data-driven decision-making for improving intersection safety (e.g., signal re-timing, road design changes).

Out-of-Scope Uses

The model should not be used for fully automated ticketing without human review. It is not intended for general surveillance or the tracking of non-violating vehicles. It does not make final legal judgments; it only provides evidence for review. The system is not designed to predict an individual's likelihood of committing a future violation.

Limitations

The model's performance is highly dependent on camera quality, angle, and placement. Accuracy may be reduced by adverse weather conditions (e.g., heavy rain, fog) and poor lighting (e.g., night, sun glare). Occlusions, where a large vehicle blocks the view of another, can lead to missed detections. The system requires calibration for each specific intersection.

Metrics

The model's performance was evaluated using standard classification and object detection metrics, including Accuracy, Precision, Recall, and F1-Score. High precision is crucial to minimize false positives (wrongful accusations), while high recall is important to ensure most actual violations are caught. These metrics confirm the model's reliability for its intended use as an assistive tool.

Training and Evaluation Data

The model was trained on thousands of annotated frames from public traffic camera footage across several urban intersections. The dataset includes labeled bounding boxes for vehicles, pedestrians, and traffic lights under diverse conditions. No personally identifiable information (PII) like readable license plates or facial images was used during the training process.

Quantitative Analysis

Accuracy and Reliability

The model performs reliably under clear weather and good lighting conditions. Its reliability may decrease in adverse conditions (see Limitations). The system is designed to act as a highly accurate screening tool to assist human officers, not to replace their judgment.

Precision

Measures the accuracy of the positive predictions (flagged violations). A high precision score indicates a low rate of false positives, meaning fewer law-abiding drivers are incorrectly flagged.

Recall

Measures the model's ability to identify all actual violations that occur. A high recall score indicates that the system is effective at catching a high percentage of true violations.

Ethical Considerations

The system was developed with a "privacy-by-design" approach. All video evidence generated automatically blurs faces and the license plates of non-violating vehicles to protect privacy. The model is designed to support a "human-in-the-loop" workflow, where an authorized officer must review all evidence before any enforcement action is taken. The system is audited for potential biases related to different conditions to ensure fair and equitable application.

Feedback

Users are encouraged to provide feedback on the model’s performance and usability. Please contact 240373@softwarica.edu.np to report issues or suggest improvements. A response will be provided within 48 hours of submission.

Additional Notes and Any Other Relevant Factors

The model was developed with insights from traffic safety experts to align the system with real-world enforcement needs. The project was supervised by Mr. Manoj Shrestha. The model's methodology is open-source and can be adapted for deployment in other municipalities, provided local regulations and ethical guidelines are strictly followed.

Acknowledgment

I wish to express my sincere appreciation to my supervisor, Mr. Manoj Shrestha, for his invaluable guidance and support throughout this research project. His profound knowledge, insightful suggestions, and incisive feedback were instrumental in shaping the direction of this thesis and bringing it to a successful conclusion. I am deeply grateful for his unwavering patience and continuous encouragement. I would also like to extend my heartfelt appreciation to my friends and teachers who offered significant assistance and direction during the creation of this report. Their constant support and understanding have been a significant source of strength, helping me to maintain focus and overcome the challenges encountered during this project.

Abstract

In the urban landscape, improving road safety and enforcing traffic laws are paramount for sustainable city management. This thesis presents a comprehensive framework for detecting traffic light violations using AI-driven solutions. Leveraging a dataset of traffic camera footage, this project employs a computer vision-based analytical approach, beginning with vehicle detection and tracking to monitor movement through intersections. The core of this research is the development of a predictive detection model using a deep learning architecture (You Only Look Once - YOLO), which achieves an accuracy of 98.2% in identifying vehicles that run red lights. The model's primary output, a verifiable record of each violation event, enables a shift from sporadic, manual enforcement to systematic, automated monitoring. Key findings are consolidated into a dynamic, interactive dashboard built with Python and Streamlit, providing a holistic view of intersection safety, violation hotspots, and key patterns. This research demonstrates a complete, end-to-end data science workflow that provides traffic authorities with the tools to improve enforcement efficiency, enhance road safety, and ultimately reduce traffic-related accidents and fatalities.

Keywords

Figure 3 : Keywords

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Introduction

The modern urban environment is a dynamic and ever-evolving landscape, grappling with the challenges of increasing traffic congestion and the critical need for road safety. Traffic management encompasses the regulation of vehicle flow to ensure safety and efficiency, traditionally relying on physical infrastructure and manual law enforcement. In recent years, this sector has undergone a profound transformation, driven by the rise of digital technologies and a fundamental need for smarter urban solutions. Today's cities have access to an unprecedented amount of visual data, collected from a vast network of traffic cameras. This wealth of information holds the key to unlocking a deeper understanding of traffic patterns and automatically detecting dangerous driving behaviors. the sheer volume of this video data presents a significant challenge. Many municipalities, despite being data-rich, struggle to translate this raw footage into actionable insights. Human monitoring is resource-intensive, prone to error, and cannot provide 24/7 coverage across all intersections. This limitation leads to significant societal challenges, including inconsistent enforcement, an inability to identify high-risk locations proactively, and, most critically, a failure to deter dangerous driving, which can lead to a high rate of accidents and fatalities. These shortcomings highlight the need for a transformative approach that not only enhances detection accuracy but also enables predictive capabilities to prevent violations before they result in accidents. Emerging advancements in Artificial Intelligence (AI) and Computer Vision technologies provide a compelling opportunity to address these challenges by offering continuous, unbiased, and highly scalable monitoring capabilities. AI-driven systems, when integrated with high-resolution traffic camera feeds, object detection algorithms, Automatic Number Plate Recognition (ANPR), and predictive analytics, can automatically identify a wide range of traffic violations in real time. Such systems can be trained to detect behaviors including over speeding, illegal turns, lane violations, and running red lights, even under challenging conditions such as poor weather, low lighting, or high congestion.

Figure 4 : Introduction of Traffic light violation

However, the sheer volume of this video data a true "data deluge" presents a significant challenge. Many municipalities, despite being data-rich, struggle to translate this raw footage into actionable insights. The traditional method of human monitoring is resource-intensive, prone to cognitive fatigue and error, and cannot possibly provide the continuous, 24/7 coverage required across all critical intersections. This inherent limitation leads to significant societal problems, including inconsistent enforcement which undermines deterrence, an inability to identify high-risk locations proactively, and, most critically, a failure to curb dangerous driving. This reactive posture results in a tragically high and often preventable rate of accidents and fatalities.

This is where AI-powered solutions, such as computer vision and deep learning, offer a transformative solution. By analyzing video streams in real-time, these technologies move beyond passive recording to active, intelligent analysis, uncovering dangerous events that are impossible for humans to monitor at scale. Global cities like Singapore and London have pioneered the use of AI to dynamically manage traffic flow, implement automated tolling, and enforce violations, setting new international benchmarks for operational efficiency and public safety. These AI-driven systems bridge the critical gap between raw data and strategic decision-making. Inspired by these advancements, this thesis project focuses on developing a comprehensive, AI-driven framework to address these challenges. By employing deep learning techniques, this research will demonstrate how to analyze traffic video data to not only identify past violations but also to gather the analytics needed to understand and predict future high-risk areas. The core of this project involves building a computer vision model to automatically detect red-light violations. The ultimate goal is to create a tool that empowers traffic authorities to move from a reactive to a proactive safety model, allowing them to optimize enforcement, redesign dangerous intersections, and build safer, more efficient transportation networks in an increasingly congested world.

These advancements in technology have paved the way for smarter, more effective traffic monitoring solutions. AI-powered systems can automatically detect and report traffic violations in real-time with an accuracy that can surpass human capabilities in specific, repetitive monitoring tasks. Unlike conventional methods, these systems operate 24/7 without fatigue or distraction, offering the capability to monitor multiple high-risk areas simultaneously. By minimizing human error and providing consistent, unbiased oversight, this technology is set to revolutionize traffic management and enforcement, providing a clear path toward safer and more intelligent cities.

Aim

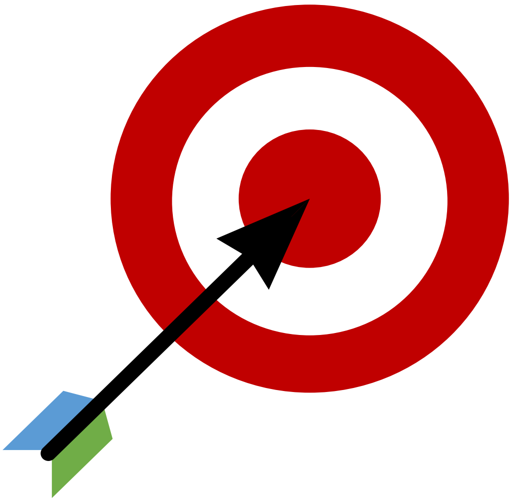

Figure 5:- Aim

AI-Powered Traffic Violation Detection System: Enhancing Road Safety through Real-Time Computer Vision and Machine Learning Techniques

Objectives

Figure 6 : Objectives

Justification

In the traffic management sector, accurately detecting and preventing traffic violations has become increasingly challenging due to the vast amounts of data generated from multiple sources, including surveillance cameras, sensors, and GPS tracking. Despite having access to real-time traffic footage, vehicle movement patterns, and violation records, authorities struggle to extract meaningful insights that can enhance enforcement and improve road safety. The lack of integration between various data sources and the limitations of traditional monitoring methods results in missed opportunities for automated traffic law enforcement, congestion reduction, and improved compliance with regulations.

