IMUSAFE: A COMPUTER VISION-BASED VEHICULAR ACCIDENT DETECTION MOBILE APPLICATION USING YOLOV8 IN IMUS CAVITE

Submitted in Partial Fulfillment

Of the Requirement for the Degree

Bachelor of Science in Computer Science with Intelligence Systems Track

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CHAPTER I

INTRODUCTION

1.1 PROJECT CONTEXT

According to the World Health Organization (2023), approximately 1.19 million people die each year due to road traffic crashes, making it the leading cause of death for children and young adults aged 5–29 years. Over 90% of these fatalities occur in low- and middle-income countries, despite these regions having only 60% of the world's vehicles. Vulnerable road users, including pedestrians, cyclists, and motorcyclists, account for more than half of all road traffic deaths. The economic impact is severe, with crashes costing most countries about 3% of their gross domestic product. Speeding, distracted driving, and driving under the influence are major risk factors that significantly increase the likelihood of fatal crashes.

In the 2020 Cavite Ecological Profile statistics, the province of Cavite recorded a total of 8,019 road crash incidents, which is part of the increasing trend observed over the years. These incidents were categorized into 6,121 cases of Reckless Imprudence Resulting (RIR) in Damage to Property (76.33%), 1,735 cases of RIR in Physical Injury (21.64%), and 163 cases of RIR in Homicide (2.03%). The rise in vehicular accidents may be attributed to the province's rapid urbanization, leading to increased traffic and improved monitoring systems that enhance reporting accuracy. The highest number of incidents occurred in highly urbanized areas, particularly in the cities of Bacoor, Imus, and Dasmariñas. Imus City recorded a total of 1,914 road crash incidents, including 1,467 cases of Reckless Imprudence Resulting (RIR) in Damage to Property, 433 cases of RIR in Physical Injury, and 14 cases of RIR in Homicide.

Current traffic management technologies heavily rely on human perception of the footage that was captured. This takes a substantial amount of effort from the point of view of the human operators and does not support any real-time feedback to spontaneous events. Intelligent traffic management and surveillance have been widely implemented using computer vision-based techniques. The general pipeline of computer vision-based methods includes the following: Road entity and vehicle segmentation from moving and stationary backgrounds video scene, categorizing all vehicle types, extracting spatiotemporal data for various traffic-related tasks such as vehicle tracking, vehicle counting, trajectory tracking, and identifying accidents. It is also necessary for these computer vision-based devices to function in different traffic and lighting scenarios. Traditional traffic management measures inefficiencies and worsened congestion result from solutions that are frequently centralized and reliant on set signal timings, which are unable to adapt to the fluctuations in traffic volumes and patterns. Although traffic flow can be improved by artificial intelligence-based traffic systems, they frequently cost expensive (Koch, 2022) and don't have enough real-time adaptability Genitha et al. (2023). You Only Look Once, or YOLO, is a popular object detection architecture used in real-time applications like autonomous vehicles and surveillance systems. It divides input images into grids, predicting class and bounding boxes. Faster R-CNN is known for accurate localization and is used in high-accuracy applications like satellite images and medical imaging (Ramana et al., 2023).

1.2 PURPOSE AND DESCRIPTION

The study aims to improve emergency response in Imus City through the development of a mobile application designed to reduce response times for responders and authorities. By developing a mobile application, this enables Imus citizens to request immediate assistance, ensuring swift and decisive action during critical situations. Featuring an intuitive and user-friendly interface, the app is tailored to support Imus residents during vehicular accidents, allowing them to navigate emergency situations with assistance. Its function is to build communication between individuals in distress and emergency personnel by requiring the user to input their phone number and to be called when a vehicular accident happens.

At the heart of this study is the objective to minimize delays in contacting the appropriate emergency responders, facilitating prompt intervention and improving the overall handling of crises. By addressing existing challenges in emergency response, such as the lack of vehicular accident detection system, and delays in communication between responders, this project seeks to enhance the safety and well-being of the community, promoting a more resilient and responsive approach to managing accidents and urgent incidents. Through this innovative solution, the study contributes to the advancement of emergency communication systems, paving the way for a more effective and proactive emergency management framework in the future.

1.3 STATEMENT OF THE PROBLEM

Minimizing response times for emergency responders is crucial for every city's safety, as it significantly reduces accidents and saves lives. However, several challenges persist. Encouraging greater compliance with road laws remains a pressing issue, complicated by the presence of reckless drivers and a general lack of awareness among many road users. Even those familiar with traffic rules sometimes fail to follow them, which only worsens road safety concerns. Despite the rapid evolution of the internet and artificial intelligence, ImuSafe contributes to both theory and practice by leveraging YOLOv8 to improve vehicular accident response efficiency while integrating structured human oversight to prevent over-reliance on automated systems. This study, therefore, seeks to evaluate the effectiveness, reliability, and usability of ImuSafe through the following research questions:

1. How effective is the YOLOv8 in detecting vehicular accidents based on pre-processed, labeled vehicular accident images from the Imus Local Government Unit?

2. To what extent does the developed mobile application provide real-time and accurate vehicular accident notifications to the Imus Local Government Unit?

3. How effective is the web dashboard in enabling the Imus Local Government Unit to monitor and respond to vehicular accidents reported by the mobile application?

4. What are the users' perceptions of the usability and reliability of the ImuSafe application in detecting and reporting vehicular accidents?

5. How can insights from system deployment and user feedback inform future improvements and broader implementation of AI-based emergency detection systems.

1.4 HYPOTHESIS

Implementing a computer vision-based vehicular accident detection mobile application in Imus City, Cavite will improve the emergency response of local authorities and decrease response times, as evidenced by increased usage of emergency features such as accident reporting, hotline services, along with positive feedback regarding the app's functionality and usefulness.

1.5 RESEARCH OBJECTIVES

1.5.1 General Objectives

To develop ImuSafe: A Computer Vision-Based Vehicular Accident Detection Mobile Application using YOLOv8.

1.5.2 Specific Objectives

a. To communicate with the Imus Local Government regarding the process and suggestions in developing the mobile application.

b. To provide the Imus Local Government Unit with an alternative method for notification when a vehicular accident occurs.

c. To train a YOLOv8 model for detecting vehicular accidents.

d. To test and evaluate the model's performance using several YOLOv8 metrics such as mean average precision, Fl score, precision, and recall.

e. To develop a website dashboard for the Imus Local Government Unit to view live accident reports from the registered users.

f. To endorse and implement the system to the Imus Local Government Unit

1.6 SIGNIFICANCE OF THE STUDY

The study aims to assist the Imus Local Government Unit (LGU) in reducing vehicular accident response time. With ImuSafe, citizens of Imus can receive faster emergency responses and medical assistance when needed during a vehicular accident. The insights derived from this study can also be applied to other domains, such as fire incidents, natural disasters, and infrastructure-related emergencies. The research also promotes a culture of responsible driving and raises public awareness about road safety, aligning with global efforts to minimize vehicular accidents and improve urban resilience.

a. Imus Citizens - Residents benefit from an improved emergency response system, enabling quicker access to medical and rescue services in the event of a vehicular accident. This fosters a greater sense of security and support during emergencies, contributing to community well-being and trust in public services.

b. Imus Local Government Unit - The LGU gains a data-driven approach to addressing vehicular accidents through the implementation of ImuSafe. Real-time alerts and incident reports enable faster coordination among emergency responders, traffic enforcers, and healthcare providers, significantly reducing response time.

c. Future Researchers - This study serves as a foundation for further research on intelligent accident detection systems and emergency response technologies. It provides a practical framework for integrating computer vision, mobile development, and real-time alert systems in the context of public safety.

