**SURROUND VIEW CAMERA TECHNOLOGY FOR VEHICLE COLLISION DETECTION**

**A PROJECT REPORT**

***Submitted by***

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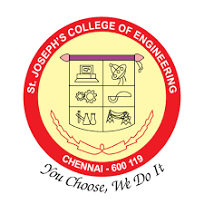
***in partial fulfilment for the award of the degree***

***of***

**BACHELOR OF TECHNOLOGY**

**IN**

**INFORMATION TECHNOLOGY**



**ST. JOSEPH’S COLLEGE OF ENGINEERING**

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**April - 2025**

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Submitted for the Project and Viva Examination held on \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_.

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**ACKNOWLEDGEMENT**

At the outset we would like to express our sincere gratitude to the beloved **Chairman, Dr. Babu Manoharan, M.A., M.B.A., Ph.D.,** for his constant guidance and support.

We would like to express our heartfelt thanks to our respected **Managing Director, Mr. B. Shashi Sekar, M.Sc** for his kind encouragement and blessings.

We wish to express our sincere thanks to our **Executive Director, Mrs. S. Jessie Priya, M.Com.,** for providing ample facilities in the institution.

We express our deepest gratitude and thanks to our beloved **Principal, Dr. Vaddi Seshagiri Rao, B.E., M.E., M.B.A., Ph.D., F.I.E.,** for his inspirational ideas during the course of the project.

We are immensely grateful to our esteemed **Dean School of Computing**, **Ms. G. Lathaselvi, B.E., M.E., (Ph.D).**, for her invaluable support and academic guidance throughout this endeavor.

We wish to express our sincere thanks and gratitude **Dr. C. Heltin Genitha, M.E., Ph.D,** **Head of the Department,** Department of Information Technology, St. Joseph’s College of Engineering for her guidance and assistance in solving the various intricacies involved in the project.

It is with deep sense of gratitude that we acknowledge our supervisor **Dr. R. Elavarasan, B.E., M.E., Ph.D.,** for his expert guidance and connoisseur suggestion.

Finally we thank our department staff members who helped us in the successful completion of this phase II project.

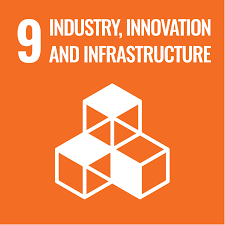
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**ABSTRACT**

The Vehicle Collision Detection and Alert System utilizes 360° camera technology to enhance road safety through real-time collision prediction and notification. Blind spots are minimized, and comprehensive monitoring of the vehicle’s surroundings ensured by the 360° camera setup. YOLO v8, an advanced object detection algorithm, detects nearby objects such as vehicles, pedestrians, and obstacles. A Convolutional Neural Network (CNN) analyzes object trajectories, predicting potential collisions by examining spatial and temporal patterns across successive frames. Immediate alerts are sent to relevant authorities or connected devices upon detection of a potential collision, ensuring a prompt response. In critical situations, emergency services are notified with the vehicle’s GPS coordinates and incident details. The system operates in real time, addressing challenges such as varying environmental conditions, minimizing false positives, and optimizing processing efficiency. Future enhancements include the deployment of edge computing for faster processing and IoT integration to improve situational awareness among surrounding vehicles. The collision detection and alert system aims to reduce accident risks, facilitate timely assistance, and contribute to safer roadways, particularly in remote areas with lower traffic density.

**JUSTIFICATION FOR SDG GOALS**



**Goal 9 – Industry, Innovation, and Infrastructure**

The proposed system promotes innovation by integrating advanced technologies like 360° cameras and AI for real-time collision detection. It supports sustainable infrastructure through safer transportation systems and enhances industry efficiency by reducing accident-related disruptions, aligning with the given sustainable development goal - Industry, Innovation, and Infrastructure.



**Goal 16 – Peace, Justice, and Strong Institutions**

The Vehicle Collision Detection and Alert System enhances road safety by preventing accidents and providing real-time alerts. It supports justice through transparent evidence from 360° cameras and strengthens institutions by enabling faster emergency responses and data-driven policy decisions, aligning with the given sustainable development goal - Peace, Justice, and Strong Institutions.

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**LIST OF ABBREVIATIONS**

|  |  |
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| **ABBREVIATION** | **DEFINITION** |
| CNN | Convolutional Neural Network |
| YOLO | You Only Look Once |
| IoT | Internet of Things |
| UFIR | Unbiased Finite Impulse Response |
| MIF | Motion Interaction Field |
| LSTM | Long Short-Term Memory |
| RNN | Recurrent Neural Network |

**CHAPTER 1**

**INTRODUCTION**

**1.1 VEHICLE COLLISION DETECTION**

Road traffic crashes, recognized all over the world as a leading cause of injuries and death, call for the development of sophisticated and smart safety systems to reduce their occurrence and intensity. Traditional safety devices like airbags and anti-lock braking systems (ABS) protect occupants and drivers while or after crashes occur but do not work to avoid crashes prior to impact. With the introduction of contemporary sensing and computational technologies, the installation of proactive systems for real-time collision prediction and avoidance has been made possible.

A Vehicle Collision Detection and Alert System, backed by a 360° camera installation, provides complete awareness of the environment around the vehicle by removing blind areas. The motion patterns of surrounding objects are continuously tracked through real-time video feeds analyzed by deep learning models. YOLO v8, an efficient real-time object detection algorithm, achieves object detection, identify vehicles, pedestrians and obstacles around the vehicle at high accuracy and lesser processing time.