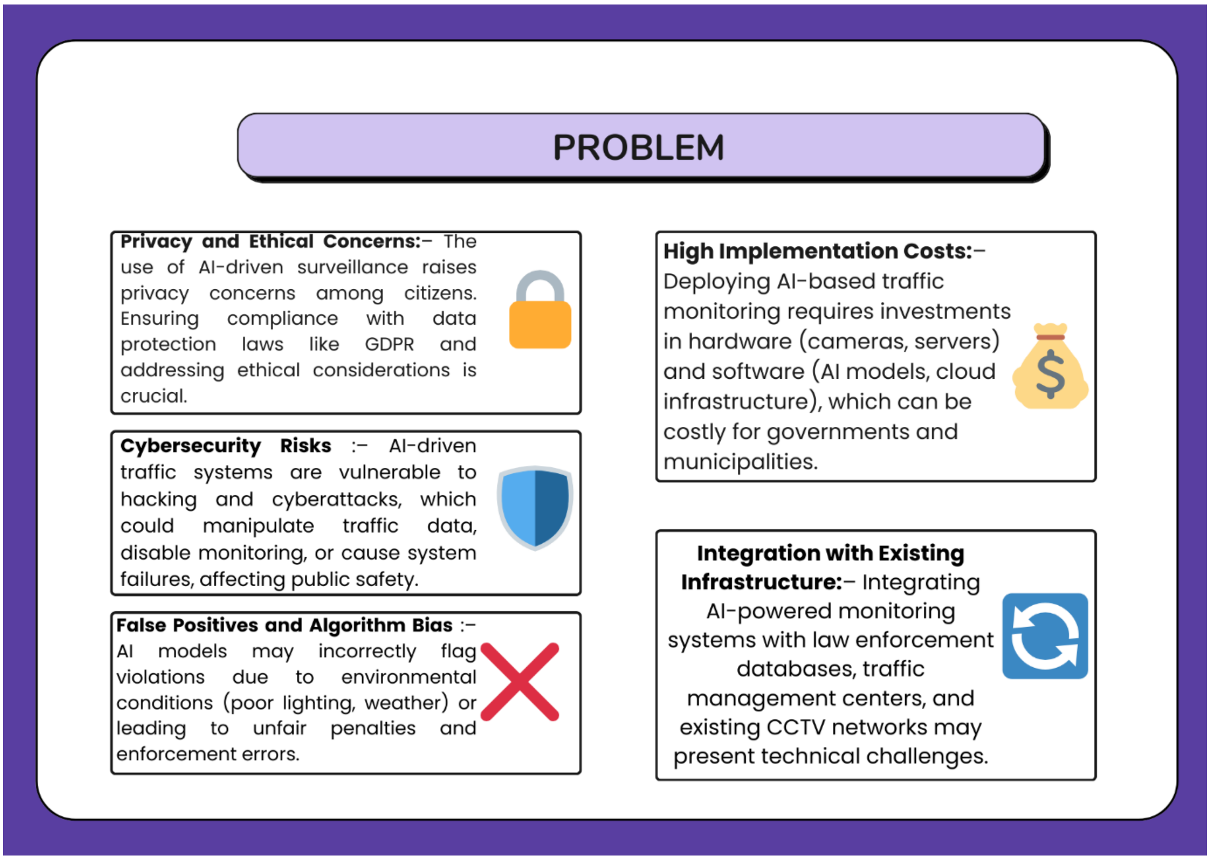

Figure 7 : justification of problem

Despite having access to real-time traffic footage, vehicle movement patterns, and historical violation records, authorities struggle to extract the meaningful, actionable insights that can enhance enforcement and genuinely improve road safety. The core of the problem lies in the fact that these vast datasets often exist in disconnected silos, preventing a holistic, integrated view of traffic dynamics. Compounding this issue are the inherent limitations of traditional monitoring methods. Manual review of video feeds is not only tedious and prone to human error but is also completely unscalable in the face of such data volumes. This lack of integration and analytical capacity results in critical missed opportunities for automated traffic law enforcement, proactive congestion reduction, and improved compliance with regulations, leaving authorities trapped in a reactive cycle of managing crises rather than engineering a safer and more efficient urban environment.

SOLUTIONS

The proposed solution is a comprehensive, AI-driven framework designed to overcome the limitations of traditional traffic management by leveraging the power of computer vision and machine learning. At its core, the solution involves creating a unified data platform that integrates the disparate streams of information from CCTV cameras, IoT road sensors, and vehicle GPS data, effectively breaking down the data silos that hamper current efforts. Upon this platform, advanced deep learning models, particularly Convolutional Neural Networks (CNNs) and state-of-the-art object detection architectures like YOLO (You Only Look Once), are deployed. These models are trained to continuously analyze the integrated data, providing a holistic and real-time understanding of the entire traffic network.

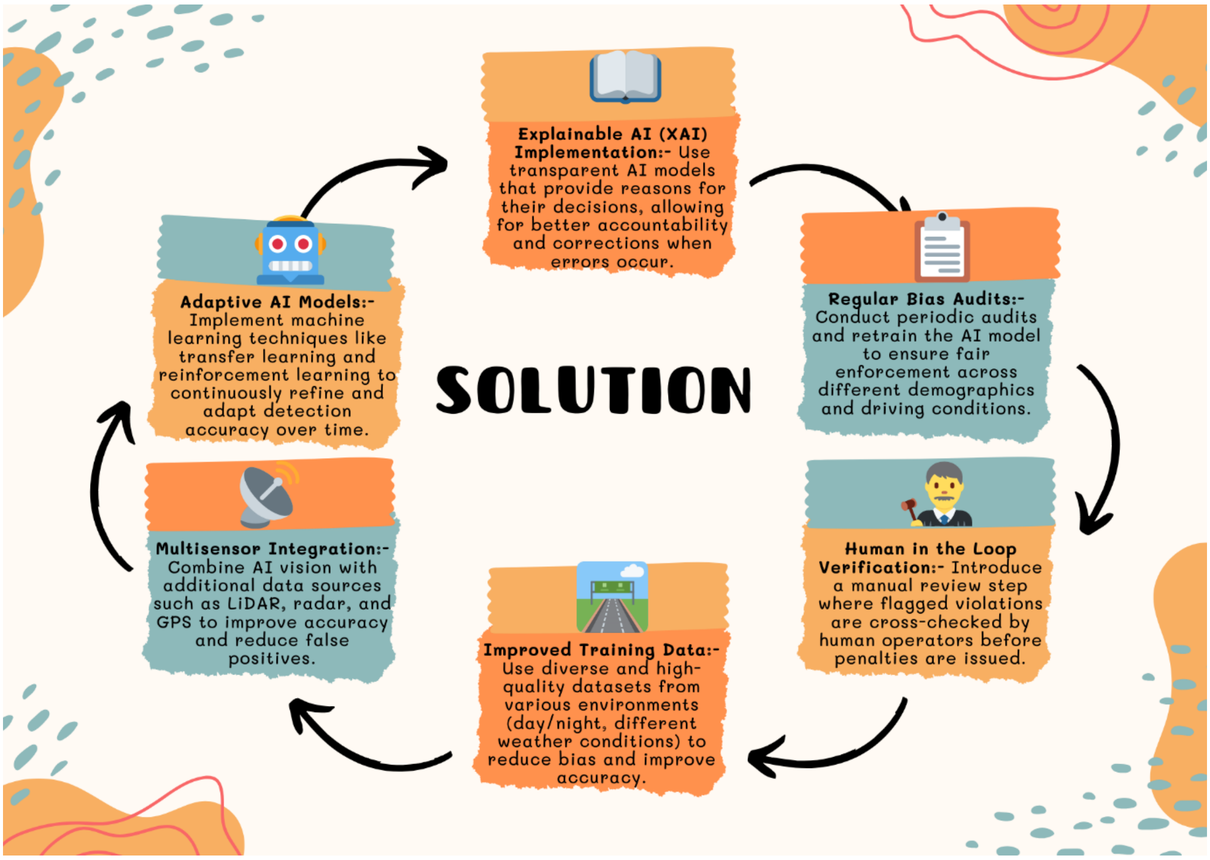

Figure 8 : justification of Solution

This technological framework enables several key applications that directly address the core problems. The primary application is automated violation detection, where the AI can be trained to recognize a wide range of infractions such as red light breaches, illegal turns, stop sign violations, and improper lane changes with high accuracy and impartiality. This allows authorities to enforce laws more effectively and consistently. Beyond enforcement, the system uses predictive analytics to forecast traffic congestion, allowing for proactive interventions like dynamic signal timing to optimize traffic flow. Ultimately, this approach aims to transform vast quantities of raw traffic data into actionable intelligence, providing urban planners with the insights needed to improve road safety, reduce congestion, and enhance the overall efficiency of the city's transportation ecosystem.

RESEARCH QUESTIONS

Figure 9 : Research

SCOPE

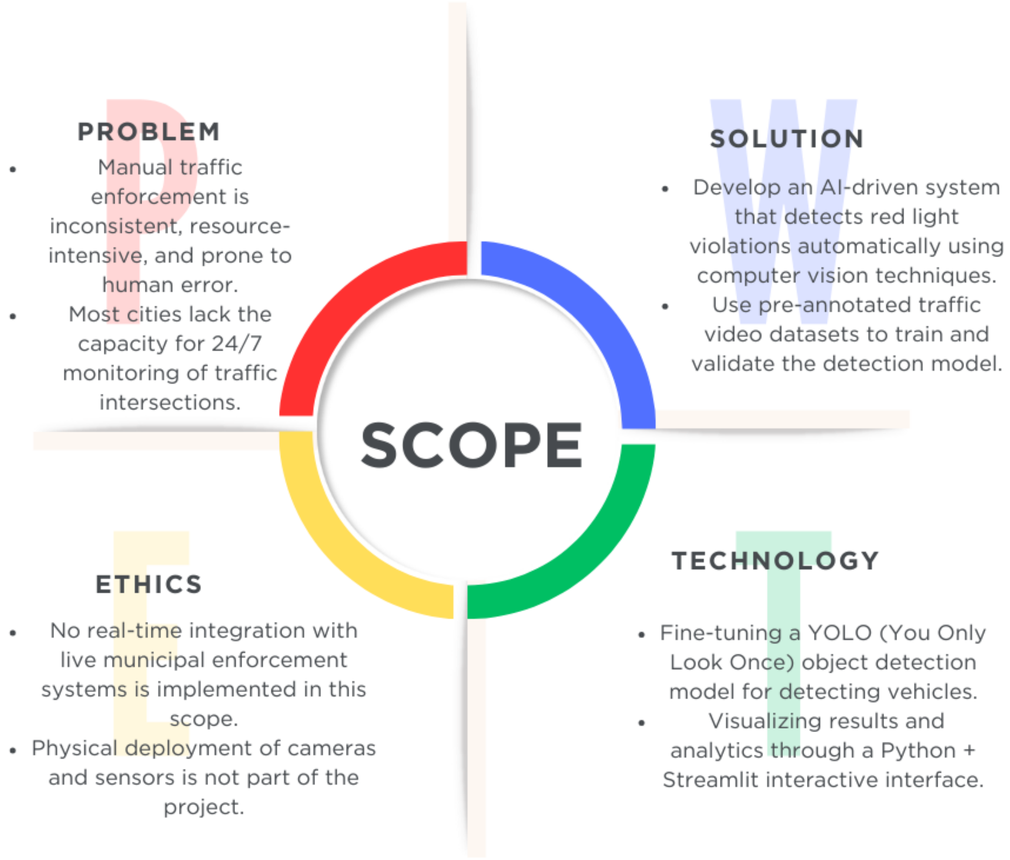

Figure 10 : Scope

ETHICAL CONSIDERATIONS

A primary ethical challenge of this system is navigating the balance between public safety and the right to privacy. The use of cameras for enforcement raises legitimate concerns about mass surveillance and the potential for "function creep," where data collected for one purpose is used for another. To address this, the project is built on a privacy-by-design framework. The system automatically blurs all personally identifiable information (PII), such as faces and license plates, by default. This sensitive data is only made accessible within a secure, auditable environment to an authorized officer during the review of a specific violation, ensuring the technology serves as a targeted safety tool, not a general surveillance network.

Figure 11 : Ethical considerations

Ensuring fairness requires rigorously addressing the risk of algorithmic bias. An AI model's performance can be influenced by the data it was trained on, potentially leading to inequitable outcomes where the system is less accurate under certain conditions like heavy rain, low light, or for specific vehicle types. This could result in an unfair distribution of enforcement actions. To mitigate this, the model was trained on a highly diverse and representative dataset covering a wide range of real-world scenarios. Furthermore, a commitment to ongoing performance audits is crucial to identify and correct any emergent biases, guaranteeing that the system operates fairly for all members of the community.