1.7 SCOPE AND LIMITATIONS

The mobile application is intended exclusively for residents of Imus, providing a dedicated channel for swift communication with the Imus Local Government Unit (LGU) in the event of vehicular accidents. While the app focuses on incidents within Imus City, real-time emergency responses may vary based on external factors, such as the availability of rescue personnel. For accidents occurring outside the city, the Imus LGU will coordinate with the nearest LGU based on the location of the incident, ensuring users receive necessary assistance despite jurisdictional limits. By promoting inter-LGU communication, the application reinforces its commitment to public safety, streamlining the emergency response process for Imus residents.

CHAPTER II
REVIEW OF RELATED LITERATURE

The chapter presents an extensive literature review which establishes both theoretical and empirical bases through an examination of computer vision systems used for vehicular accident detection. This section examines fundamental principles alongside past study conclusions and technical approaches that lead to deeper insights into this new research domain. A comprehensive analysis of scholarly perspectives shows both knowledge gaps in current research while demonstrating why this work remains crucial. The existing research depends primarily on static surveillance cameras together with ego-vehicle information that fails to explore portable user-driven systems. Numerous critical functions remain disconnected from emergency services and real-time operation platforms while environmental elements such as dim lighting, harsh weather conditions and traffic congestion need better understanding. Security threats and privacy concerns often go unaddressed in modern designs while specific emergency situations continue to lack user-friendly solutions. ImuSafe addresses these problems by focusing on offering assistance during vehicular accidents and emergencies.

2.1 FOREIGN LITERATURE

In the study of Hammoudeh ed al. (2022), several limitations and research gaps were identified, pointing to areas of further exploration. The review covers the state of object detection techniques in video streams, hinting at the shortcomings of CNNs, RNNs, and tracking algorithms, all of which apply to the real world, the aim of this work. However, these remain issues such as poor lighting, occlusions, cluttered backgrounds, and motion blur, which greatly hinder the accuracy and reliability of detection models. Additionally, the study highlights the absence of standardized datasets specialized to dynamic environments like real-time road traffic or emergencies for benchmarking model performance. In the same breadth, there is another gap for not exploiting the lightweight architectures that perform very well on mobile or edge devices required for applications such as emergency response systems. The work also highlights the requirement for more comprehensive integration between object detection and decision-making systems to respond to real-time action, but stops short of providing practical, deployable frameworks to realize this aspiration. Further research is possible into more efficient, mobile-compatible, and context-aware computer vision systems that can operate reliably in unconstrained, high-stakes environments, including urban accidents or disaster response.

The proposed framework from the study authored by Md Faysal Kabir and Sahadev Roy (2022) implements deep learning models, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks for real-time detection of accident potential scenarios. This research shows promising system accuracy achievements while highlighting multiple areas that need improvement. The main problem exists because controlled datasets and simulation-based environments fail to recreate the unpredictable behavior of real-world road conditions, including weather variations, together with diverse traffic behaviors, along unusual driving patterns. The research fails to provide comprehensive information about how the system handles various infrastructure setups and geographic locations, which directly impacts performance measures. The system lacks essential functionality because it is incompatible with genuine emergency response services or mobile communication platforms, which reduces its suitability for immediate emergency response applications. Although the architecture enables accident prevention, the research lacks sufficient analysis regarding driver alert systems and the behavioral responses of users to detection warnings. The research needs additional investigation into real-world deployments of the system, along with mobile platform integration to enable user interaction and emergency communication to achieve practical and impactful results.

A real-time accident detection framework proposed by Dorokar et al. (2024) focuses on utilizing YOLOv8 and Convolutional Neural Networks (CNNs) for vehicular accident identification from surveillance video streams. The system demonstrates promise for automated road safety improvements, but several important problems must be solved. The technical design takes center stage in this research, while the performance under real-world situations such as dark lighting conditions, congested roads, and extreme climate remains unvalidated. The research fails to demonstrate how the system interacts with real-time emergency response procedures, which is a critical element for implementation in operational settings. The study omits essential details about the dataset, which hinders understanding regarding its content distribution and generates uncertainty regarding broad applicability. The paper fails to explore privacy concerns and ethical aspects of video surveillance for deploying such systems in public settings. Future research must investigate all aspects encompassing actual field implementation together with communication standards and protective frameworks and environmental stress tests.

This study by Dilek & Dener (2023) presents an extensive examination of CV implementation methods within ITS by tracing progress made in traffic monitoring systems and automated vehicle identification procedures alongside streamlining traffic patterns. Various shortcomings become visible in this research. The survey classifies CV applications under ten headings but explains the performance-degrading effects of real-world conditions such as variable lighting and weather disturbances and visual obstructions on CV system performance. Standardized datasets specific to dynamic traffic environments are missing which creates problems when evaluating different CV models against each other. First responders need real-time CV applications during emergency situations but the survey highlights that contemporary systems fail to maximize lightweight mobile-compatible frameworks. The research fails to provide detailed examination of how CV technologies integrate into current mobile infrastructure for emergency response operations even though it emphasizes CV capability in safety and efficiency improvements. The article overlooks detailed examination of ethical risks including data privacy and surveillance issues which will arise from using CV technology in public areas. The successful implementation of CV technologies in ITS demands solving these identified gaps for practical and ethical purposes.

The research authored by Muhammad Haris et al. (2021) investigates how computer vision technologies can identify upcoming vehicular accidents to create a proactive safety framework for roads. The research brings forth multiple essential problems. Real-world traffic conditions are difficult to address due to missing diverse annotated datasets that cover unpredictable driver behavior alongside poor weather along with low lighting conditions. The models struggle to achieve effective generalization across diverse environmental conditions because of this limitation. Many vision-based models face difficulties with real-time deployment because of high computational requirements which make them unsuitable for scenarios requiring fast accident prevention. No improvements are proposed in the study regarding how automated systems can merge with existing vehicle infrastructure networks which poses a challenge for practical deployment. The study fails to provide comprehensive examination of privacy issues affecting data protection and moral aspects arising from persistent video surveillance. The present study reveals essential knowledge gaps which justify additional research efforts dedicated to creating datasets along with optimizing models for real-time use and studying infrastructure integration and establishing ethical standards.

This research by Jasbir Singh and Dr. Sourabh Jain (2022) presents an analysis of computer vision approaches for vehicular accident detection particularly when used by autonomous vehicle systems. Two available methods include Gaussian Mixture Models (GMM) and Stacked Auto-Encoders that show promise for detecting accident occurrences. The review demonstrates these breakthroughs yet exposes vital knowledge deficiencies. The system does not address the requirement of standardized diverse datasets essential for benchmarking model performance under actual real-world situations. The evaluation fails to address how such systems will integrate within existing emergency response frameworks because real-time intervention requires this understanding. The research area lacks detailed investigation about environmental factors such as lighting and weather which heavily affect vision-based systems. Public road monitoring faces limitations regarding ethical aspects of privacy and surveillance along with insufficient assessment of standardized datasets needed to benchmark model performance in real-world conditions. Additional research is necessary to establish comprehensive connections between technological advancements and actual field implementation as well as ethical considerations.