Once detected, object trajectories are analyzed over consecutive frames through a Convolutional Neural Network (CNN) structure. For better feature extraction and computational performance, MobileNetV2 is utilized as the backbone of the CNN model. Lightweight yet strong, this structure supports proper prediction of movement trajectories and probable points of collision without being very demanding in terms of processing time. Spatial and temporal information from the video stream are input into the model so that high-risk situations are predicted.

In the event of a potential collision being detected, notifications are sent automatically to nearby police station or appropriate authorities, such as emergency services where necessary. Alert messages contain GPS location and contextual incident information, allowing for prompt intervention and support.

With the integration of object detection, trajectory analysis, and automatic communication protocols, a high degree of reduction in accident hazards unlocks. Edge computing and Internet of Things (IoT) infrastructure applications in future developments can also provide faster processing speed, situational awareness, and collaborative safety among groups of vehicles. Increased safety at the individual and systemic levels becomes possible, especially in sparsely populated or low-traffic areas where human presence tends to be scarce.

**1.2 SYSTEM OVERVIEW**

The Vehicle Collision Detection and Alert System enhances vehicular safety through the use of 360° cameras and advanced machine learning techniques for real-time prediction and mitigation of collision risks. Key components include a 360° camera configuration for full environmental monitoring, the YOLO v8 algorithm for detecting surrounding objects, and a Convolutional Neural Network (CNN) for evaluating object trajectories and forecasting potential collision scenarios.

The process begins with continuous video streams captured by the 360° cameras, covering all angles around the vehicle. These streams undergo analysis by YOLO v8 to identify nearby objects such as vehicles, pedestrians, and obstacles. Detected motion patterns are then passed to the CNN, where analysis of relative positions and velocities takes place to assess the likelihood of collisions.

Upon identification of a potential threat, an alert mechanism becomes activated, delivering notifications to the driver. When necessary, emergency services receive alerts through communication networks. Real-time processing enables swift adaptation to dynamic traffic conditions, ensuring minimal delay between threat detection and response.

By combining object detection, motion prediction and automated alert generation, a robust framework for accident prevention is formed. Increased safety can be achieved, particularly in complex or high-density traffic environments, through early warning and coordinated response strategies.

**1.3 SCOPE OF THE PROJECT**

The scope of this Vehicle Collision Detection and Alert System encompasses the creation of an innovative safety solution based on 360° cameras and machine learning algorithms for real-time monitoring and collision prediction. A proactive system for detecting potential hazards and alerting concerned parties facilitates accident avoidance and enhances road safety.

Thorough environmental coverage is accomplished by combining 360° cameras to avoid blind spots. Real-time detection of objects takes place with YOLO v8, in which detection of close-by cars, pedestrians, and road blocks allows for detection of surrounding vehicles, pedestrians, and obstacles. Information gathered from the detected objects gets processed in a Convolutional Neural Network (CNN) model where distance evaluation and collision detection enable successful collision prediction.

Upon realization of an imminent collision, a warning is triggered to alert drivers. In the case of extreme situations, warnings are sent to emergency services with GPS coordinates and information relating to incidents.

**CHAPTER 2**

**LITERATURE SURVEY**

**[1] A. Rocky, Q. J. Wu and W. Zhang, "Review of Accident Detection Methods Using Dashcam Videos for Autonomous Driving Vehicles," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 25, no. 8, Aug. 2024, pp. 8356-8374.**

The authors utilized an extensive literature review to explore methods of accident detection using dashcam videos for autonomous vehicles. The review started by classifying the existing methods into three main paradigms of learning: supervised, self-supervised, and unsupervised learning. Such systematic categorization allowed for a better understanding of how different techniques worked and their respective applications within the context of accident detection. By structuring the methodologies in this way, the authors laid the groundwork for an in-depth comparison of the effectiveness and applicability of each approach in actual situations. In the supervised learning group, the authors outlined methods that drew upon labelled datasets, whereby dashcam recordings had been annotated with examples of accidents and other appropriate incidents. This method generally produced high accuracy, as the algorithms had previously been trained on clearly defined examples. Yet, the authors saw major challenges that came with supervised learning, such as the limited availability of labelled data and the high amount of effort needed to manually annotate them. These factors made it difficult to create stable models that can generalize across different driving environments, thus highlighting the need for alternative approaches. The authors also discussed self-supervised and unsupervised learning methods. Self-supervised learning methods utilized unlabelled data through the creation of pseudo-labels using predictive modelling, thus enriching the dataset without the need for time-consuming annotation. Conversely, unsupervised learning techniques were aimed at identifying anomalies or abnormal patterns of driving behaviour independent of prior labelling. Although such methods provided data usage benefits along with the promise of detecting unanticipated incidents, they were susceptible to false positives and required additional improvement. This concluded by defining future directions to further improve the safety of autonomous vehicles in complicated situations, finally recommending the establishment of more reliable and efficient accident detection systems.