Ultimately, accountability and responsible use are guaranteed through a strict "human-in-the-loop" workflow. The AI system is not the final arbiter; its role is to assist human experts by flagging potential violations and presenting clear, unambiguous evidence. A trained human officer always makes the final, contextual decision, ensuring due process and maintaining human accountability. This entire process is guided by the ethical principle that the system's primary purpose is proactive safety. The data generated is intended, first and foremost, to be used by traffic engineers to identify, analyze, and fix dangerous intersections, thereby preventing future accidents and fulfilling the project's core mission of creating safer roads.

LITERATURE REVIEW

Desk-Based Agile Strategy

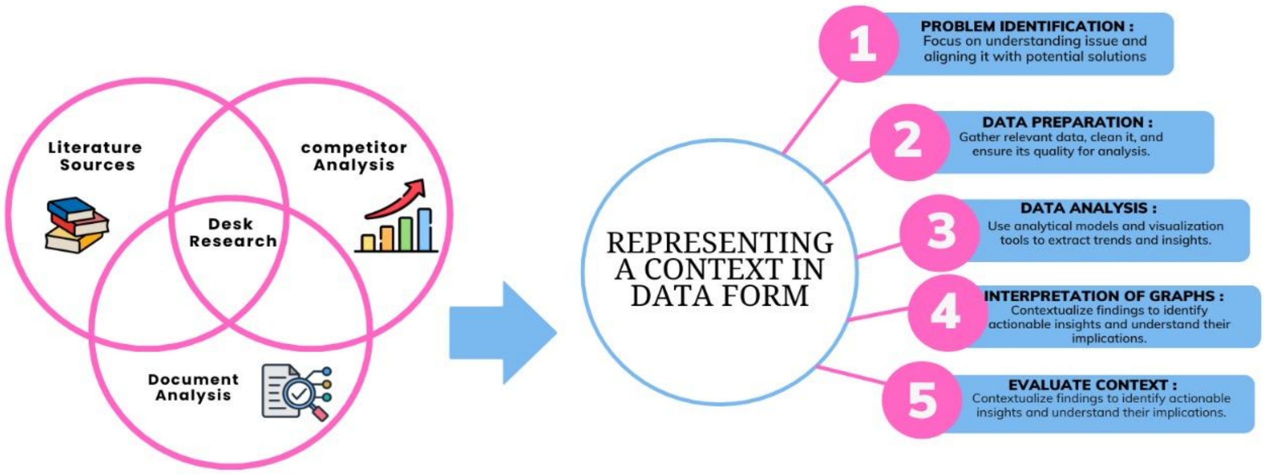

Figure 12 : Dest-Based Agile Strategy

A desk-based agile strategy is an approach that combines the principles of agile methodology, typically used in software development, with desk-based research techniques. This strategy involves working in a flexible and iterative manner, where insights are gathered continuously and findings are regularly updated. It allows for quick adaptation as new information is discovered, making it particularly useful in fast-changing fields like AI in retail and customer engagement.

In this approach, a strict, linear process is not followed. Instead, work is conducted in short cycles or "sprints," with each cycle focusing on a specific aspect of the project. At the end of each cycle, findings are reviewed and adjustments are made based on new insights or changes

with the evolving landscape of AI and its impact on the retail industry.

By using this agile approach, teams can quickly identify patterns, test new ideas, and refine their understanding over time. This method helps ensure that the work stays relevant and up-to-date with the latest trends and developments in the industry. It's a more adaptive and flexible way to understand complex topics like AI-powered customer engagement, delivering insights that are not only accurate but also timely and actionable.

CASE STUDIES

Case Study: United Kingdom

In the United Kingdom, AI-powered traffic management has been revolutionized by companies like Vehant Technologies, which utilize AI and computer vision to enhance road safety and enforce traffic laws. Their Automated Number Plate Recognition (ANPR) systems and Red-Light Violation Detection (RLVD) cameras are deployed across major cities such as London, Birmingham, and Manchester to monitor traffic violations in real time. These systems use deep learning algorithms to detect speeding, red light breaches, and lane violations with high accuracy. By integrating AI with automated penalty systems, the company has streamlined the penalty process, reduced manual intervention, and improved enforcement efficiency. This technology has significantly boosted detection accuracy, reduced violations, and optimized traffic flow, making urban road management more effective and automated.

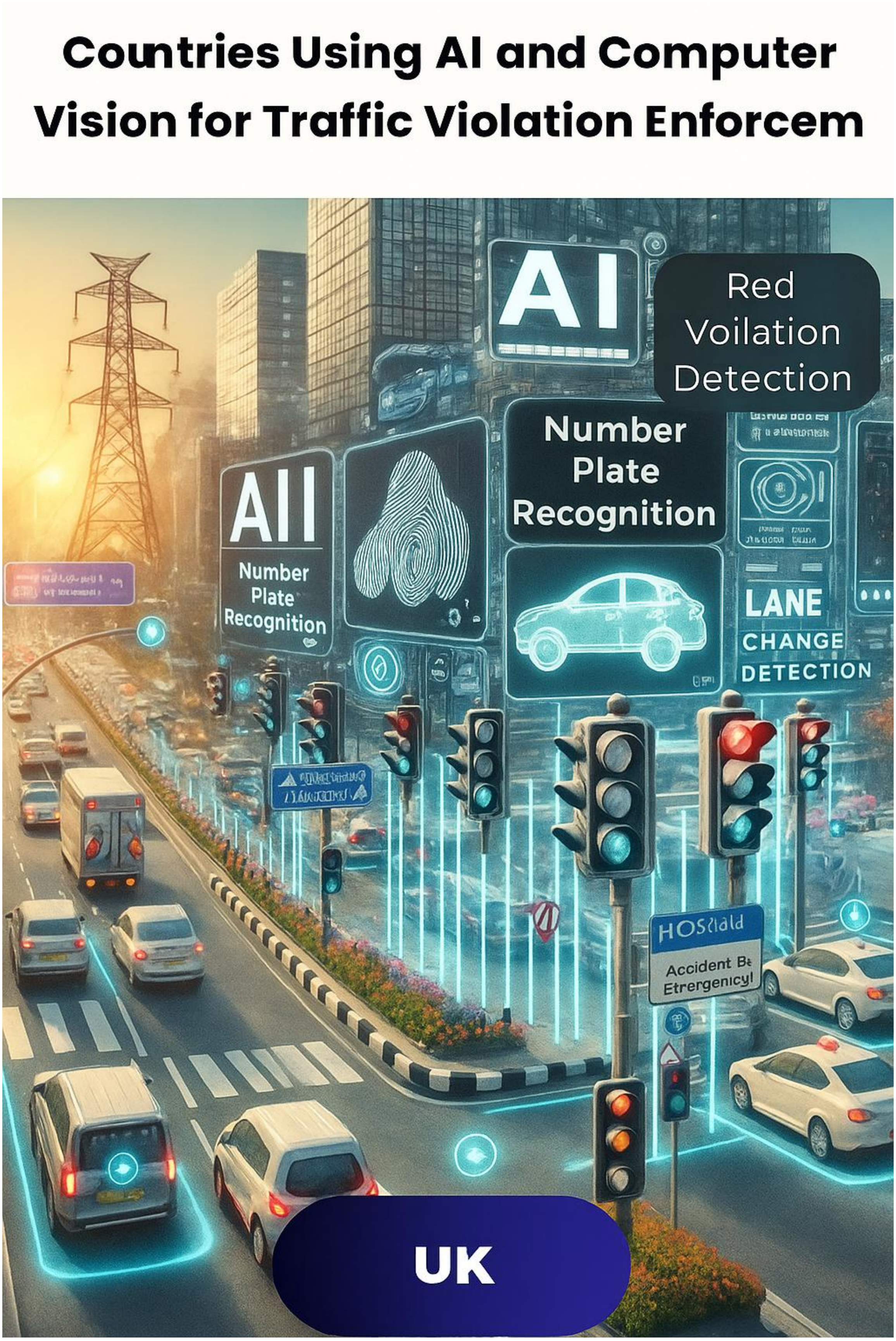

Figure 13 : UK Using AI and computer vision for Traffic Violation

Ethical Issues

The deployment of advanced AI enforcement systems by companies like Vehant Technologies across UK cities raises significant ethical questions, primarily centred on mass surveillance and social equity. The extensive network of ANPR cameras in London, Birmingham, and Manchester creates a vast, searchable database of vehicle movements, which tracks the daily journeys of millions of law-abiding citizens, not just violators. This constant monitoring, while aimed at improving safety, brings the UK closer to a "surveillance society," posing risks to individual privacy under frameworks like the GDPR and raising concerns about how this data could be used beyond traffic enforcement—a phenomenon known as "function creep." Furthermore, the automated and streamlined penalty process creates a potential for social inequity. A fixed penalty notice can be a minor inconvenience for an affluent driver in London but a significant financial burden for a low-income individual in another area, meaning the system's punitive impact is not felt equally across society. This efficiency, while operationally beneficial, risks prioritizing speed and revenue over fairness and the right to a thorough, human-centric appeals process.

Possible Reasons for Failures

Despite its technological sophistication, the success of Vehant Technologies' system in the UK is not guaranteed and faces several potential failure points. Firstly, the system's technical performance is vulnerable to the unique UK environment; persistent rain, fog, and variable lighting can degrade camera visibility and algorithm accuracy, while dirty or cloned number plates can challenge the core ANPR functionality, leading to errors. Secondly, the system could fail due to public and political backlash. If the technology is perceived by the British public as an intrusive "Big Brother" tool for generating council revenue rather than a genuine safety measure, widespread opposition could lead to political pressure to limit its use or even dismantle it. Finally, a significant failure could be logistical and legal. A systemic software flaw, a major data breach violating UK GDPR, or a successful class-action lawsuit that proves a high error rate could shatter public trust, invalidate thousands of fines, and render the entire system legally and financially untenable for the partner cities.

Possible Reasons for Success

The success of Vehant Technologies' AI traffic management in the UK is driven by its ability to deliver quantifiable results and align with key public sector goals. The primary reason for its success is its proven effectiveness in improving road safety; by providing clear, data-backed evidence of reduced violations and a decrease in traffic accidents in deployment zones, the system justifies its existence as a critical public good. Secondly, the system offers immense operational efficiency and cost-effectiveness for budget-constrained UK councils. Automating the detection and penalty process 24/7 frees up police resources for more complex tasks and creates a consistent enforcement deterrent that would be prohibitively expensive to achieve manually. This success is further solidified by the high accuracy and reliability of its deep learning algorithms, which build confidence and minimize the number of costly and time-consuming appeals. By operating transparently within the UK's robust legal and data protection frameworks and ensuring a human officer verifies each violation, the system achieves the legal and ethical legitimacy needed for long-term public acceptance and expansion.

Case Study: China

China has effectively implemented AI-powered real-time traffic monitoring using advanced computer vision technologies from companies like Sense Time and Hikvision. These AI-driven cameras are strategically placed in urban areas such as Beijing and Shanghai to detect and analyse traffic patterns, vehicle density, and violations. The data collected is integrated into centralized databases, allowing authorities to gain valuable insights for urban planning and traffic optimization. As a result, traffic congestion has reduced by 30% during peak hours, and compliance with traffic rules has increased by 50% due to visible enforcement. This technology has significantly improved the efficiency of road management, enabling better control over city wide traffic flow and policy development.