This study by Basheer Ahmed et al. (2023) develops a full framework that utilizes innovative computer vision methods to continuously detect and categorize traffic situations for raised road security. The proposed system combines three major component models to achieve its objective. The system features three core modules: YOLOv5 and DeepSORT run a vehicle detection and tracking system, and ResNet152 analyzes incident severity while an alert generation system sends alerts to authorities in real-time. Through this multifaceted system, vehicles can be identified while monitoring activities, yet the severity evaluation process alongside fire detection allows for prompt emergency assistance. A prototype interface combines these models for demonstrating the system's readiness to function in actual traffic monitoring environments. The research delivers promising results about system functionality, but additional examinations need to determine its performance across different realistic urban conditions, which include different weather patterns along with lighting conditions and traffic congestion levels.

The research by G. Jhansi Lakshmi, K. Krishna Jyothi, and G. Kalyani (2023) implements computer vision technology to automate road accident identification through CCTV video analysis. The system evaluates video frames by using supervised Convolutional Neural Network (CNN) classifiers to calculate accident probability. The system evaluates road accidents through an on-screen warning followed by an SMTP email sent to emergency contacts to minimize response duration and boost survival odds in car accidents. The functionality of this system to automate accident discovery and warning production shows potential but multiple constraints decrease its effectiveness. The study lacks comprehensive evaluation of system performance throughout different real-world operating conditions including diverse lighting conditions and various weather patterns along with complicated road scenarios that determine system robustness. The paper lacks comprehensive research on how this system can harmonize with current emergency response platforms and standards thus affecting practical implementation feasibility. The proposed deployment lacks important information about data privacy and ethical consequences of persistent surveillance while assessing the system's operational readiness. Getting these scenarios necessitates both testing protocols and ethical evaluations in addition to integration methods to develop effective implementation systems for real-world use.

The research by Tiago Tamagusko et al. (2022) presents a new method based on computer vision for autonomous road accident recognition. Research on the scarcity of actual accident footage led scientists to create synthetic images for accident simulation training, which allowed them to develop a binary image classification model that detected normal versus accident scenes. The analysis utilized transfer learning methods through pre-trained convolutional neural networks, including both EfficientNetB1 and MobileNetV2, to boost model effectiveness. Testing with Finnish road surveillance camera data yielded an mAP score of 0.89 along with an MCC rating of 0.77 when the system used EfficientNetB1. MobileNetV2 generated a similar performance with an mAP of 0.88 and an MCC of 0.71. Although the study generated promising results, its methodology raises concerns about using synthetic data alongside requiring additional verification across varied environmental conditions for robust, reusable solutions. The implementation process of these systems within current emergency response technologies requires additional areas of research.

This research by Navaneeth Dontuboyina evaluates the performance of different deep learning models for dashcam crash detection. This research uses the Car Crash Dataset (CCD) consisting of 801 ego-vehicle crash videos alongside 3,000 non-crash scenarios to examine incidents where the camouflaged vehicle was involved. This work utilizes two main strategies as its methodology structure. The first method combines pre-trained Long Short-Term Memory (LSTM) models InceptionV3 VGG16 and ResNet50 together with Recurrent Neural Networks (RNNs) for sequential prediction while the second method develops a custom Convolutional Neural Network (CNN) model to evaluate simpler architectures for crash detection. Experimental data revealed InceptionV3 delivered 93% accuracy which surpassed the performance of VGG16 at 87% and ResNet50 at 88%. A custom CNN model performed with 64% accuracy which demonstrates that pre-trained models demonstrate better results in this specific scenario. The study presents encouraging results but points out restrictions such as viewing only from ego-vehicle cameras while using one viewing angle without incorporating Vehicle-to-Everything (V2X) systems. Computer vision-based crash detection systems need further research to increase their performance across different real-world conditions according to the identified constraints.

2.2 LOCAL LITERATURE

A retrospective study conducted an analysis of the Department of Health's Online National Electronic Injury Surveillance System (ONEISS) data from 2010 to 2019 to investigate transport and vehicular crash (TVC) cases throughout the Philippines. Among 894,989 injury incidents reported in this study, TVC caused 296,760 incidents (31 percent of total cases) with 25.58 percent annual injury case growth. There was an accounted 72.5 percent of all victims, with both drivers and young adults in the 0–30 age range at the highest risk. Fatal crashes occurred repeatedly between 6:00 PM and 5:00 AM during periods of recreational activities. The main causes behind drunk driving and traffic fatalities included poor usage of protective equipment and 25,537 intoxicated driving cases. Motorcycles were responsible for the majority of crashes reported based on accident data. However, the publication emphasized the need to enhance motorcycle safety regulations while improving the post-crash responses of municipal organizations and medical facilities to reduce both the economic burden and health issues resulting from accidents.

In order to learn more about the factors and challenges in road crash events, a study was done to identify these elements with the basis for enhanced interventions. The study examined road crash incidents throughout Metro Manila's five regions while studying human actions alongside community awareness and attitudes toward traffic as well as infrastructure design and technological measures and enforcement practices. The study has identified five major factors that influence road crash incidents: human behavior and public awareness, along with attitudes and road infrastructure and design, and technological interventions and enforcement measures. Human mistakes stood as the primary trigger for road collisions, according to study findings, along with major relevant driving behaviors that included speeding and driving under the influence of alcohol, as well as distracted, rule-breaking, and aggressive driving, which took prominent roles. The examination revealed how public unawareness combined with inadequate roads and insufficient enforcement and technological solutions contributed to enhanced road crash frequencies. The researchers emphasized that such interventions need to be provided to lower road crash occurrences while improving road safety standards. Through these interventions, the PNP-HPG can advance its mission to create safer roads for every Metro Manila Road user by implementing targeted education initiatives and improving infrastructure alongside law enforcement and technology adoption.

One of the elements that can be focused on is the influence of alcohol intoxication, which has been studied for its effect on fatalities and injuries of road users in Metro Manila. The study analyzed road crash data from 2005 to 2020 from the Metro Manila Accident Recording and Analysis System (MMARAS). They found alcohol-related crash numbers decreasing in 2005 with the quantity of 45 crashes, 2011 with 36, and 2020 with 31. Most of the involved vehicles were cars and motorcycles, and the most reported incidents were in Quezon City and Marikina City. The suspected alcohol intoxication was statistically associated with an increased risk of driver fatality with the odds ratio of 9.16 and driver injury with the odds ratio of 5.22. Additionally, risks of fatal crash outcomes involved specific crash types, including collisions with objects and truck-related accidents. The researchers stressed that alcohol-related road crashes are preventable, and there should be collaborative efforts in the area of road safety education and law enforcement to minimize their occurrences.

With these given factors and challenges in the road, there now exists the question of what can be done to negate these issues. A study about traffic incident prediction and classification was conducted and adopted an algorithm, called the Naïve Bayes algorithm, in order to build their traffic incident prediction and classification system that utilizes historical traffic data. The study shows how machine learning helps transportation safety by enhancing authority capabilities for quick response and optimal resource distribution. The system operates with structured datasets to generate more precise incident detection outcomes and examines multiple elements like traffic movement levels alongside weather patterns and the patterns from previous incidents. This demonstration shows the capability of the algorithm to classify incidents, which supports both traffic management operations and emergency response activities. Both smart transportation development and analytical road disruption reduction reach an advanced stage through these outcomes.