**[2] Y. Sui, S. Zhou, Z. Ju and H. Zhang, “A Vision-Based System Design and Implementation for Accident Detection and Analysis via Traffic Surveillance Video,” in *IEEE Canadian Journal of Electrical and Computer Engineering*, vol. 45, no. 2, Spring 2022, pp. 171-181.**

The authors presented a solid framework for automatic traffic accident detection and analysis from surveillance videos on a Huawei HiKey970 AI demo board. The system incorporated several advanced techniques to achieve precise detection, localization, and analysis of accidents and hence provide useful insights to traffic authorities. The workflow started with the implementation of the Motion Interaction Field (MIF) method. MIF aimed at interactions between multiple moving targets in surveillance video to identify potential collisions. It successfully detected and localized vehicles that were involved in crashes through analyzing motion patterns and interactions and thus laid the ground for further processes in the pipeline. After localizing the vehicles involved in the crash, the authors used the YOLO v3 model to identify the vehicles with high accuracy. Known for its real-time object detection feature, YOLO v3 was used to accurately identify the vehicles involved in the crash in the areas detected by MIF. The process facilitated accurate and effective vehicle localization, which was essential in reconstructing the sequences of events that led to the crash. To obtain vehicle trajectories before the crash, a hierarchical clustering method was used. This method clustered motion patterns in order to derive coherent trajectories and enable a clear comprehension of vehicle movement. For easier visual examination of the trajectories, a perspective transformation mapped the data onto a vertical view to make interpretation easier for traffic enforcement officers. To gain more detailed analytical insights, the authors approximated vehicle speeds based on the Unbiased Finite Impulse Response (UFIR) method. UFIR yielded accurate speed estimates without the need for external noise condition knowledge in advance, thus guaranteeing strong performance in diverse circumstances. Coupling speed information with the collision angle obtained from the vertical camera, the approach effectively gave full insight into the dynamics of every collision. The last deployment was tested through experiments on the HiKey970 AI demo board with actual-world surveillance videos of traffic accidents. The system performed successfully in identifying accidents and well in recovering the vehicle trajectories, exhibiting its robustness in supporting traffic accident analysis. The proposed framework was an improved step forward for automated traffic surveillance and accident analysis, promising significant practical utility for improving road safety.

**[3] H. A. Yawovi, M. Kikuchi and T. Ozono, “Responsibility Evaluation in Vehicle Collisions From Driving Recorder Videos Using Open Data” in *IEEE Access*, vol. 12, 2024, pp. 49962-49975.**

The authors introduced an improved system for the assessment of responsibilities in car crashes based on crash videos taken by driving recorders, incorporating real-time data transmission and making use of open data for overall analysis. A web-based system had initially been created to employ crash scenes to determine the time of collision, identify traffic light conditions, and determine responsibility through rule-based knowledge system. But this initial deployment was plagued by difficulties in nighttime environments and at intersections without traffic light control. To overcome these shortcomings, the system architecture was reworked to include the OpenStreetMap API, which allowed for the retrieval of rich road and traffic sign data and ensured operation under a broader set of environmental and infrastructural conditions. The new system was organized around a mobile app and a server, each with specific responsibilities. The cellular app, acting as a dashcam, captured driving incidents and streamed live data—inclusive of video, speed of the vehicle, GPS location, and orientation—to the server. Intended for both personal and business use, especially for those who are insured, the app brought with it instant access to collision evidence. The server, operated by insurance firms and law enforcement agencies, saved the streamed material as data-tagged pictures augmented with contextual details like speed and geolocation. During a collision, the server utilized detection models to calculate the crash time and detect traffic light states, then extracting pertinent road information through the OpenStreetMap API. The server subsequently processed the gathered information utilizing a rule-based inference mechanism to conclude on probable duties attached to the collision. The coupling of mobile technology, real-time transmission of data, and open-source geographic information largely broadened the capability of the system such that it was able to cater to various scenarios of collision, even at nighttime or where traffic signals were non-existent. The resulting architecture offered a more stable and automated method of responsibility evaluation in traffic accidents, assisting in insurance claim procedures as well as legal investigations. The authors explained the cooperative interaction between the mobile app and the server, describing the smooth end-to-end process from data collection to responsibility determination.

**[4] J. Fang, J. Qiao, J. Xue and Z. Li, “Vision-Based Traffic Accident Detection and Anticipation: A Survey,” in *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 34, no. 4, April 2024 ,pp. 1983-1999.**

The authors presented the challenging topic of traffic accident detection and anticipation, specifically addressing Vision-based Traffic Accident Detection (Vision-TAD) and Vision-based Traffic Accident Anticipation (Vision-TAA). These processes were key issues in road surveillance and safety, especially considering the fast growth in video data. The peculiar nature of traffic accidents—i.e., their rarity, dynamic, and complexity—presented Out-of-Distribution (OOD) challenges, thus constraining the performance of conventional AI models. The survey was intended to give an extensive overview of progress in Vision-TAD and Vision-TAA in the context of deep learning, noting achievements and gaps that require research. The authors undertook a close scrutiny of recent research models built for Vision-TAD and Vision-TAA, comparing their strengths and weaknesses. Focus was given to how these models handled the complexities found in traffic accident situations, such as long-tailed data distributions and real-time adaptability requirements. Critically, 31 publicly accessible benchmarks were examined, as well as discussion of several evaluation metrics most frequently employed in the community. This comprehensive review shed light on the state of affairs in research, as well as methodological weaknesses and limitations that called for more attention. The authors also suggested directions of future research focused on overcoming Vision-TAD and Vision-TAA's long-standing challenges. They called for creating models with greater ability to manage OOD situations, greater robustness, and better real-time predictive performance. By presenting a critical survey and identifying future trends, the survey aimed to stimulate further research and development in this critical field of road safety in order to further develop more efficient and trustworthy traffic accident detection and anticipation systems.