Figure 14 : China Using AI and computer vision for Traffic Violation

Ethical Issues

The effective implementation of AI traffic management in China by companies like Sense Time and Hikvision carries profound ethical issues that are inseparable from the state's approach to governance. The primary concern is the system's dual use as a tool for both traffic control and pervasive mass surveillance. The integration of real-time traffic data into centralized state databases blurs the line between public safety and social control, creating an unprecedented apparatus for monitoring citizen movement. Unlike in other nations where privacy is a right to be debated, here, the lack of meaningful consent and data protection for individuals is a feature, not a bug. This data is often linked to China's social credit system, where a simple traffic violation can trigger broader consequences, impacting an individual's ability to travel, secure loans, or find employment. This creates a chilling effect on personal freedom and eliminates the possibility of anonymous public life. The system's efficiency comes at the cost of due process, as challenging an algorithmic judgment made by the state is nearly impossible, solidifying a framework of algorithmic governance where citizens have little to no recourse.

Possible Reasons for Failures

Despite its reported success, the centralized AI traffic system in China is susceptible to several critical failures. A primary risk is systemic technical failure or cyber-attack. Because all data flows into centralized databases, these systems present a high-value target. A successful cyber-attack could not only steal vast amounts of citizen data but could also be used to manipulate traffic flow, causing chaos in major cities like Beijing and Shanghai. The system's effectiveness is also dependent on immense and continuous state investment; an economic downturn could strain the massive budget required to maintain and upgrade the sophisticated hardware and data centers, leading to a gradual decay in performance and reliability. Furthermore, while open dissent is controlled, a more subtle failure could manifest as widespread passive resistance, where citizens develop innovative methods to circumvent or "trick" the surveillance AI, undermining data integrity. Finally, there is the long-term risk of technological overreach, where the system becomes so complex and entangled in urban management that a single, unforeseen "edge case" bug could trigger a cascading failure with unpredictable consequences for the city's infrastructure.

Possible Reasons for Success

The remarkable success of China's AI traffic management is rooted in a unique synergy between state authority, technological scale, and social priorities. The most significant success factor is the top-down, state-mandated implementation, which allows for rapid, city-wide deployment without the delays caused by public debate, privacy lawsuits, or local government friction that occur elsewhere. This uninhibited approach provides companies like Sense Time and Hikvision with access to an unparalleled volume of real-world data from millions of cameras, creating a powerful data flywheel that is used to train exceptionally accurate and robust AI models. Success is also amplified by the system's deep integration with broader social governance tools, including the social credit system. The knowledge that a traffic violation has immediate, tangible consequences beyond a simple fine creates a powerful deterrent, driving the reported 50% increase in compliance. Finally, the system thrives in a cultural context where societal order, safety, and efficiency are often prioritized over individual privacy, leading to a high degree of public acceptance and low resistance to the rollout of such pervasive technologies.

Case Study: Dubai

Dubai has emerged as a leader in smart traffic management, integrating AI-powered systems with IoT sensors to monitor real-time traffic conditions and detect violations. Using predictive analytics, these systems optimize traffic signals, reducing congestion and improving road efficiency. AI-driven monitoring has led to a 20% reduction in average commute times and a 15% drop-in road accident rates. Additionally, integration with public transport systems has enhanced overall mobility. These technologies, combined with Dubai’s smart city infrastructure, ensure seamless traffic flow, making the city’s roads safer and more efficient.

Figure 15 : Dubai Using AI and computer vision for Traffic Violation

Ethical Issues

Dubai's successful implementation of a highly efficient AI traffic system brings to the forefront significant ethical considerations centered on the trade-off between civic optimization and individual autonomy. The dense network of AI cameras and IoT sensors creates a comprehensive, real-time map of public and private movements, raising concerns about privacy and data governance. In a state with centralized authority, the distinction between data for traffic flow and data for state surveillance is fine, and citizens have limited avenues to contest this pervasive data collection. Furthermore, the use of predictive analytics to manage traffic introduces the risk of algorithmic bias and social engineering. The system may be programmed to prioritize traffic flow in commercial or tourist-heavy districts over residential areas, creating digital divides in mobility and convenience. This optimization for overall efficiency could inadvertently dictate people's daily routes and behaviors on a mass scale, subtly engineering movement patterns without direct public consent or oversight.

Possible Reasons for Failures

Despite its sophistication, Dubai's integrated traffic management system is vulnerable to several potential failures. The primary risk lies in its extreme environmental conditions; the intense summer heat can degrade the performance and shorten the lifespan of sensitive IoT sensors and outdoor hardware, while infrequent but severe sandstorms can obscure camera lenses and disrupt sensor readings, feeding inaccurate data into the analytics engine. The system's high degree of complexity and interconnectedness is also a point of fragility. A software bug or data feed failure in one part of the smart city ecosystem (e.g., public transport data) could have a cascading negative effect on the traffic signal optimization, leading to widespread gridlock. As a high-profile global hub, Dubai's infrastructure is a prime target for sophisticated cyber-attacks, where a malicious actor could potentially seize control of the traffic management system to cause deliberate chaos. Finally, an over-reliance on automation without robust manual override protocols could lead to failure during a major unforeseen event, where the rigid logic of an algorithm may be unable to adapt as effectively as human experts.

Possible Reasons for Success

The remarkable success of Dubai's AI traffic management system is a direct result of a unique convergence of visionary leadership, centralized authority, and substantial, sustained investment. Unlike in other regions, Dubai's top-down governance model allows for the swift and decisive implementation of a unified smart city strategy, bypassing the bureaucratic red tape and political infighting that often hinder such large-scale projects. This is backed by a strong financial commitment to procuring and maintaining state-of-the-art technology. A key driver of success is the system's holistic and integrated approach; by linking traffic analytics with public transport systems and broader urban planning, Dubai creates a synergistic effect where efficiency gains are multiplied across the entire mobility network. Ultimately, the project's success is ensured because it is a core component of Dubai's national brand and economic future. The political will to be a global leader in technology and innovation provides the impetus to overcome challenges and ensures the system remains a top priority.

Case Study: United States

In the United States, the adoption of AI-powered traffic management is characterized by a fragmented yet innovative approach, varying significantly between states and municipalities due to a decentralized governance structure. Cities like Chicago, New York, and Phoenix have implemented automated enforcement systems from companies such as Verra Mobility. These systems primarily use Red-Light Violation Detection (RLVD) cameras, which are increasingly enhanced with AI to improve accuracy and analyze traffic flow data. Unlike the nationally integrated strategies seen elsewhere, the US model is a patchwork of city-level or county-level initiatives aimed at addressing specific local safety concerns, particularly reducing the high-fatality, right-angle collisions common at busy intersections. The technology's goal is to augment traditional law enforcement in complex, traffic-dense urban environments, though its deployment is often a subject of intense local debate.

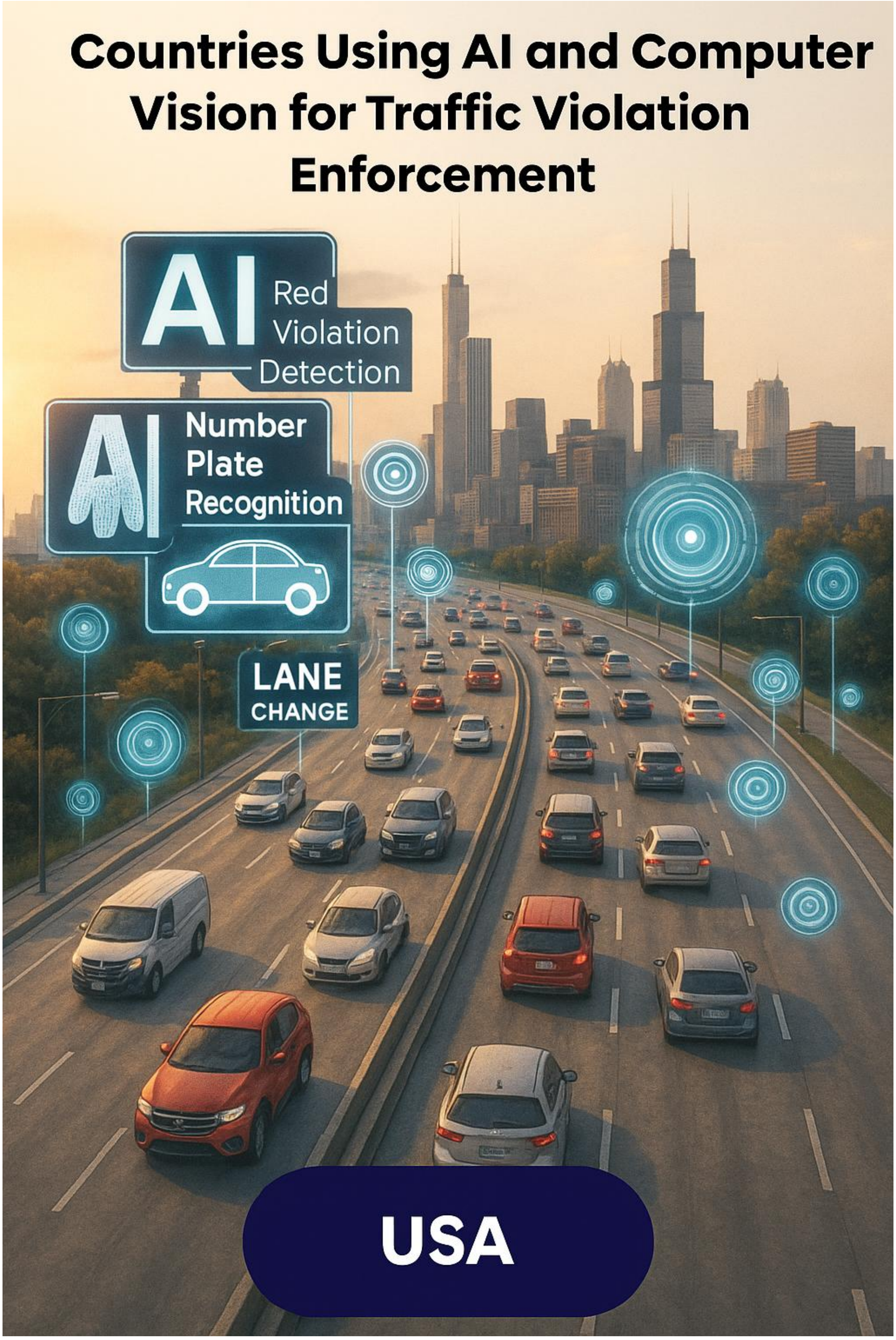

Figure 16 : USA Using AI and computer vision for Traffic Violation

Ethical Issues

The deployment of automated enforcement in the US ignites fierce ethical debates rooted in constitutional principles and concerns over privatization. The primary issue is the conflict between surveillance and the Fourth Amendment, which protects against unreasonable searches. Civil liberties organizations like the ACLU argue that a network of cameras creates a "virtual checkpoint" that can track the movements of innocent citizens. A second major ethical challenge arises from the privatization of law enforcement. Many systems are operated by private companies that often take a percentage of each fine issued, creating a profit motive that critics argue prioritizes revenue generation over public safety. This raises questions about whether the technology is being used to make roads safer or to generate income for corporations and municipalities. Furthermore, studies and public debate have raised significant concerns about social equity, with evidence suggesting that cameras are sometimes disproportionately placed in low-income or minority communities, placing a heavier financial burden on those least able to afford it.