Exploring more on the implementation of reducing and detecting road crash accidents, machine learning is also given focus, especially on its approach to road accidents, which a study was created to provide analysis in Calabarzon, Philippines, in order to provide input to road safety management. In this study, the research team analyzed traffic accident records from 2016 to 2019 to develop methods for preventing road accidents for both policymakers and everyday commuters. Traffic accidents were examined through data mining methods together with classification algorithms to develop predictive modeling. A comparison among decision trees, k-NN, naïve Bayes, and neural networks revealed how these methods distinguished different felony stages most effectively. Accident frequency levels in the data reveal a significant problem that needs an immediate solution. The process of building a predictive model for traffic accidents used data mining technology with classification algorithms to help traffic policymakers and the general public stop these incidents before they happen. This intelligent pattern analysis leads to specific improvements in existing road safety practices while helping develop future road safety frameworks.

Emphasizing more on the visualization, a study was created on investigating a visual attention-based traffic accident detection model. In this study, the detection of abnormal occurrences by street and road cameras relies significantly on human observers, yet these observers experience fatigue together with competing interests and limited simultaneous attention. The research then evaluates traffic accident detection systems that combine task-oriented functions and visual attention mechanisms. The TaskFix system functions to adjust the visual attention framework called TaskNet. The study also shows numerical data that demonstrates that predicting an observer's current visual focus shows promising capability. Now TaskNet stands apart from conventional anomaly detection systems because its approach is based on visual attention mechanisms. The system functions with fixation maps that are acquired from observers' performance of the task. Thanks to its design, TaskNet successfully resolves the problems of unbalanced event distribution while eliminating rare anomalous occurrences. The automatic detection of anomalous events, including traffic accidents, represents a critical operational requirement, which proved TaskNet's ability to function as an alert system through its designed applications to support authorities.

With the understanding of machine learning and data visualization, a study on machine learning, with an emphasis on regression model development and data visualization, was conducted to evaluate traffic accidents in Urdaneta City. Road accidents routinely lead to a substantial number of annual fatalities. Various organizations involved in road safety management continue to combine information technology with their efforts toward quality improvements to both predict and lower the frequency of accidents. The study aims to develop a machine-learning model that predicts traffic accidents in Urdaneta City within the Philippines. Three years (2021-2023) of traffic accident information from the Emergency Medical Services compose this dataset. The predictive analysis relies on five models, including Random Forest, XGBoost, AdaBoost, Decision Tree, and LGBM, for analyzing road accidents. Permutation feature importance analysis reveals the exact influence of individual features on prediction outcomes because it shows that accident frequency depends strongly on the time of day, especially during peak and late-night periods, and the visualization through box plots shows relevant data at upper-level points.

Deep learning is another factor that can fully support and enhance these systems. Focusing on this, a study about deep learning-based traffic accident detection in smart transportation was conducted, which also focuses on a machine vision-based approach. In this study, the YOLOv8 architectural design couples with machine vision technology to create a deep learning detection system for smart transportation accidents. The study aims to achieve precise element detection, which improves standards in transportation security while optimizing system operational efficiency. This study conducted primary assessments of both model testing and inference analysis for determining operational functionality. Tests under different circumstances demonstrated solid detection capabilities that established the program's ability to recognize diverse accident scenarios, including vehicle crashes alongside non-vehicle events. The model in this study delivered this dependability and accuracy by identifying non-accident stimuli during execution to prevent erroneous model predictions. The performance metrics of YOLOv8 architecture testing confirm that it delivers advanced capabilities to enhance transport system safety while advancing operational efficiency for direct deployment applications. The performance of YOLOv8 reaches 94.4% while also achieving precision of 91.6% and recall of 92.3%, which outperform traditional deep learning techniques.

Emphasizing the use of YOLOv8, a study about motor vehicle crash detection using the YOLOv8 algorithm was also conducted. In this study, a growing number of motor vehicle accidents leads to substantial mortality and morbidity worldwide. A machine learning model with YOLOv8 detects motor vehicle accidents, and the paper presents this solution to address the problem. An algorithm suggested for accident detection conducts video examination of traffic infrastructure camera footage. The analysis employs a publicly accessible dataset that sorts vehicle accident videos into four categories: two-wheel accidents, four-wheel accidents, and large vehicle accidents. The data includes accidents involving two-wheel vehicles, four-wheel vehicles, and large vehicles. The model achieves performance assessment through evaluation metrics, which include accuracy along with recall and mean average precision. The developed model demonstrates promising real-world application potential through its 92.4% precision accuracy together with 78.1% recall rating. An intersection over a unit threshold of 0.5 reveals that the model achieves 87.6% mean average precision in accident detection.

The last challenge or factor that must be given focus is about the challenge in the implementation of road policies that conduct Metro Manila. The study investigated difficulties that occur during road policy implementation in Metro Manila. Secondary data was analyzed through multivariate multiple regression methods when studying Philippine government agencies such as the Metropolitan Manila Development Authority (MMDA), the Philippine Statistics Authority (PSA), and the Department of Transportation (DOTr). Road policies encounter multiple barriers to their execution despite existing at national and local levels. Road policies face major implementation challenges because of overlapping agency jurisdictions, insufficient infrastructure, limited public awareness, and weak enforcement capabilities. The research demonstrates how roads across Metro Manila would benefit from stronger coordination between various responsible parties.

2.3 SYNTHESIS

Figure 2.3.1

Synthesis Table.

Authors	***Application***	***Algorithms***	***Key Features***	***Results***
Hammoudeh et al. (2022)	*Object detection in videos*	*General computer vision algorithms*	*Comprehensive review of challenges and techniques*	*Lacks emergency system integration; highlights need for real-world robustness*
Md Faysal Kabir & Sahadev Roy (2022)	*Vehicular accident prevention*	*CNN, SSD*	*Prevention-focused system using deep learning*	*Accurate detection; lacks real-time alert functionality*
Dorokar et al. (2023)	*Accident detection*	*YOLOv8, CNN*	*Real-time detection using YOLOv8*	*Effective detection; not tested in field scenarios*
Dilek & Dener (2023)	*ITS applications*	*Various CV algorithms*	*Broad survey of computer vision in transport systems*	*Lacks specific focus on real-time accident systems*
Muhammad Harris (2021)	*Crash prediction*	*Vision-based models*	*Visual analysis for crash*	*Predictive potential; lacks*

			forecasting	*integration*
Jasbir Singh & Dr. Sourabh Jain (2022)	*Accident detection*	*GMM, Auto-Encoders*	*Brief overview of techniques*	*Basic detection; lacks deployment context*
Basheer Ahmed et al. (2023)	*Traffic classification*	*YOLOv5, DeepSORT, ResNet152*	*Real-time detection and classification*	*Strong results; limited real-world validation*
Lakshmi et al. (2023)	*Detection and alert system*	*CNN*	*Email alert system using camera input*	*Lacks mobile/real-time response integration*
Tamagusko et al. (2022)	*Accident detection*	*Transfer learning (EfficentNet, MobileNetV2)*	*Synthetic data to improve learning*	*Accurate model; needs real-world deployment*
Naveneeth Dontuboyina (2023)	*Crash detection*	*InceptionV3, VGG16, LSTM*	*Ego-vehicle detection using deep learning*	*High accuracy; limited to specific camera views*
Libnao et al. (2023)	*Traffic classification*	*Naïve Bayes*	*Basic classification framework*	*No real-time detection features*
Segun et al. (2024)	*Crash response factors*	*Statistical analysis*	*Identifies intervention barriers*	*No use of automation or CV*
Lu et al.	*Crash case*	*Statistical tools*	*National*	*Lacks algorithmic*