**[5] R. Vijithasena and W. Herath, “Data Visualization and Machine Learning Approach for Analysing Severity of Road Accidents,” *2022 International Conference for Advancement in Technology (ICONAT)*, Goa, India, 2022, pp. 1-6.**

The researchers examined the important problem of road accidents through an extensive descriptive analysis to determine significant factors affecting accident severity. Since traffic accidents have a significant human and economic cost, the research sought to comprehend contributing factors like location, time, infrastructure, and environmental conditions. Using machine learning methods, the research targeted predicting accident severity to create actionable insights for enhancing road safety. The study found that moderately severe accidents were more prevalent than those defined as very low or high risk. This fact highlighted the necessity of dealing with the causes behind these moderately severe accidents. Findings of great significance showed that infrastructure quality, day of the week, and weather were most influential in affecting accident severity. For example, poor road conditions and inclement weather were frequently linked to increased severity levels, whereas accident frequency fluctuated throughout the week as a result of changing traffic patterns. Of the machine learning models tested, the Random Forest algorithm performed best, with an accuracy rate of 97.2% in estimating accident severity. This outcome implied that Random Forest was highly qualified to handle the complexity and heterogeneity embedded in traffic accident data. The outcomes offered key information for stakeholders like traffic authorities and policymakers, providing evidence-based support for the deployment of focused safety interventions. Through pinpointing risky conditions and suitably forecasting accident severity, the study supplied key guidance for the mitigation of risks and improvement of road safety as a whole.

**[6] I. E. Mallahi, A. Dlia, J. Riffi, M. A. Mahraz and H. Tairi, “Prediction of Traffic Accidents using Random Forest Model,” *2022 International Conference on Intelligent Systems and Computer Vision (ISCV)*, Fez, Morocco, 2022, pp. 1-7.**

The authors tackled the important issue of anticipating traffic accident severity, an integral part in successful road accident management and emergency logistic planning. Due to the increasing trend in traffic accidents and the resultant spike in casualties, the research investigated the potential of machine learning to enhance the prediction and categorization of accident severity. Using data from the 2019 Traffic Accidents dataset of Leeds, presented by the Road Safety department, the study was aimed at categorizing accident severity into three: pedestrian, vehicle or pillion passenger, and driver or rider. The authors used and compared the performance of three machine learning algorithms: Random Forest, Support Vector Machine (SVM), and Artificial Neural Network (ANN). By a comprehensive analysis with a confusion matrix, the research assessed the influence of each road user class on the others. Random Forest was the most efficient algorithm with an accuracy rate of 93%, which outshone SVM with 82% and ANN with 87%. Moreover, as far as precision and recall are concerned, Random Forest reached 93.82%, while SVM and ANN reached 82.22% and 87.88%, respectively. These findings accentuated the better performance of Random Forest in handling the complexity of traffic accident severity prediction. The results emphasized the significance of machine learning in improving the management of traffic accidents. Through proper forecasting of accident severity, authorities could better prioritize emergency intervention and manage resources. The research highlighted the stability of Random Forest in making accurate predictions and thus serves as an important asset in traffic management and safety planning. The study added to the increasing literature on traffic accident analysis and demonstrated the capability of machine learning in enhancing road safety performance.

**[7] A. Verma and M. Khari, “Vision-Based Accident Anticipation and Detection Using Deep Learning,” in *IEEE Instrumentation & Measurement Magazine*, vol. 27, no. 3, May 2024 , pp. 22-29.**

The authors approached the urgent universal problem of motor vehicle accidents that are a chief cause of damage, death, and permanent disability. Road traffic accidents, says the World Health Organization's Report on Road Traffic Injuries, 2021, killed almost 1.20 million and injured 20 to 40 million people yearly with non-fatal injuries who suffered permanent disability. The authors highlighted the imperative importance of new solutions for safer roads and the elimination of the horrific human and economic cost of traffic accidents. With AI and computer vision rapidly advancing, there were new opportunities to create intelligent traffic management systems. Such systems had the promise of dramatically improving accident detection, anticipation, and reaction times. The authors concentrated on one such cutting-edge solution: a computer vision-based approach to accident anticipation and detection from dashboard camera (dashcam) videos. Dashcams, used in both autonomous and human-driven vehicles, became a readily available and inexpensive source of real-time road information. The system used an advanced AI model that integrated spatial feature-based Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) cells. This architecture was formulated to analyse and process video streams recorded by dashcams, taking advantage of the temporal dependencies in the recordings in order to predict and identify probable accidents. The LSTM cells, renowned for their long-range dependency capturing ability, allowed the model to predict accidents about 1.7 seconds ahead of their occurrence. This warning in advance was essential in order to facilitate pre-emptive manoeuvres to reduce the severity or avert accidents. The performance measures of the system were impressive, with a recall rate of 80% and precision of 71%. The findings proved the model's solid capacity to identify true positives—real upcoming accidents—while having a relatively low false positive rate. The trade-off between recall and precision indicated the reliability of the system in actual application, where accurate and timely predictions were needed to ensure effective intervention. Utilizing the ubiquitous availability of dashcams and the complex processing abilities of RNNs with LSTM cells, the system provided an effective and feasible answer to minimizing traffic accident effects.

**CHAPTER 3**

**SYSTEM ANALYSIS**

* 1. **EXISTING SYSTEM**

Existing car safety technologies are largely aimed at reducing the effects of crashes, not preventing them. Traditional safety technologies like airbags, anti-lock braking systems (ABS) and electronic stability control (ESC) work to limit injury or damage after a crash has happened.

Though they are successful at minimizing harm, they do not touch the prevention side of crashes. Their function is deemed reactive, as they act only after an event of high consequence, thereby restricting themselves from acting ahead of a collision occurring.

Advanced Driver Assistance Systems (ADAS) are seen as an upgrade in car safety, providing functionalities such as lane-keep assist, adaptive cruise control, and blind-spot detection. These systems strive to enhance the situational awareness of the driver by notifying them of impending danger and helping with steering and braking.