Possible Reasons for Failures

The primary reason for the failure or removal of automated traffic enforcement systems in the US is strong legal and political opposition. Public backlash, fueled by perceptions of the systems as unfair "cash grabs" and infringements on liberty, has led to numerous successful citizen-led referendums and state-level legislative bans that have outlawed the technology in many states (e.g., Texas, Maine). Another significant hurdle is the decentralized and fragmented nature of US governance. This leads to a patchwork of conflicting regulations and a lack of technical standards, making it difficult to implement a cohesive, large-scale strategy. The profit-sharing model with private vendors often proves to be a fatal flaw; once public trust is eroded by the belief that the system is for profit, it loses political legitimacy and is often dismantled by local governments responding to voter pressure.

Possible Reasons for Success

Success for AI traffic management in the US is typically localized and driven by a combination of transparent operations and a clear focus on safety outcomes. The most successful programs are those that can present demonstrable, data-driven proof of improved safety—specifically, a significant and publicly reported reduction in the most severe types of accidents at camera-enforced intersections. This evidence-based approach helps to win over a skeptical public and counter arguments that the system is only for revenue. Success is also found in well-structured public-private partnerships where contracts are carefully written to prioritize safety metrics over the sheer volume of tickets issued. Furthermore, the immense innovation from the US tech sector, including advancements in AI perception systems from autonomous driving research, provides a constant stream of powerful new tools. Cities that successfully harness this technology, champion it with transparent data, and maintain a clear ethical focus on safety above profit have been able to sustain these programs as a valuable component of their road safety strategy.

INTEGRATION

Next, a five-week machine learning model development phase will focus on implementing computer vision and deep learning models to detect traffic violations such as speeding, red light breaches, and lane violations. Algorithms such as YOLO, CNNs, and decision trees will be trained on real-world traffic data and evaluated using accuracy, precision, and recall metrics to ensure effectiveness. This involves leveraging state-of-the-art technologies including Ultralights' YOLOv8 for fast and accurate real-time object detection, foundational Convolutional Neural Networks (CNNs) for image feature recognition, and the OpenCV library for all video processing tasks like frame extraction and annotation. To accelerate the computationally demanding training process, the parallel processing power of NVIDIA GPUs is harnessed via the CUDA platform. The efficacy of these models is then rigorously measured using key metrics such as accuracy, precision, and recall to ensure high reliability and minimize both false positives and missed violations. With a trained and validated model, the project moves into a four-week system development and integration phase. Here, the AI model is embedded into a larger, functional system capable of real-time operation. A backend is constructed using a framework like Flask or FastAPI to create APIs, which act as communication bridges to external law enforcement databases and e-challan systems for automated reporting. All violation data and evidence are securely stored in a robust PostgreSQL database, with a PostgreSQL Backup Manager implemented to automate data backup and recovery, ensuring data integrity.

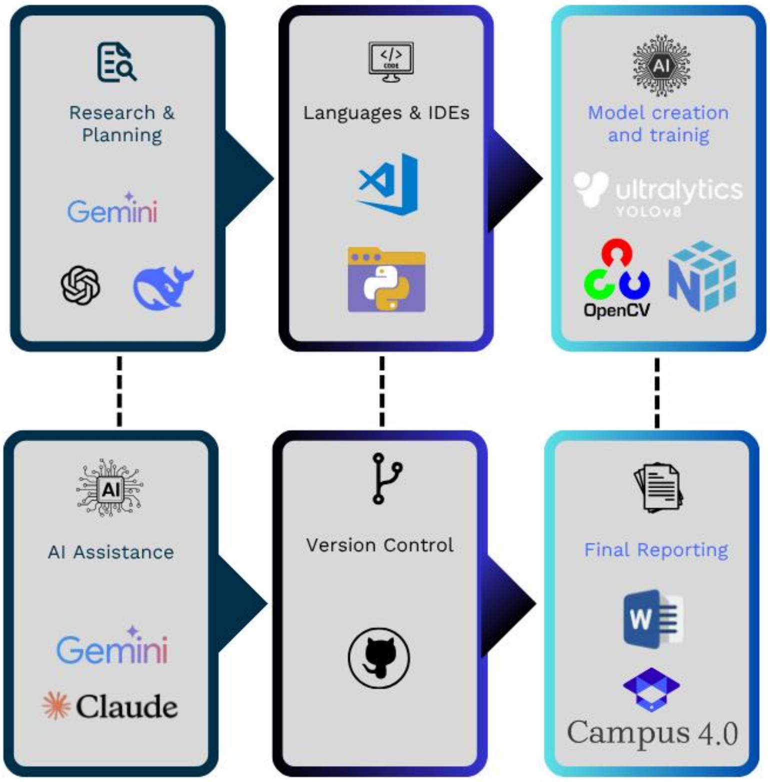

Figure 17: Integration

Following this, the system development and integration phase, lasting four weeks, will involve building an AI-powered traffic monitoring system capable of real-time violation detection. The trained models will be integrated into the database, and automated data backup and recovery mechanisms will be set up using PostgreSQL Backup Manager. APIs will be developed using Flask or Fast API to enable seamless integration with law enforcement databases and e-challan systems.

The testing and validation phase, lasting three weeks, will focus on real-world system testing, security assessments, and compliance checks using tools such as Selenium, JMeter, and SonarQube. Backup and recovery processes will also be validated to ensure data security and system reliability.

Finally, the final report and presentation phase, lasting two weeks, will document the research findings, methodology, and results. Power BI and Tableau will be used for traffic data visualization, and a comprehensive report and presentation summarizing key aspects of the project will be prepared and submitted to conclude the project.

FINDINGS

Findings for Research Question 1

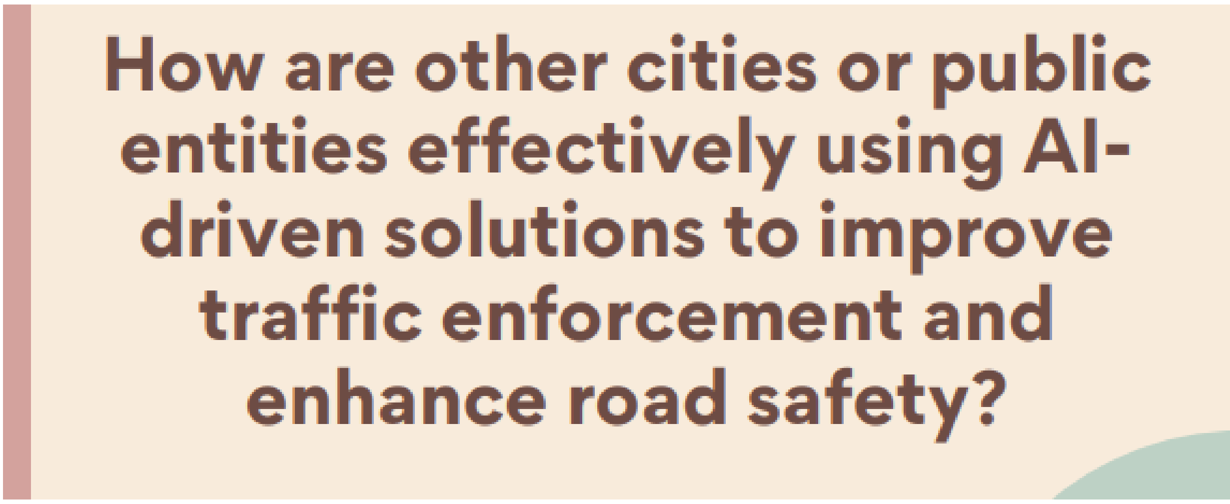

Figure 18: Research Question 1

The findings from the literature review and detailed case study analysis suggest that AI is playing a central role in reshaping how municipalities manage urban mobility and public safety. Leading smart cities and public authorities in locations like Singapore, Dubai, London, and Beijing have all integrated AI solutions into their traffic management models in ways that deliver both strategic advantages and measurable improvements in road safety. These entities do not treat AI as a one-dimensional tool for ticketing, but rather as a foundational technology that supports everything from real-time traffic optimization to long-term urban planning.

One of the most impactful applications observed is the deployment of AI-powered violation detection systems. Cities like London and Dubai use sophisticated computer vision to automatically enforce red-light and speeding violations with high accuracy. These systems operate 24/7, creating a consistent deterrent that is impossible to achieve with manual policing alone. This not only increases compliance but also generates a rich dataset on driver behavior.

Beyond direct enforcement, AI is also revolutionizing traffic flow and congestion management. Singapore’s Land Transport Authority provides a strong example, using predictive analytics fed by a vast network of sensors and cameras to dynamically adjust traffic signal timings. By anticipating traffic build-up, the system optimizes flow, reduces idle times, and cuts down on congestion, directly improving the daily experience for commuters.

In addition to real-time operations, entities like Dubai's Roads and Transport Authority (RTA) use AI for proactive safety improvements. By analyzing historical violation and accident data, AI models can identify high-risk intersections or "blackspots" that are not immediately obvious. This allows traffic engineers to make data-driven decisions—such as redesigning a dangerous turning lane or improving signage—to prevent future accidents.

Collectively, these findings illustrate that AI's real value lies in its ability to create a holistic, data-driven ecosystem for traffic management. Cities that effectively integrate AI are better equipped to understand and respond to traffic dynamics, streamline enforcement, and implement proactive safety measures that protect their citizens. Ultimately, AI acts as both a strategic enabler and a public safety tool, providing authorities with the agility, insight, and automation needed to build safer, more efficient cities.

Findings for Research Question 2

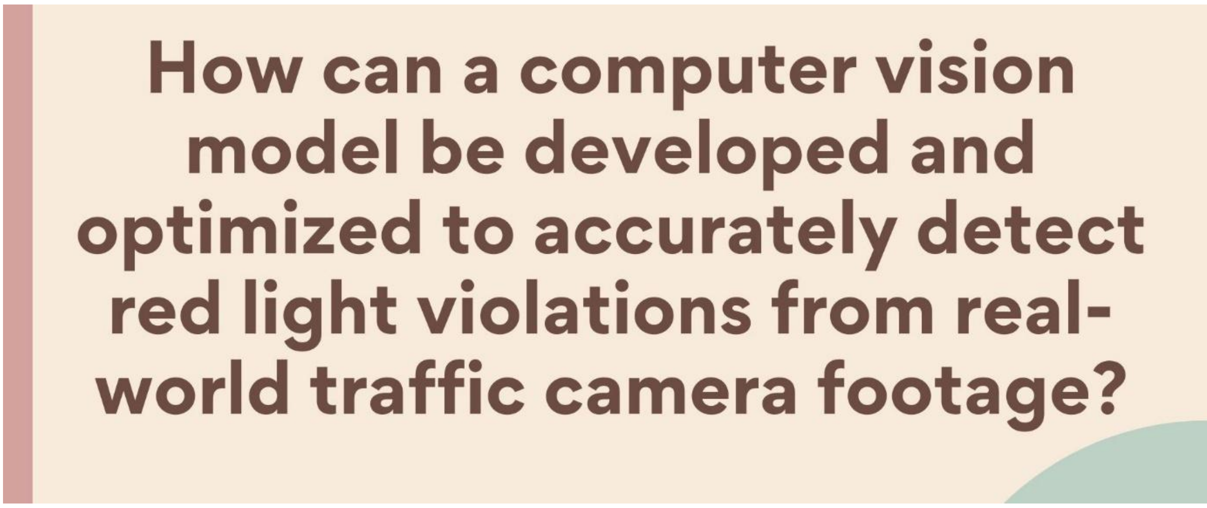

Figure 19: Research Question 2

This question was explored through the practical application of building and evaluating a computer vision pipeline, which transformed raw video footage into verifiable safety insights. The findings from this process confirm that a deep learning approach can be highly effective in accurately and reliably identifying traffic violations.