(2022)	*trends (2010-2019)*		*surveillance analysis*	*detection tools*
Lu et al. (2022)	*Alcohol's impact on crash injuries*	*Statistical analysis*	*Data over 15 years*	*No tech-based accident handling*
Capellan et al. (2022)	*Road policy implementation*	*Qualitative study*	*Examines urban policy gaps*	*Focus on policy; no tech system tested*
Torres & Asor (2021)	*Road safety in Calabarzon*	*Machine learning*	*Regional ML modeling*	*No live detection/alert function*
Juan et al. (2021)	*Attention-based detection*	*Deep learning with visual attention*	*Enhances focus on relevant frames*	*Promising; not field-tested*
Dorado & Aviles (2025)	*Pangasinan road accident model*	*ML regression*	*Local predictive analysis*	*Lacks CV or detection capability*
Melegrito et al. (2024)	*Smart transportation detection*	*Deep learning, CV*	*Computer vision for smart cities*	*Theoretical model; not linked to mobile alerts*
Rosales et al. (2023)	*Crash detection*	*YOLOv8*	*YOLOv8 real-time application*	*High accuracy; not field validated*

When it comes to enhancing our traffic policies, particularly with road accidents, the employment of computer vision is contentious in terms of preserving order and offering assistance on the road. Although it has been improved over time, it is still difficult for us to maintain its accuracy, particularly when attempting to pinpoint the fatality of the crash. ImuSafe should assist in filling in the gaps left by earlier studies, adapt to what it lacks, and develop the concept of employing computer vision on the road more efficiently. While it requires a mobile hotspot or an internet connection to function, every citizen should have access to immediate responders in the event of an accident, as it aids in the identification of crash fatalities, reduces response time for responders and authorities, and, once improved, the application can be used in other LGUs.

The considered literature and studies provide a comprehensive overview of contemporary methodologies of vehicular accident detection using computer vision (CV), machine learning (ML), and deep learning (DL) technologies. Many of the other foreign works that have noted the flaws, including the works by Hammoudeh et al. (2022), Kabir & Roy (2022), and Dorokar et al. (2024), note the key drawbacks in current systems, especially to address real-world difficulties, including low lighting, bad weather, occlusions, and traffic congestion. These works provide insights into the requirement of standardized and diverse datasets relevant to rapidly changing environments, mobile-compatible architecture, and integration with relevant emergency services in real time. In addition, ethical issues of privacy and surveillance are not yet well covered. As it stands, a number of frameworks indicate technical promise but could not be tested for validity under uncontrolled urban conditions, nor could they implement workable, deployable answers to emergency response.

Additionally, such reveals these gaps in local studies as well. The studies based on the national information from the Department of Health's ONEISS and MMARAS highlight the emerging trend of road accidents, particularly the cases of motoring accidents and inebriated drivers. However, although the majority of studies used ML algorithms for traffic incident prediction and classification (Naïve Bayes, Random Forest, XGBoost, etc.), they are limited to analysis of historical data rather than real-time accident detection and broadcasting. Other works that leverage visual attention models such as TaskNet, and deep learning techniques (of which YOLOv8 is an example) have demonstrated high detection accuracy yet continue to be limited by variability in such variables as the environment or the absence of a mobile system, as well as integration with local emergency response protocols.

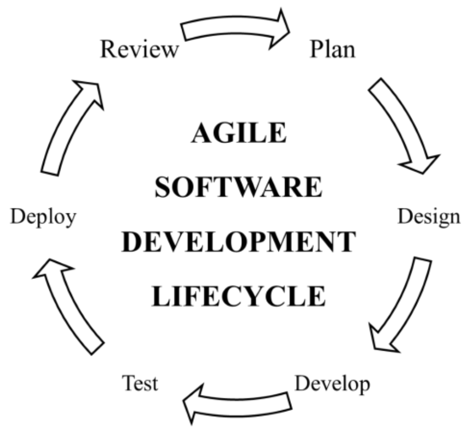
However, the current literature indicates several research gaps that mainly are due to the lack of existence of real-world validated, mobile-integrated, end-user-friendly systems able to work consistently in real-life settings while preserving the user's privacy. These are the exact gaps that the ImuSafe system aims to close. ImuSafe is unlike earlier works in that it is a mobile-first and context-aware accident detection paradigm, which caters to bringing down the emergency response time by integrating computer vision with real-time alerts and communication capabilities into the proposed framework. It also emphasizes usability among daily commuters and emergency responders, particularly in Imus Cavite. By filling these technology and practice gaps, ImuSafe offers an important step toward an effective, ethical, and equitable emergency response capability.

CHAPTER III
RESEARCH METHODOLOGY

3.1 SOFTWARE DEVELOPMENT METHODOLOGY

Figure 3.1.1

Agile Software Development Life Cycle of ImuSafe



Plan - In this process, the proponents analyzed the recommended research topics provided by the De La Salle University – Dasmariñas University Research Office and formulated a comprehensive plan for developing a mobile application aimed at reducing response time for authorities and medical personnel in vehicular accidents, integrating computer vision and deep learning.

Design - In this process, the proponents will use Figma to design the User Interface (UI) and User Experience (UX) of the mobile application. The design will later be transformed into a functional mobile app during the development stage.

Development - For the mobile application, Flutter handles both frontend and backend tasks and is connected to Google Firebase for database management. Both Google Colab and local desktop development will be used for training and refining the machine learning model. TensorFlow will be used to implement the Convolutional Neural Network, which will then be converted into a TensorFlow Lite file for integration into the mobile application.

Test - In this process, the proponents will conduct a thorough logic test to verify that all app functions work correctly without bugs and to identify possible improvements to the Convolutional Neural Network.

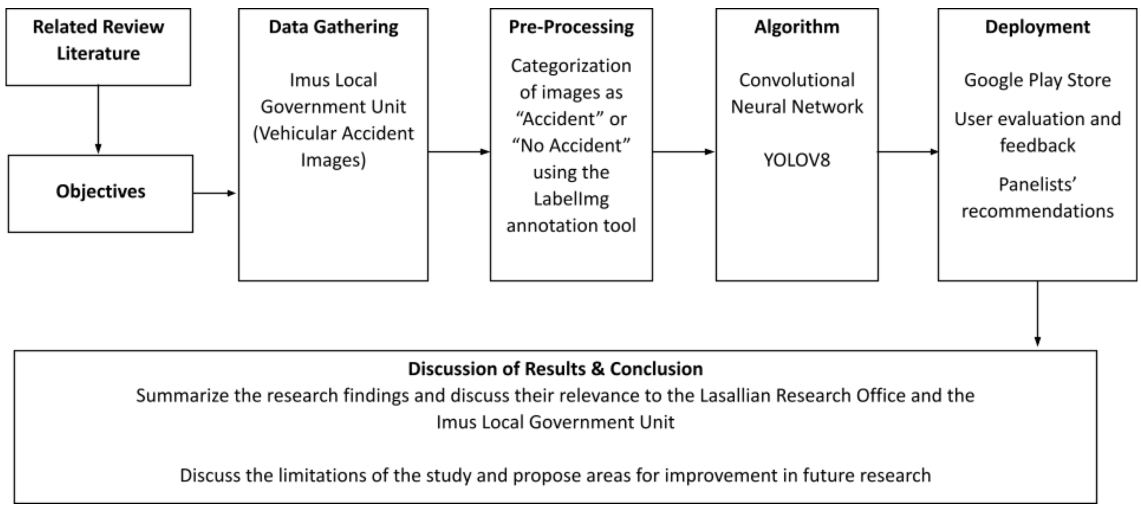
Deploy - In this process, the proponents will package the application's code into an APK file, preparing it for the presentation in the proposal defense.