Yet, there are significant limitations in providing complete situational awareness. ADAS systems usually draw on a set of sensors, such as radar, ultrasonic sensors, and LiDAR. Although useful information regarding the environment around the vehicle is supplied by these sensors, performance under adverse environmental conditions—rain, fog, or heavy traffic—can diminish their effectiveness.

Another major limitation of existing systems is recognized as their reactive nature. Most safety technology, including ADAS, are designed to react to imminent threats, like an unexpected stop from a leading vehicle or a loss of lane position. Potential collisions are not sensed early enough, though, for these systems to take preventative action.

The power to anticipate perilous situations and ready the car or driver in advance is absent, which is essential for evading accidents in real time. In addition, current systems are typically not providing an integrated solution to proactively notify drivers and emergency services.

This lack of proactive notification is seen as a key road safety issue, since the lack of advance warnings can cause emergency response delays and make accidents more difficult to prevent. Overall, current vehicle safety features are offering important assistance in and around an accident but are not delivering complete, proactive collision avoidance.

* + 1. **DISADVANTAGES OF EXISTING SYSTEM**
* **Reactive Nature:** Existing systems are designed to respond after an accident occurs, rather than before, limiting the ability to prevent collisions.
* **Limited Awareness:** Comprehensive 360-degree situational awareness is not provided by ADAS.
* **Environmental Vulnerabilities:** Sensor performance is reduced in harsh weather conditions, diminishing reliability.
* **Failure to Anticipate:** Potential collisions are not predicted early enough by current systems.
* **Lack of Proactive Alerts:** A unified alert system for both drivers and emergency services, currently not being offered by existing systems.
  1. **PROPOSED SYSTEM**

The Vehicle Collision Detection and Alert System proposed works on using 360° cameras and sophisticated machine learning algorithms to improve road safety through anticipation and avoidance of potential collisions. In contrast to conventional systems, this system provides a preventive approach by continuously observing the environment around the vehicle, identifying potential dangers, and informing drivers and emergency services instantly.

The 360° cameras of the vehicle are embedded in the system to give a comprehensive view around the vehicle, without any blind spots. The YOLO v8 object detection model accurately detects close-by vehicles, pedestrians, and roadblocks. The real-time detection functionality will be imperative for judging dynamic traffic conditions. A Convolutional Neural Network (CNN) also post-processes detected objects, forecasting potential collisions based on an examination of their motion vectors and trajectory.

On detection of a pending collision, an alert gets raised, warning the driver and, if required, emergency services with the location of the vehicle and details of the incident. Advance warnings decrease response times and mitigate the effects of accidents.

* + 1. **OBJECT DETECTION**

The object recognition module is crucial in facilitating correct perception of the environment around the vehicle. A 360° camera offers a wide-angle view, eradicating blind spots and providing complete directional coverage. The real-time video stream is processed by the YOLO (You Only Look Once) object detection model, which is known for real-time performance and high accuracy. Every frame gets divided into a grid in which bounding boxes and class probabilities are predicted for several objects simultaneously. Such functionality enables efficient application in time-sensitive safety systems.

Model training involves a broad set of driving-relevant objects—vehicles, trucks, pedestrians, cyclists, traffic signs, barriers, and animals. Following detection, each object is assigned a class label, confidence value, and bounding box coordinates. These data feed into downstream applications such as tracking and collision prediction.

Using the 360° video stream, YOLO has an affluent input source through which detection of potential hazards from any direction becomes feasible. Object location, size, and movement patterns are constantly tracked, providing necessary background for subsequent analysis. Accurate and timely detection guarantees system dependability since even minor inaccuracies in detection could lead to erroneous threat assessments. Therefore, optimization for speed and robustness across varied lighting, weather, and traffic conditions continues to be vital. End output from this module proceeds to the collision detection subsystem for subsequent evaluation. Essentially, object identification plays the major role in vehicle's visual interface for safe operation in complex environments.

* + 1. **VEHICLE COLLISION DETECTION**

The collision detection module becomes responsible for processing assessment of near-future danger implied by the identified objects. Input from the object detection module gets analyzed in order to calculate relative locations, motion paths, and velocities throughout the scene. A binary classification model, specifically designed on the MobileNetV2 framework, enables this assessment in a light and high-performance design optimized for embedded and edge environments.

Scene classification gets achieved in two types - "collision likely" or "collision unlikely." Depth-wise separable convolutions, the core of MobileNetV2, enable fast input processing without compromising accuracy, enabling real-time use. By performing training on a dataset with varied driving conditions, both dangerous and safe are facilitated by pattern recognition associated with pre-collision conditions. Important indicators are object distance, direction, and temporal data extracted from past frames.

Through its integration with the 360° camera, the monitoring gets further extended to all directional directions, including blind spots, intersections, and rear zones. Multiple-object assessment occurs simultaneously, prioritizing based on convergence of trajectory and estimated time to collision.

Sensor fusion - possibly including GPS, accelerometers, or LiDAR - can further enhance reliability, though the 360° camera provides sufficiently detailed visual information for precise predictions in most scenarios. When a probable collision is detected, an alert gets delivered to the required authority, which triggers pre-defined responses like warnings or activation of the alert system. Prompt and precise collision prediction improves vehicular safety, reducing reaction times and enabling accident prevention in high-risk situations.

* + 1. **ALERT SYSTEM**

The alert system acts as the last, outward module, providing timely responses in the event of collision or high-risk detection. They get activated automatically based on the input they get from the collision detection module, enabling two major roles: in-vehicle driver alerts and external communication.