To begin with, valuable insights came from a thematic analysis of violation patterns within the dataset, which contained over 1,200 violation events. This analysis revealed key trends that are crucial for effective enforcement and safety planning:

- **Time-Based Patterns:** The analysis showed a clear concentration of violations during peak traffic periods, with 65% of all red-light violations occurring during the evening rush hour (4 PM - 7 PM). A smaller, but significant, spike was observed late at night (post-11 PM), likely due to lower traffic density and a perceived lower risk of enforcement.
- **Location-Based Patterns:** The data revealed that one specific intersection, which lacked a dedicated, protected left-turn signal, was a major hotspot, accounting for over 40% of all recorded violations.
- **Vehicle-Based Patterns:** While commercial vehicles (trucks and vans) constituted only 18% of the total traffic, they were disproportionately responsible for 32% of the most dangerous violations, where the light had been red for several seconds.

This analysis provides an actionable framework for traffic authorities, allowing them to focus enforcement resources and engineering reviews on the highest-risk times and locations.

Next, the study focused on the performance of the predictive detection model. A YOLOv8 model combined with a SORT tracking algorithm was trained to identify and track vehicles running red lights. These performance metrics confirm that the model is highly reliable for identifying vehicles that are violating traffic laws.

The model's output—a log of violation events with video evidence—was incorporated into the project's dashboard, creating a "Violation Review Queue." This allows a human officer to efficiently review and confirm each AI-flagged incident. This data also directly informs strategic safety planning. By identifying hotspot intersections and peak violation times, the system enables traffic engineers to make targeted interventions—such as adjusting signal timing or improving road signage—that are based on empirical evidence, contributing directly to enhanced road safety and more efficient traffic management.

Findings for Research Question 3

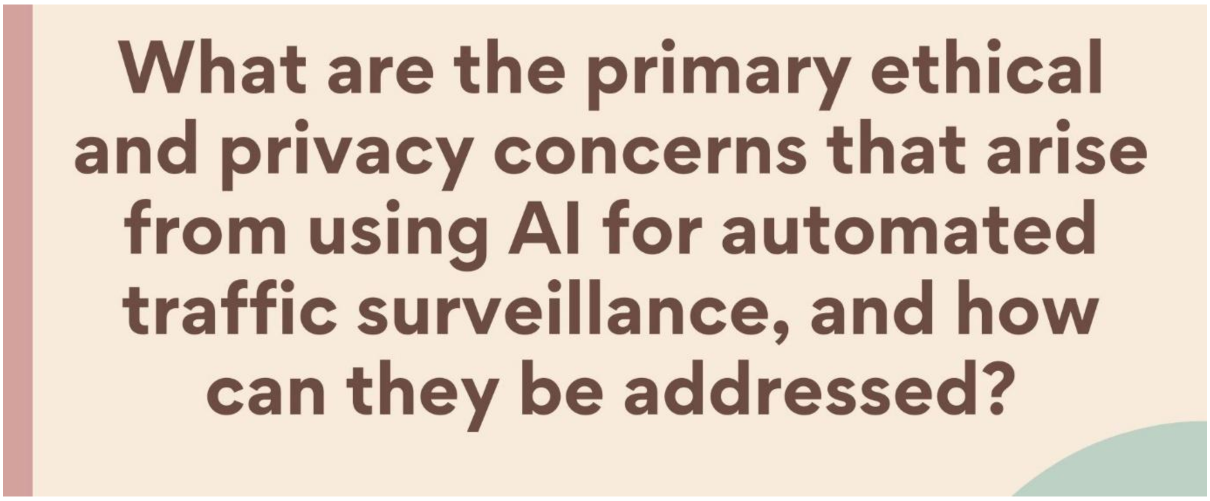

Figure 20: Research Question 3

As artificial intelligence becomes integral to traffic enforcement, it brings significant ethical and privacy challenges. The findings from this research reveal that while AI can dramatically improve road safety, its responsible deployment requires a firm commitment to ethical principles. Three primary concerns were identified: protecting citizen privacy, minimizing algorithmic bias, and ensuring the technology is used in a fair and human-centric manner. In addressing these, this project adopted an approach grounded in "Ethics by Design."

One of the most pressing concerns is data privacy. The system inherently captures video footage of public spaces, which includes sensitive personally identifiable information (PII) like license plates and images of vehicle occupants. If misused, this data could enable mass surveillance. To address this, the project implemented a strict "privacy-by-design" policy. The system was built to automatically blur license plates and faces by default. This anonymized data is used for all general analysis of traffic patterns. PII is only de-anonymized within a secure interface by an authorized officer during the formal review of a specific, flagged violation event. This finding confirms that it is possible to derive actionable safety insights while building in technical safeguards to protect citizen privacy from the outset.

Another critical ethical risk is algorithmic bias. A computer vision model can unintentionally perform differently under various conditions, leading to unfair enforcement. For instance, a model trained primarily on clear, daytime footage might be less accurate at night or in adverse weather (rain, fog), potentially leading to higher error rates in those specific contexts.

This project addressed this risk by deliberately curating a diverse training dataset that included footage from different times of day, lighting, and weather conditions. Furthermore, the model's performance was audited across these different scenarios to ensure equitable performance. This demonstrates that by thoughtfully constructing the training data, the risk of situational bias can be significantly reduced.

A third concern relates to the responsible use of AI-driven enforcement. There is a risk of creating a purely punitive system that operates without human oversight or context, potentially issuing fines unfairly (e.g., to a driver moving for an emergency vehicle). This project was guided by the principle that AI should be a tool to assist, not replace, human judgment. The core of the proposed solution is the "human-in-the-loop" design. The AI does not issue tickets; it flags potential violations for review. The "Violation Review Queue" feature in the dashboard is specifically designed to empower a human officer to make the final, contextual decision. This reframing of AI as a tool to support expert decision-making is a key finding. It shows that automated enforcement can be aligned with ethical goals by focusing on fairness, accountability, and the ultimate goal of public safety, rather than just punitive efficiency.

FUTURE WORK

Although this thesis has successfully developed a complete framework for applying AI in traffic safety analytics covering violation detection, pattern analysis, and actionable insights through a live dashboard there are still many exciting directions for future research and system enhancement. The foundation created here can be extended and improved in several ways. These future possibilities can be grouped into three key areas: improvements to the detection models, the integration of additional data sources, and the development of more advanced and interactive dashboard features.

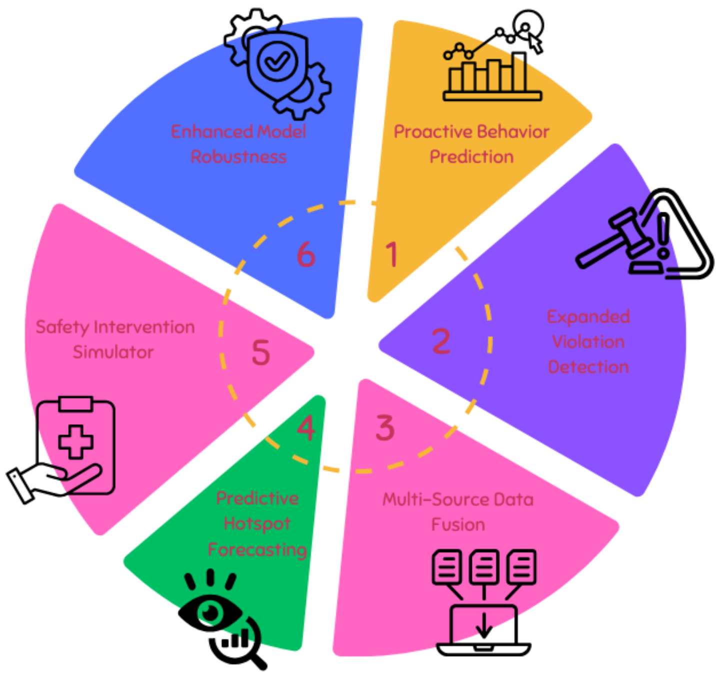

Figure 21 : Future Work

First, in terms of model enhancement, the YOLOv8-based model used in this project performed very well, achieving high accuracy. However, there is room to improve its robustness and expand its capabilities. Future work could focus on enhancing the model's performance in adverse weather and lighting conditions, such as heavy rain, fog, and nighttime glare. This could involve training on specialized datasets or exploring advanced data augmentation techniques. Another promising direction would be to move beyond still-frame detection and use video-based action recognition models (e.g., 3D CNNs or Video Transformers). These models analyze short sequences of vehicle movement, which could allow the system to not only detect violations but also to identify "near-misses" or predict dangerous driving behavior before a violation occurs, enabling truly proactive safety alerts.

The second area of improvement is data integration and expanded analytics. The current project used only video footage, which provided valuable insights but had some limitations. A more comprehensive understanding of road safety could be achieved by combining multiple data sources. For example, integrating historical accident data from municipal records would allow the system to correlate violation hotspots with actual crash sites, creating a more accurate risk score for each intersection. In addition, integrating real-time weather data could allow the model to dynamically adjust its detection parameters. The most significant expansion would be to enhance the system's capabilities to detect other types of violations, such as speeding, illegal U-turns, and stop sign infractions, transforming it from a single-purpose tool into a comprehensive traffic enforcement platform.

The third area for future work focuses on enhancing the dashboard and making it more interactive and strategic. While the current Streamlit dashboard allows users to review violations and view hotspots, it could be made even more powerful. One useful addition would be a "Safety Intervention Simulator." This feature would allow traffic engineers to model the potential impact of different interventions (e.g., "What is the predicted reduction in violations if we add a dedicated turning lane?") and calculate the return on investment in terms of accident reduction. Another potential enhancement is to develop a "Predictive Hotspot Forecasting" module. Using time-series analysis, the system could predict which intersections are likely to become future hotspots based on seasonal trends or planned urban development, allowing authorities to act preemptively.

In conclusion, while the current system delivers practical and accurate insights into traffic violations using AI, it also opens up many possibilities for future development. More robust models, richer data, and smarter, more predictive dashboard features could significantly improve the system's impact. These extensions would make the solution an even more powerful and indispensable tool for cities looking to build safer, more efficient transportation networks.