Review - In this process, the proponents will analyze the feedback and recommendations provided by the panelists during the proposal defense and implement them to improve the mobile application and accuracy of the deep learning model for the final defense.

3.2 CONCEPTUAL FRAMEWORK

Figure 3.2.1

Conceptual Framework of ImuSafe



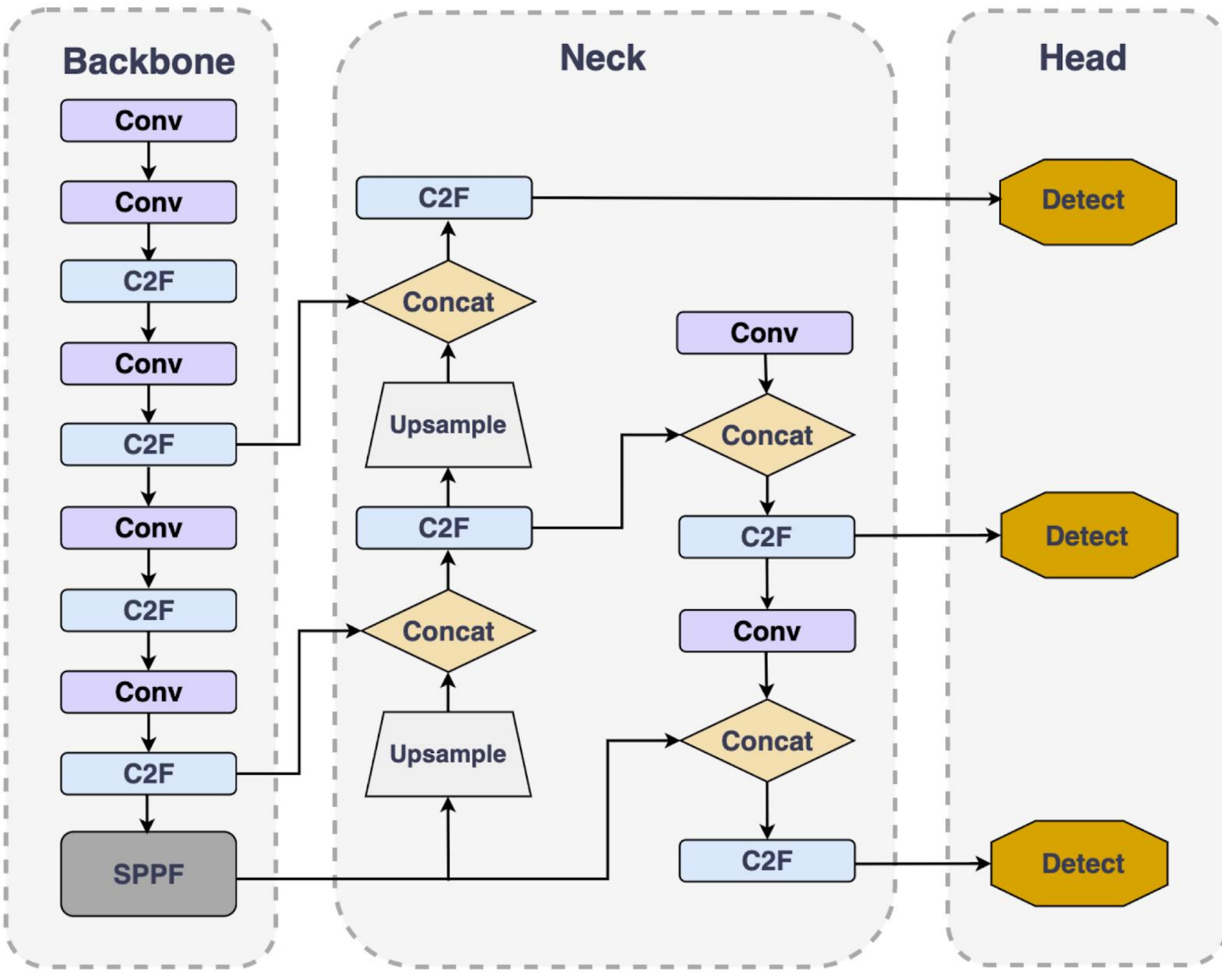
The conceptual framework of the study is divided into several stages. First is the literature review, which forms the basis for the objectives. This is followed by data acquisition from the Imus Local Government Unit. During the pre-processing phase, the images will be manually categorized and labeled using the Labeling annotation tool, which will then be used to train the Convolutional Neural Network. The deployment stage involves releasing the mobile application on the Google Play Store and collecting user assessments and feedback. Lastly, the discussion of results and conclusion will present the research findings, their value to the Lasallian Research Office and Imus Local Government Unit, the limitations of the study, and suggestions for future research.

3.3 ALGORITHM AND ITS RULES

In developing the vehicular accident detection algorithm, the researchers will use YOLOv8n.

Figure 3.3.1

YOLOV8 Architecture



YOLOv8 is a neural network framework that combines object localization and classification tasks. It uses a convolutional neural network (CNN) backbone to extract multi-scale features from input images, capturing hierarchical feature maps that represent low-level textures and high-level semantic information. The backbone is optimized for speed and accuracy, incorporating depth wise separable convolutions or other efficient layers. The Neck module refines and fuses the multi-scale features extracted by the backbone, leveraging an optimized version of the Path Aggregation Network (PANet). This multi-scale feature integration is crucial for detecting objects of varying sizes and scales. The Head module generates final predictions, including bounding box coordinates, object confidence scores, and class labels. YOLOv8 introduces an anchor-free approach to bounding box prediction, simplifying the prediction process, reducing hyperparameters, and improving the model's adaptability to objects with varying aspect ratios and scales. The sigmoid function was employed as the activation function for the objectness score in the YOLOv8 output layer. This score indicates the likelihood that an object is present in the bounding box. It represents the objects' probabilities of belonging to each potential class using the softmax function for the class probabilities.

The YOLOv8 architecture introduces five distinct models, each tailored to different computational environments, from the highly efficient YOLOv8n to the most advanced YOLOv8x. The YOLOv8n model is a lightweight, rapid, and optimized convolutional layer for limited computational resources, ideal for edge deployments, IoT devices, and mobile applications. Its compact size and integration with ONNX Runtime enhance its deployment flexibility. The YOLOv8s, the baseline model in the YOLOv8 series, offers a balance between speed and accuracy, suitable for inference tasks on CPUs and GPUs, with enhanced spatial pyramid pooling. The YOLOv8m is a mid-tier model with 25 million parameters, offering a balance between computational efficiency and precision, ideal for real-time applications with high accuracy and limited computational resources. The YOLOv8l, with 55 million parameters, enhances precision in high-resolution image detection by employing a complex feature extraction process with additional layers and refined attention mechanism. The YOLOv8x, the largest model in the YOLOv8 family, has 90 million parameters and high mAP, making it ideal for precision applications like surveillance systems and industrial inspections.