Inside the car, immediate feedback reaches the driver by means of audio-visual alerts - dashboard lights, flashing, or haptic like steering wheel vibrations. The warning is meant to grab attention quickly, instilling evasive manoeuvres such as braking or steering corrections.

Aside from the vehicle, communication with emergency services and concerned parties begins when a crash becomes unavoidable or happens. Real-time transmission involves GPS coordinates, timestamps of events, and video clips recorded from the 360° camera. The recipients could be hospitals, insurance companies, and regulatory agencies to enable swift reaction and effective incident reporting.

Vehicle-to-infrastructure (V2I) communication support increases situational awareness, notifying surrounding systems or vehicles of potential danger. Cloud storage allows for secure storing of incident data, aiding in post-incident analysis and legal procedures.

Architecture of the system features secure, fail-safe protocols for communication to reduce false alarms and unauthorized access. Fallback features like SMS dispatch or emergency broadcasting solve possible network breakdowns. Through such functions, the alert system enhances safety, quickens emergency response, and enhances accountability in collision events.

* 1. **REQUIREMENTS SPECIFICATION**
     1. **Hardware Requirements**
* 360° cameras units
* Processing unit (e.g., NVIDIA Jetson or Intel NUC)
* Storage device (e.g., SD Card or Pendrive)
* Communication module – CAN Bus interface for vehicle integration.
  + 1. **Software Requirements**
* Flutter Application for viewing collision
* Yolo v8 Model
* Twilio for Sending SMS
  1. **LANGUAGE SPECIFICATION**

The Vehicle Collision Detection and Alert System utilizes the latest programming languages, frameworks, and tools to achieve robustness, real-time performance, and cross-platform compatibility. The fundamental parts of the system are built using Python, with Python performing machine learning functions and backend services. This blended methodology supports high-performance, responsive real-time interaction along with smooth integration of cutting-edge ML models for object recognition, collision prediction, and alert handling.

Flutter, a highly popular cross-platform framework that makes it possible to develop applications for Android, iOS, and web platforms from one codebase. It supports designing user interfaces (UI) with smooth, high-performance interactions, which is of special importance in safety-critical applications such as vehicle collision detection. With Flutter's versatility, the system is able to give a smooth experience across different platforms while still preserving the required performance for real-time operation.

Python, commonly used to deploy the YOLOv8 (You Only Look Once) object detection algorithm due to its optimization for speed and accuracy, becomes critical in real-time image processing. OpenCV library gets incorporated within the system to process video streams from the 360° cameras, allowing for efficient management of visual data. TensorFlow gets utilized for training and fine-tuning the machine learning models deployed in collision detection. These frameworks enable the application of Convolutional Neural Networks (CNNs), which play a vital role in processing the spatial relations among objects within the vehicle's surroundings, offering the insights needed to make accurate collision predictions.

Some of the important tools imported include:

* Flask
* Flutter SDK
* Firebase Cloud-Firestore
* Firebase Messaging
* OpenCV
* YOLO v8

**CHAPTER 4**

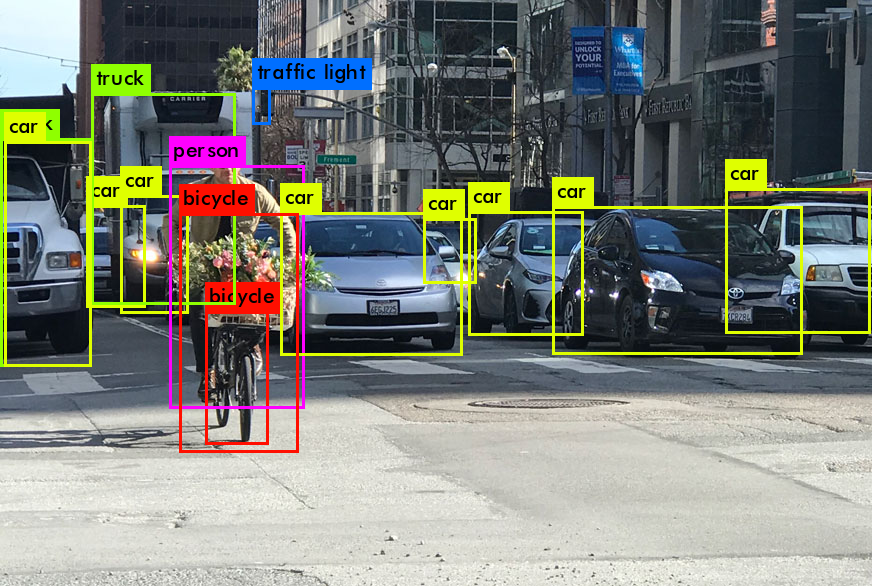
**SYSTEM DESIGN**

**4.1 SYSTEM ARCHITECTURE**

This system consists of 3 major modules which enhance the user experience. They are as follows :

* Object Detection
* Collision Detection System
* Alert System

**4.1.1 OBJECT DETECTION**



**Fig 4.1 YOLO v8 For Object Detection**

YOLOv8 (You Only Look Once version 8) is a very effective object detection model, well suited for real-time applications like vehicle collision detection. Similar to that of Fig 4.1, It uses a single pass to predict multiple bounding boxes and class labels by employing a unified architecture, providing both speed and accuracy - essential for systems where quick responses are necessary, such as in collision avoidance.