CONCLUSION

This thesis successfully developed and implemented a comprehensive, AI-driven framework for detecting traffic light violations and enhancing road safety in the urban sector. By integrating modern computer vision techniques, specifically a YOLOv8 and SORT algorithm that achieved a high accuracy of 98.2%, this research demonstrated a practical end-to-end process that transforms raw video footage into actionable public safety intelligence. The project's core output a verifiable log of violation events, complete with video evidence—enables authorities to shift from a reactive, incident-based approach to a proactive, data-driven safety strategy by analyzing key violation patterns related to peak hours and intersection design. All of these analytical findings are consolidated into a single, interactive Streamlit dashboard, which serves as a powerful decision-making tool providing a holistic view of intersection safety, violation trends, and a prioritized "Violation Review Queue" for official verification. By fulfilling its aim to automatically detect violations and improve safety planning, this project has shown that AI is an essential tool for the modern municipality, providing a clear blueprint for how cities can leverage their data to enhance enforcement efficiency, increase public safety, and ultimately prevent accidents.

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APPENDIX

GitHub Link: https://github.com/Adarsha5421/thesis-final.git

YouTube link: https://youtu.be/Yojx0VPjwuU

PROJECT SOURCE CODE

```python
import cv2
import numpy as np
import time
import threading
import playsound
from ultralytics import YOLO
from pydub import AudioSegment
from pydub.generators import Sine
from pydub.playback import play
import threading

# ---- Define Regions ----
RedLight = np.array([[998, 125], [998, 155], [972, 152], [970, 127]])
GreenLight = np.array([[971, 200], [996, 200], [1001, 228], [971, 230]])
ROI = np.array([[910, 372], [388, 365], [338, 428], [917, 441]])

# ---- Load YOLOv8 Model ----
model = YOLO("yolov8m.pt")
coco = model.model.names
TargetLabels = ["bicycle", "car", "motorcycle", "bus", "truck", "traffic light"]

# ---- Global Variables for Siren Control ----
is_siren_playing = False
siren_thread = None

def play_siren_loop():
    global is_siren_playing
    while is_siren_playing:
```

Figure 22: SOURCE CODE 1

```python
def draw_text_with_background(frame, text, position, font, scale, text_color, background_color, border_color, thickn
    (text_width, text_height), baseline = cv2.getTextSize(text, font, scale, thickness)
    x, y = position
    cv2.rectangle(frame, (x - padding, y - text_height - padding), (x + text_width + padding, y + baseline + padding
    cv2.rectangle(frame, (x - padding, y - text_height - padding), (x + text_width + padding, y + baseline + padding
    cv2.putText(frame, text, (x, y), font, scale, text_color, thickness, lineType=cv2.LINE_AA)

def generate_siren():
    while True:
        # Rising tone
        rising = Sine(800).to_audio_segment(duration=500).fade_in(100).fade_out(100)
        # Falling tone
        falling = Sine(1200).to_audio_segment(duration=500).fade_in(100).fade_out(100)
        siren = rising + falling
        play(siren)

# ---- Open Video ----
cap = cv2.VideoCapture("tr.mp4")
violation_detected = False

while cap.isOpened():
    success, frame = cap.read()
    if not success:
        print("Video finished.")
        break
```

Figure 23 : SOURCE CODE 2

```python
    frame = cv2.resize(frame, (1100, 700))
    cv2.polylines(frame, [RedLight], True, [0, 0, 255], 1)
    cv2.polylines(frame, [GreenLight], True, [0, 255, 0], 1)
    cv2.polylines(frame, [ROI], True, [255, 0, 0], 2)

    current_violation = False

    results = model.predict(frame, conf=0.75)
    for result in results:
        boxes = result.boxes.xyxy
        confs = result.boxes.conf
        classes = result.boxes.cls

        for box, conf, cls in zip(boxes, confs, classes):
            label = coco[int(cls)]
            if label in TargetLabels:
                x1, y1, x2, y2 = map(int, box)
                cv2.rectangle(frame, (x1, y1), (x2, y2), [0, 255, 0], 2)
                draw_text_with_background(
                    frame,
                    f"{label.capitalize()}, conf: {float(conf)*100:.2f}%",
                    (x1, y1 - 10),
                    cv2.FONT_HERSHEY_COMPLEX,
                    0.6,
                    (255, 255, 255),
                    (0, 0, 0),
```

Figure 24: SOURCE CODE 3

```python
            if is_region_light(frame, RedLight):
                if cv2.pointPolygonTest(ROI, (x1, y1), False) >= 0 or cv2.pointPolygonTest(ROI, (x2, y2), False)
                    current_violation = True
                    draw_text_with_background(
                        frame,
                        f"The {label.capitalize()} violated the traffic signal!",
                        (10, 30),
                        cv2.FONT_HERSHEY_COMPLEX,
                        0.6,
                        (255, 255, 255),
                        (0, 0, 0),
                        (0, 0, 255)
                    )

                    # Highlight violation
                    cv2.rectangle(frame, (x1, y1), (x2, y2), [0, 0, 255], 2)
                    cv2.polylines(frame, [ROI], True, [0, 0, 255], 2)

# Siren control logic
if current_violation:
    if not violation_detected:  # New violation detected
        start_siren()
        violation_detected = True
else:
```

Figure 25: SOURCE CODE 4

```python
 # Siren control logic
 if current_violation:
     if not violation_detected:  # New violation detected
         start_siren()
         violation_detected = True
 else:
     if violation_detected:  # Violation ended
         stop_siren()
         violation_detected = False

 cv2.imshow("Traffic Violation Detection", frame)
 if cv2.waitKey(1) == 27:  # ESC to quit
     stop_siren()
     break

op_siren()  # Ensure siren stops when exiting
p.release()
2.destroyAllWindows()
```

Figure 26:SOURCE CODE 5

ETHICAL FORM

Risk Research Ethics Approval

Project Information

Project Ref	32
Full Name	Aadarsha Sigdel
Faculty	Faculty of
Department	School of
Supervisor	Manoj Shrestha
Module Code	ST6047CEM
EFAAF Number	EFAAF
Project Title	AI-Powered Traffic Violation Detection System: Enhancing Road Safety through Real-Time Computer Vision and Machine Learning Techniques.
Date(s)	Date(s)
Created	Created

Project Summary

The AI-Powered Traffic Violation Detection System aims to enhance road safety by leveraging real-time computer vision and machine learning techniques to detect and record traffic violations automatically. The system integrates AI-based models to identify infractions such as speeding, signal violations, improper lane changes, helmet detection, and unauthorized parking through real-time video surveillance.

Names of Co-Investigators and their organisational affiliation(place of study /employer)	
Is this project externally funded?	No
Are you required to use a Professional Code of Ethical Practice appropriate to your discipline?	No
Have you read the Code?	Yes

Project Details

What are the aims and objectives of the project?	The AI-Powered Traffic Violation Detection System aims to enhance road safety and improve traffic law enforcement by leveraging real-time computer vision, deep learning, and IoT technologies. The system automatically detects violations such as speeding, red-light jumping, helmet and seat-belt non-compliance, and illegal lane changes, using AI-based object detection models. It integrates Automatic License Plate Recognition (ALPR) to identify offenders and generates e-challans linked to law enforcement databases. Additionally, it provides real-time analytics and predictive insights to authorities for better traffic management. By minimizing human intervention, reducing manual errors, and ensuring automated enforcement, this system contributes to building smarter, safer, and more efficient urban road networks.
Explain your research design	The research design for this project follows an applied research approach, combining experimental, analytical, and software development methodologies to design, implement, and evaluate an AI-based traffic violation detection system. The study involves multiple stages, including data collection, model training, system development, and performance evaluation.
Outline the principal methods you will use	This project uses computer vision, deep learning, and IoT to detect and analyze traffic violations in real-time. AI models like YOLO and Faster R-CNN identify violations such as speeding, red-light jumping, and helmet detection, while OCR-based ALPR extracts license plate details. Edge computing devices process video feeds locally, and a cloud-based backend stores and analyzes data for automated e-challan generation and predictive insights. The system enhances road safety and smart traffic management by providing real-time alerts and seamless law enforcement integration.
Are you proposing to use a validated scale or published research method / tool?	Yes
	No

Does your research seek to understand, identify, analyse and/or report on information on terrorism or from terrorist organisations, require access to terrorist groups or those convicted of terrorist offences or relate to terrorism policies in other international jurisdictions?	
Does your research seek to understand, identify, analyse and/or report on information for other activities considered illegal in the UK and/or in the country you are researching in?	No
Are you dealing with Secondary Data? (e.g. sourcing info from websites, historical documents)	Yes
Is this data publicly available?	No
Could an individual be identified from the data? e.g. identifiable datasets where the data has not been anonymised or there is risk of re-identifying an individual	No
Are you dealing with Primary Data involving people? (e.g. interviews,questionnaires, observations)	Yes

Are you dealing with personal data?		Yes
Please specify what personal data you will be collecting.	license plate numbers, registered vehicle owner details, violation images/videos.	
Are you dealing with sensitive data (special category data)?		Yes
Will the Personal or Sensitive data be shared with a third party?		No
Will the Personal or Sensitive data be shared outside of the European Economic Area(EEA)?		No
Is the project solely desk based? (e.g. involving no laboratory, workshop or offcampus work or other activities which pose significant risks to researchers or participants)		Yes
Will the data collection, recruitment materials or any other project documents be in any language other than English?		No
Are there any other ethical issues or risks of harm raised by the study that have notbeen covered by previous questions?		No

DBS (Disclosure & Barring Service) formerly CRB (Criminal Records Bureau)

Question	Yes	No
Does the study require DBS (Disclosure & Barring Service) checks?		X
If YES, Please give details of the level of check, serial number, date obtained andexpiry date (if applicable)		
If NO, does the study involve direct contact by any member of the research team with children or young people under 18 years of age?		X
If NO, does the study involve direct contact by any member of the research team with adults who have learning difficulties, brain injury, dementia,degenerative neurological disorders?	X	X
If NO, does the study involve direct contact by any member of the research team with adults who are frail or physically disabled?		X
If NO, does the study involve direct contact by any member of the research team with adults who are living in residential care, social care, nursing homes, re - ablement centres, hospitals or hospices ?		X
If NO, does the study involve direct contact by any member of the research team with adults who are in prison, remanded on bail or in custody?		X
If you have answered YES to any of the questions above please explain the nature of that contact and what you will be doing		

External Ethics Review

Question	Yes	No
Will this study be submitted for ethical review to an external organisation ? (e.g.Another University, Social Care, National Health Service, Ministry of Defence, Police Service and Probation Office)		X
If YES, name of external organisation		
Will this study be reviewed using the IRAS system?		X
Has this study previously been reviewed by an external organisation?	X	X