Table 3.3.1

YOLOV8 Models

Model	Parameters (Million)	Accuracy (mAP @ 0.5)	CPU Time (ms)	GPU Time (ms)
YOLOv8n	2.0	47.2	42	5.8
YOLOv8s	9.0	58.5	90	6.0
YOLOv8m	25..0	66.3	210	7.8
YOLOv8l	55.0	69.8	400	9.8
YOLOv8x	90.0	71.5	720	11.5

The table outlines the trade-offs of YOLOv8 models, with YOLOv8n offering faster inference times but lower accuracy, ideal for edge computing and limited computational resources, and YOLOv8x providing high accuracy but requiring more powerful hardware.

3.3.1 Formulas and Mathematical Representation

3.3.3.1 YOLOV8 Architecture

Backbone Module

Standard Convolution

$$Y(i,j) = \sum_{m=1}^{M} \sum_{u=1}^{k} \sum_{v=1}^{k} X_m(i+u, j+v) \cdot W_m(u,v)$$

Standard Convolution is a matrix operation that performs element-wise multiplication on input data, allowing weight sharing and image translation, reducing effective parameters and enabling feature detection in different input spaces.

Depthwise Separable Convolution

$$Y_m(i,j) = \sum_{u=1}^{k} \sum_{v=1}^{k} X_m(i+u, j+v) \cdot W_m(u,v)$$

Depthwise Separable Convolution divides computation into two steps: Depthwise convolution applies a single filter per input channel, and pointwise convolution creates a linear combination of the output.

Pointwise Convolution

$$Z_n(i,j) = \sum_{m=1}^{M} Y_m(i,j) \cdot P_{m,n}$$

Pointwise Convolution is a convolution method that uses a 1x1 kernel to iterate through every point in the input image, varying in depth based on the number of channels.

Neck Module

Feature Fusion

$$F_{fused} = \text{Concat}(F_{high}, \text{Upsample}(F_{low}))$$

Feature fusion is the combination of various visual cues to create a more comprehensive feature representation for tasks like object detection.

Head Module

Bounding Box Prediction

$$b_x = \sigma(\Delta x) + c_x$$

$$b_y = \sigma(\Delta y) + c_y$$

$$b_w = e^w \cdot a_w$$

$$b_h = e^h \cdot a_h$$

Where:

σ: sigmoid function

c_x, c_y: top-left coordinates of the grid cell

a_w, a_h: anchor dimensions (set to 1 in anchor-free)

b_x, b_y, b_w, b_h: predicted bounding box center and dimensions

Bounding box prediction is the process by which the model can locate things in an image by providing the coordinates and measurements of rectangular areas that firmly include the objects it has detected.

Objectness Score

$$P_{obj} = \sigma(z)$$

Objectness score measures how well the detector recognizes the objects' classes and locations when navigating. In particular, when an object is identified and the camera is far enough away, it is intended to increase.

Class Probabilities

$$P(y = c \mid x) = \frac{e^{z_c}}{\sum_{j=1}^{C} e^{z_j}}$$

Where:

z : raw output (logit)

σ: sigmoid function

C : number of classes

Every object class is given a confidence score by YOLOv8, which represents the probability that the class will be found in the bounding box.

3.3.3.2 YOLOV8 Performance Metrics

To evaluate the effectiveness of the YOLOv8 model, various performance metrics were analyzed, including mean Average Precision (mAP), F1-score, precision, and recall.

Intersection over Union

$$IoU = \frac{Area\ of\ Overlap}{Area\ of\ Union} = \frac{|A \cap B|}{|A \cup B|}$$

Where:

A: predicted bounding box

B: ground truth bounding box

$|A \cap B|$: area of overlap between the predicted and ground truth boxes

$|A \cup B|$: total area covered by both boxes

Intersection over Union is a measure that quantifies the overlap between a predicted bounding box and a ground truth bounding box. It plays a fundamental role in evaluating the accuracy of object localization.

Average Precision

$$AP = \sum_{n} (R_n - R_{n-1}) \cdot P_n$$

where:

P_n : precision at the nth threshold

R_n and R_{n-1} : recall values at the n^{th} and $(n-1)^{th}$ thresholds

Average Precision computes the area under the precision-recall curve, providing a single value that encapsulates the model's precision and recall performance.

Mean Average Precision

$$mAP = \frac{1}{k}\sum_{i}^{k} AP_i$$

Mean Average Precision extends the concept of AP by calculating the average AP values across multiple object classes. This is useful in multi-class object detection scenarios to provide a comprehensive evaluation of the model's performance.

Precision

$$\frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Positive (FP)}}$$

Precision quantifies the proportion of true positives among all positive predictions, assessing the model's capability to avoid false positives

Recall

$$\frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Negative (FN)}}$$

Recall calculates the proportion of true positives among all actual positives, measuring the model's ability to detect all instances of a class.

F1 Score

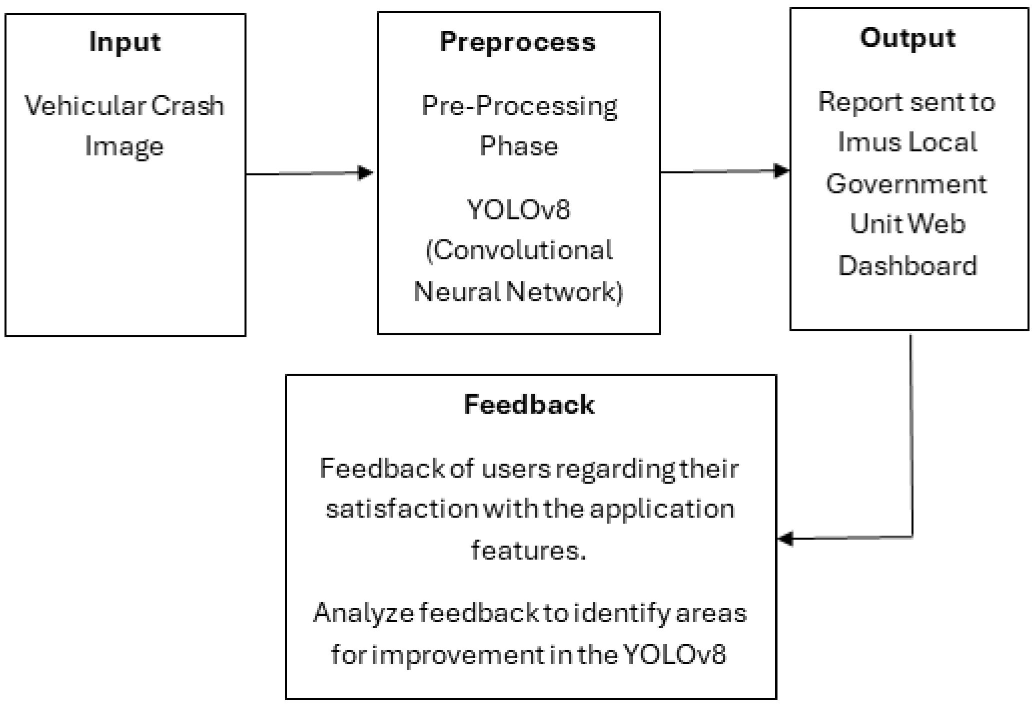
$$F_1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

F1 Score is the harmonic mean of precision and recall, providing a balanced assessment of a model's performance while considering both false positives and false negatives.