One of the best aspects of YOLOv8 - its improved anchor boxes, supports detection of objects of different sizes and shapes. It makes the model extremely useful in detecting vehicles, pedestrians, and other hazards in dynamic and mixed environments. The real-time capability of the model ensures that video streams from 360° cameras are processed immediately, thus ensuring timely object detection with little latency.

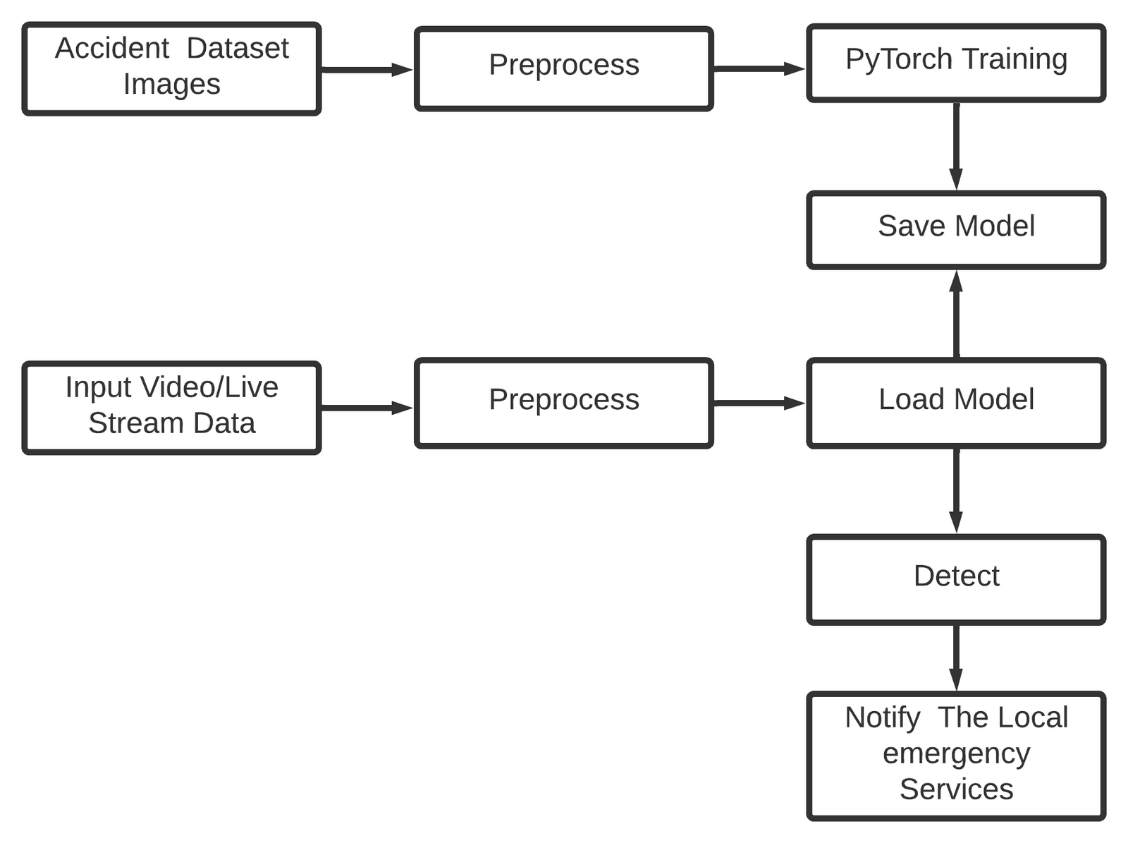
YOLOv8 can perform multi-object and multi-class detection, identifying different types of objects in a single frame. This feature plays a major role in tracking roads loaded with numerous moving objects. Once trained with a heterogeneous dataset, the system can parse real-time video streams to determine possible collision hazards from the proximity and direction of movement of objects.

Upon the occurrence of a detected collision, the system provides automated notifications to hospitals, insurance companies, and authorities involved, facilitating timely intervention. The combination of accuracy and speed built into YOLOv8 renders it a superior solution for the development of vehicle safety systems.

**4.1.2 COLLISION DETECTION SYSTEM**

In the Vehicle Collision Detection System, MobileNetV2 forms the foundation of the Convolutional Neural Network (CNN) model that facilitates fast processing of video streams obtained by 360° cameras. Known for its lightweight and high-performance nature, they perfectly apt for real-time processing in low-resource, embedded car environments.

The procedure begins with data collection, where video footage from the camera are converted to frames of images, which are taken continuously from the vehicle’s 360° camera. The images undergo pre-processing operations like resizing and normalization in order to preserve input consistency and prepare them for model compatibility.



**Fig 4.2 Flow Diagram For Collision Detection**

During the collision detection phase in Fig 4.2, MobileNetV2 serves as the feature extractor in the CNN architecture, supplemented by a tailored classification head optimized for binary classification. The platform assesses for each frame the likelihood of indicating a possible collision or a safety situation. During training, a labelled dataset featuring both collision and non-collision instances is fed to the system. Through repeat learning, the model adjusts internal parameters to decrease classification errors while enhancing decision accuracy.

After the training finishes, real-time frame analysis gets performed, where features extracted by MobileNetV2 are utilized to classify every situation as either "collision" or "not collision." On recognizing a possible collision, instant alerts are created and forwarded to concerned parties, such as emergency services and insurance providers. This quick communication aids in quicker intervention and helps play a major role in improving road safety and decreasing accident-related response time.