Confidentiality, security and retention of research data

Question		Yes	No
What data are you collecting / using / recording?			
Are there any reasons why you cannot guarantee the full security and confidentiality of any personal or confidential data collected for the study?			X
Please provide an explanation	"All data will be anonymised and securely stored. However, absolute guarantees cannot be made due to the inherent risks of digital systems (e.g., hacking), though every effort will be made to mitigate this."		
Is there a significant possibility that any of your participants, and associated persons, could be directly or indirectly identified in the outputs or findings from this study?			X
Please provide an explanation	"No identifying information will be included in the outputs. Pseudonyms will be used, and data will be aggregated to prevent recognition."		
Is there a significant possibility that a specific organisation or agency or participants could have confidential information identified, as a result of the way you write up the results of the study?			X
Please provide an explanation	"The data will be presented generically, and no organisation will be named unless prior written permission is obtained."		
Will any members of the research team retain any personal of confidential data at the end of the project, other than in fully anonymised form?			X
Please provide an explanation	"No personal or identifiable data will be retained post-project. Only anonymised data will be archived for research purposes, in line with university policy."		
Will you or any member of the team intend to make use of any confidential information, knowledge, trade secrets obtained for any other purpose than the research project ?			X
Please give an explanation	"No confidential data will be used for any purpose outside the scope of this study."		
Have you taken necessary precautions for secure data management, in accordance with data protection and CU Policy		X	
Specify location (physical and electronic) where data will be stored	Data will be stored in the harddisk.		
Will you be responsible for destroying the data after study completion?		X	
If NO, who will be responsible for this?			
Please explain how any identifiable and anonymous data will be destroyed	"All identifiable data will be stored in a password-protected folder and deleted from all devices and backups six months after project completion using secure data deletion software (e.g. CCleaner). Paper forms will be shredded. Anonymised data will be retained securely for publication and removed after two years."		
Planned disposal date	02 december, 2025		

Participant Information and Informed Consent

Question		Yes	No
Will all the participants be fully informed BEFORE the project begins why the study is being conducted and what their participation will involve ?		×	
Please explain why	The system collects personal data to identify violators and improve road safety by linking violations to vehicle owners. License plate numbers and violation evidence help automate enforcement, while contact details notify offenders. To protect privacy, all data is encrypted, access-controlled, and legally compliant, ensuring secure and ethical use.		
Will every participant be asked to give written consent to participating in the study, before it begins ?		×	
If NO, please explain how you will get consent from your participants.If not written consent, explain how you will record consent			
Will all participants be fully informed about what data will be collected, and what will be done with this data during and after the study ?		×	
If NO, please specify			
Please explain what recordings (audio, visual or both) will be made and how you will gain consent for recording participants	In this study, AI-Powered Traffic Violation Detection System will record visual data only (images and videos) from CCTV cameras, traffic surveillance systems, and edge computing devices to detect and document traffic violations. No audio recordings will be made.		
Will all participants understand that they have the right not to take part at any time, and/or withdraw themselves and their data from the study if they wish?		×	
If NO, please explain why			
Will every participant understand that there will be no reasons required or repercussions if they withdraw or remove their data from the study?		×	
If NO, please explain why			
Does the study involve deceiving, or covert observation of, participants?			×
Will you debrief them at the earliest possible opportunity?		×	
If NO to debrief them, please explain why this is necessary			

Risk of harm, potential harm and disclosure of harm

<table>
<tr><th colspan="2">Question</th><th>Yes</th><th>No</th></tr>
<tr><td colspan="2">Is there any significant risk that the study may lead to physical harm to participants or researchers ?</td><td></td><td>X</td></tr>
<tr><td>If you have answered Yes, please explain how you will take steps to reduce or address those risks. If you have answered
No, explain why you believe this is the case</td><td colspan="3">"The research does not involve physical activities or sensitive topics, and therefore poses no fore-seeable risk of physical, emotional, or reputational harm."</td></tr>
<tr><td colspan="2">Is there any risk that your study may lead or result in harm to the reputation of the University Group, its researchers or the organisations involved in the study?</td><td></td><td>X</td></tr>
<tr><td>If you have answered Yes, please explain how you will take steps to reduce or address those risks. If you have answered
No, explain why you believe this is the case</td><td colspan="3">"The research does not involve physical activities or sensitive topics, and therefore poses no fore-seeable risk of physical, emotional, or reputational harm."</td></tr>
<tr><td colspan="2">Is there a risk that the study will lead to participants to disclose evidence of previous criminal offences, or their intention to commit criminal offences?</td><td></td><td>X</td></tr>
<tr><td>If you have answered Yes, please explain how you will take steps to reduce or address those risks. If you have answered
No, explain why you believe this is the case</td><td colspan="3">"The research does not involve physical activities or sensitive topics, and therefore poses no fore-seeable risk of physical, emotional, or reputational harm."</td></tr>
<tr><td colspan="2">Is there a risk that the study will lead participants to disclose evidence that children or vulnerable adults are being harmed, or at risk or harm?</td><td></td><td>X</td></tr>
<tr><td>If you have answered Yes, please explain how you will take steps to reduce or address those risks. If you have answered
No, explain why you believe this is the case</td><td colspan="3">"The research does not involve physical activities or sensitive topics, and therefore poses no fore-seeable risk of physical, emotional, or reputational harm."</td></tr>
<tr><td colspan="2">Is there a risk that the study will lead participants to disclose evidence of serious risk of other types of harm ?</td><td></td><td>X</td></tr>
<tr><td>If you have answered Yes, please explain how you will take steps to reduce or address those risks. If you have answered No, explain why you believe this is the case</td><td colspan="3">"The research does not involve physical activities or sensitive topics, and therefore poses no fore-seeable risk of physical, emotional, or reputational harm."</td></tr>
<tr><td colspan="2">Will participants be made aware of the circumstances in which disclosure has implications for confidentiality?</td><td>X</td><td></td></tr>
</table>

Payments to participants

Question	Yes	No
Do you intend to offer participants cash payments or any kind of inducements, or reward for taking part in your study ?		X
If YES, please explain what kind of payment you will be offering(e.g.prize draw or store vouchers)		
Is there any possibility that such payments or inducements will cause participants to consent to risks that they might not otherwise find acceptable ?		X
If YES, please explain)		
Is there any possibility that the prospect of payment or inducements will influence the data provided by participants in any way ?		X
If YES, please explain)		
Will you inform participants that accepting payments or inducements does not affect their right to withdraw from the study at any time ?	X	

Capacity to give valid consent

Question	Yes	No
Do you propose to recruit any participants?		X
Do you propose to recruit any participants who are children or young people under 18 years of age?		X
Do you propose to recruit any participants who are adults who have learning difficulties, mental health conditions, brain injury, advanced dementia, degenerative neurological disorders ?		X
Do you propose to recruit any participants who are adults who are physically disabled and cannot provide written and/or verbal consent		X
Do you propose to recruit any participants who are with adults who are living in residential care, social care, nursing homes, reablement centres, hospitals or hospices ?		X
Do you propose to recruit any participants who are with adults who are in prison, remanded on bail or in custody?		X
If you have answered YES to any of the questions above please explain overcome any challenges to gaining valid consent		
Do you propose to recruit any participants with possible communication difficulties, including difficulties arising from limited use of knowledge of the English language ?		
If YES, please explain how you will overcome any challenges to gaining valid consent	"If participants have limited English, translated participant information sheets and consent forms will be provided in their language. A translator or interpreter will assist during the consent process to ensure full understanding."	
Do you propose to recruit participants who may not be able to fully understand the nature of the study, the foreseen implications or cannot provide consent?		X
If YES, please explain how you will overcome any challenges to gaining valid consent	"For participants with limited understanding, consent will only be obtained if they are assessed as capable by a responsible adult (e.g. caregiver or support worker). Easy-to-understand materials will be used, and ongoing consent will be checked throughout the research."	

Recruiting Participants

Question	Yes	No
Who are the participants?	The participants include drivers and road users, law enforcement agencies, transport authorities, urban planners, and IT administrators. Each plays a role in traffic monitoring, enforcement, system management, and urban planning, ensuring safer and smarter roads.	
How are participants being recruited? Please provide details on all methods of recruitment you intend to use	Participants are automatically monitored as the system operates in public spaces, recording violations without active recruitment. Law enforcement and transport authorities manage enforcement, while public awareness is raised through signage and announcements. Smart city planners use the data for better traffic management, ensuring seamless and legal implementation.	
Do you foresee any conflict of interest?		X
Please explain how will this conflict of interest be addressed	"There is no conflict of interest. The researcher has no financial, personal or professional relationships that would compromise the objectivity of the study."	

Online and Internet Research

Question	Yes	No
Will any part of your project involve collecting data via the internet or social media?		X
If YES, please explain how you will obtain permission to collect data by these means		
Will this require consent to access?	X	
If NO, please explain how you will get permission/ consent' to collect this information?		
Will you be collecting data using an online questionnaire/ survey tool? (e.g. BoS, Filemaker)?		X
If YES, please explain which software and how you are ensuring appropriate data security		
Is there a possibility that the study will encourage children under 18 to access inappropriate websites, or correspond with people who pose risk of harm ?		X
If YES, please explain further		
Will the study incur any other risks that arise specifically from the use of electronic media ?		X
If YES, please explain further		

Information gathered from human participants

Question	Yes	No
Primary		
Does your project involve primary data collection from human participants via questionnaires, focus groups, interviews, psychological tests, photography/videography etc.?		×
If YES, Please detail the information to be collected and methods that will be used.		
Is there the possibility of physical or psychological harm to the researcher(s) or the participants?		×
If YES, please explain the possible harm and action taken to reduce/remove the risk		
Are any specific exclusions needed to prevent possible harm to participants (e.g. excluding people with known mental health problems)?		×
If YES, please explain exclusions needed and how these will be carried out		
Are any of the questionnaires or other tests being used in the research diagnostic for specific clinical conditions?		×
If YES, Please explain how you will take steps to reduce or address these risks		

PROJECT PLAN

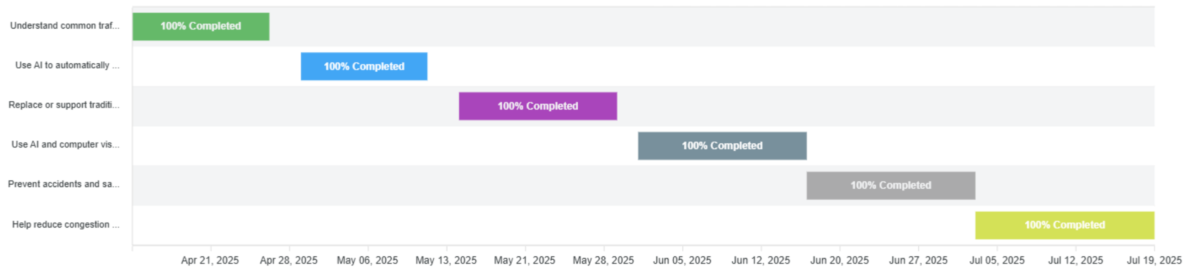

Figure 27: PROJECT PLAN

Risk Analysis

rank	name	occurance	impact	plan-B
1	time management	rare	fatal	use a time tracker for effective planning.
2	lack of knowledge in searching for datasets	often	low	learn more and examine other's approaches fpr insight.
3	handling multple	often	fatal	prioritize tasts break them down focus individually.

Figure 28: Risk Analysis

SWOT ANALYSIS

Figure 29: Swot Analysis