3.4 OPERATIONAL FRAMEWORK

Figure 3.4.1

Operational Framework of ImuSafe

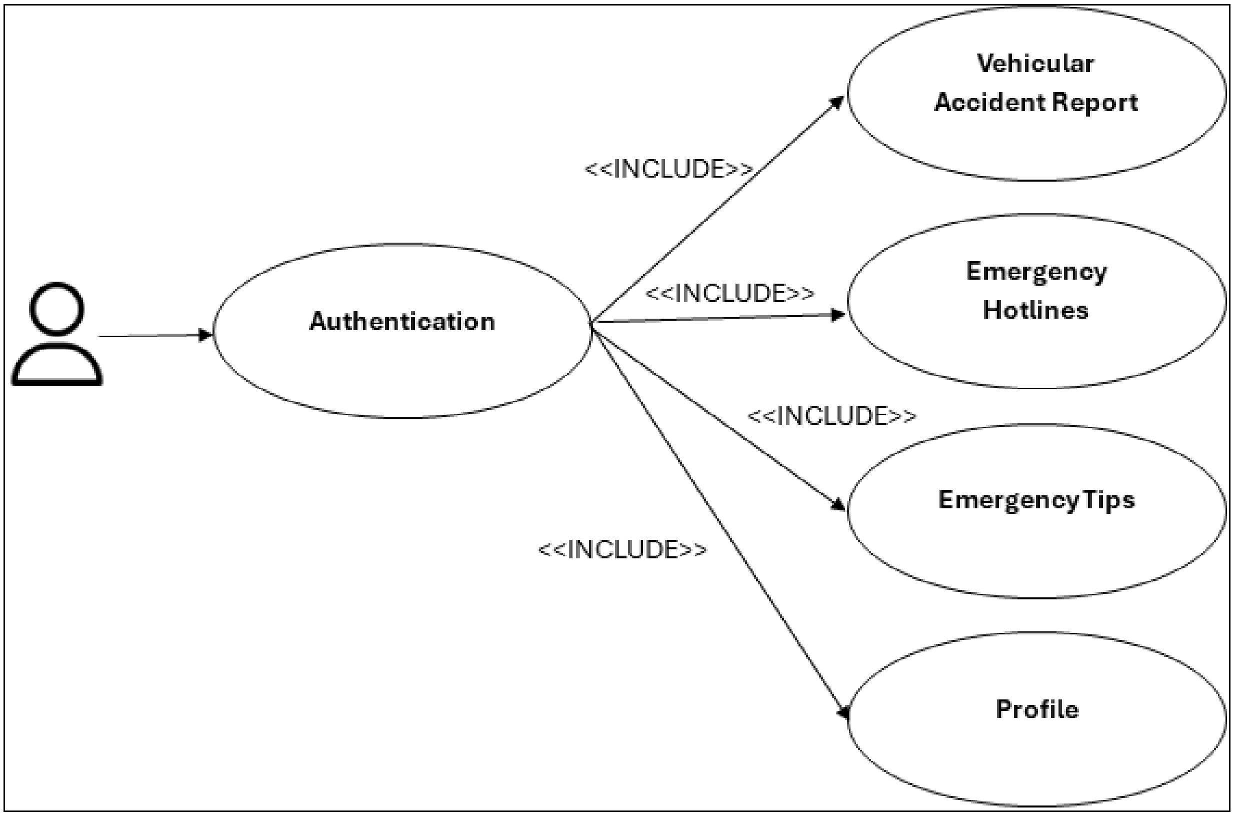


The operational framework is divided into four main sections: the input section gathers vehicular crash images detected from the camera of the mobile application. The Process section consists of the Pre-Processing Phase and the YOLOv8 converted into a TensorFlow Lite extension so that the mobile application can make an inference as to whether there's a vehicular crash detected. The Output section sends a report including the user's information, such as coordinates, location, phone number, and the vehicular crash image. Lastly, the Feedback section collects user feedback regarding their satisfaction with the application and analyzes this feedback to identify areas for improvement in the implementation of YOLOv8.

3.5 USE CASE/FLOWCHART/STATE DIAGRAM

Figure 3.5.1

Use Case Diagram of ImuSafe



The mobile application begins with an onboarding section that welcomes the user and provides insights into what the application can offer. After proceeding, the user is given two options to sign in: using Google Authentication or anonymously without the need for a Google account. After choosing which authentication method to choose, the user is asked to input their mobile phone number, which is important information for the vehicular accident report. The user can input their current phone number or skip for now, but when they choose to skip, they won't be able to send a vehicular accident report unless they add their phone number in the Profile section. There are four major options that the user can navigate to. The "Vehicular Accident Report" is the main feature of this mobile application that detects whether there's a vehicular accident using the in-app camera and then automatically sends a report to the Imus Local

Government Unit web dashboard that contains the user's coordinates, phone number, and the detected vehicular accident. The "Emergency Hotlines" screen contains different Imus emergency departments where a user can select a department, which will redirect to the phone book to call the selected department. The "Emergency Tips" contains several infographics on what to do when disasters happen, such as earthquakes, floods, typhoons, and fires. The "Profile" section displays the details of the user whether they are signed in through google or anonymously and can add or change their phone number.

3.6 RESPONDENTS OF THE STUDY

This study will utilize a quantitative research approach, as it aims to collect and analyze numerical data through structured surveys. The respondents will consist of individuals aged 18 to 50 years old who are active drivers and residents of Imus, Cavite, including students, daily commuters, working professionals, emergency responders such as police officers and paramedics, and local government officials involved in road safety. A minimum sample size of 300 respondents will be targeted to ensure statistical reliability. Data will be gathered using Google Forms, and the results will be analyzed using Microsoft Excel to identify trends. This method was chosen because it allows for the efficient collection of standardized data from a large and diverse population, enhancing the reliability, objectivity, and generalizability of the findings.

The study shall be treated with the highest level of confidentiality. The gathered data shall be strictly used only for the development and study of ImuSafe. This acknowledges that all data obtained is confidential and protected under Republic Act No. 10173, also known as the Data Privacy Act of 2012. The researchers agree to handle, process, and store such data in compliance with the said law to ensure the protection of sensitive and personal information, preventing unauthorized access, disclosure, or misuse.

Academic Use of Data. All data collected during the course of this research shall be used strictly for academic purposes related to the study entitled "ImuSafe: A Vehicular Accident

Detection Mobile Application Using YOLOv8 in Imus Cavite". The information obtained will contribute solely to the enhancement of the system's design, usability, and accuracy, and will not be used for any commercial or non-academic endeavor. The researchers ensure that the data will not be sold, transferred, or shared with third parties without explicit permission. Upon completion of the study, the data will be stored securely and will be disposed of responsibly to prevent future misuse.

Informed Consent and Privacy. All participants will be required to sign an informed consent form prior to participating in the survey. The purpose of the study, the voluntary nature of participation, and the right to withdraw at any point without consequences will be clearly communicated. The consent form will also include a brief explanation of how the data will be collected, stored, and used.

Anonymity and Confidentiality of the Respondents. The anonymity of respondents will be preserved by ensuring that no names, addresses, or other identifying details will be associated with survey responses. Confidentiality will be maintained by limiting access to the data to only the researchers involved in the study.

Responsible Use of Artificial Intelligence. The integration of artificial intelligence (AI) in this study, particularly through the implementation of the YOLOv8 model, is guided by ethical standards and responsible use. The AI system will only be used to detect and alert for vehicle accidents, which is the study's primary goal. It will not be used for unrelated or non-consensual surveillance tasks. The researchers reiterate that ethically procured datasets were used for the model's evaluation and training from the Imus Local Government Unit. These datasets were anonymized before usage to ensure that no identifiable information was included.

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