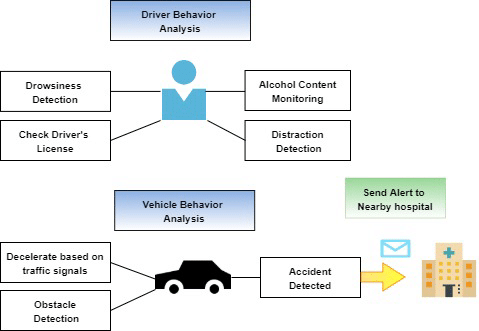
* + 1. **ALERT SYSTEM**

The alert system built into the Vehicle Collision Detection and Alert System works on the basis of the severity level of a collision detected. It works in real time, examining video streams from 360° cameras using the combined application of the YOLOv8 object detection model and a Convolutional Neural Network (CNN). These elements collectively detect surrounding vehicles, pedestrians, and roadblocks, assessing the risk and severity of possible crashes based on factors like object proximity, relative speed, and motion path.

In cases rated as low-risk or moderate-risk, in-car warnings are triggered to avoid impact incidents. Visual notifications - e.g., dashboard graphics or display messages are combined with audio notifications such as alert sounds or voice cues. This multimodal feedback should capture the driver's attention rapidly and prompt corrective actions.

For unavoidable or high-severity collision situations, the system enhances its response by triggering automatic contact with emergency responders. Critical information - such as the car's GPS coordinates, incident timestamp, and situation information regarding the identified threat - sends itself off immediately. Automated support enables quicker intervention on the part of first responders, raising the chances of receiving prompt medical attention and assistance. This tiered approach enhances situational awareness and prioritizes safety for the driver and others on the road.

With proactive driver warning and automated emergency alerts, the system improves collision avoidance as well as post-incident response and impacts greatly on enhancing road safety outcomes.



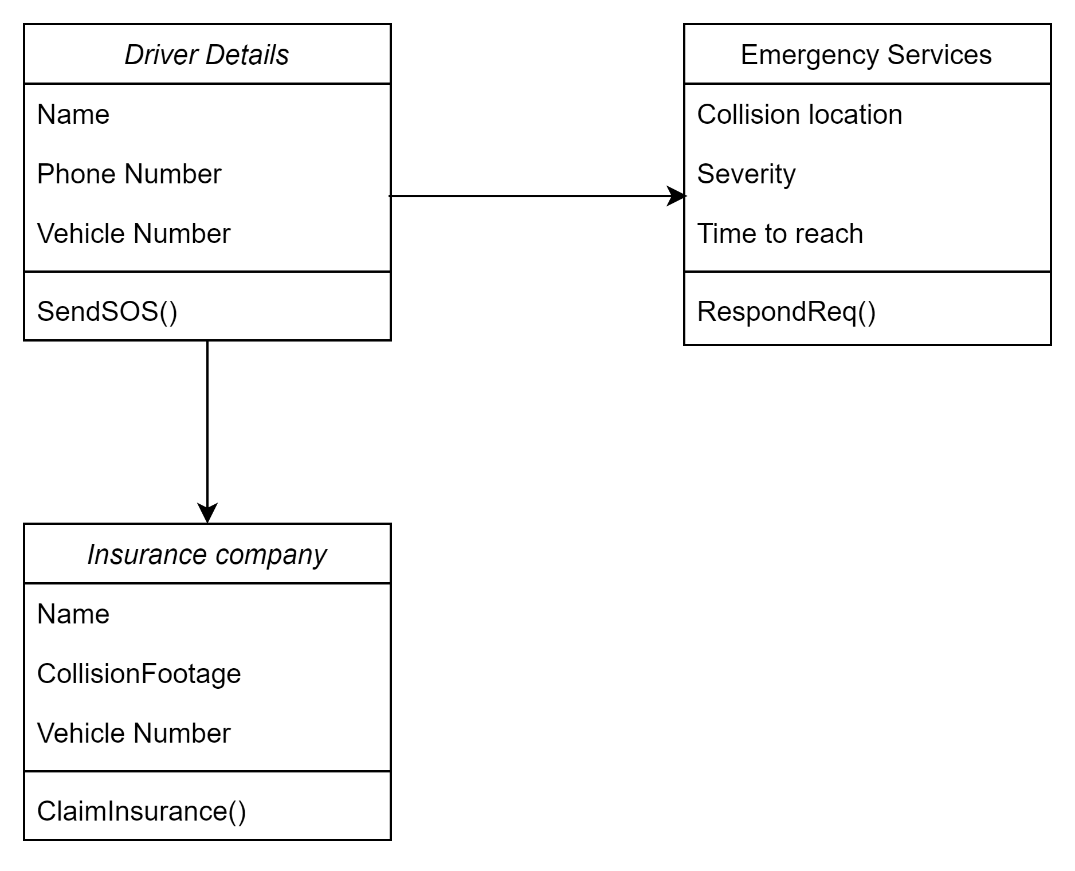
**Fig 4.3 Flow Diagram For Alert System**

Given in Fig 4.3, the alert system classifies accidents based on their severity, ensuring appropriate responses. For minor incidents, it issues visual alerts on the dashboard to inform the driver without causing panic. Moderate risks trigger auditory warnings to prompt immediate attention. In the case of severe collisions, the system generates urgent alerts, automatically contacting emergency services with vital information such as location and nature of the threat.

* 1. **SOFTWARE DESIGN**

The software design of the Vehicle Collision Detection and Alert System combines real-time object detection and collision risk assessment. YOLO v8 is used for detecting objects such as vehicles and pedestrians from 360° camera feeds, while a MobileNetV2-based CNN with a custom binary classifier evaluates the likelihood of a collision. The system processes video frames continuously, issuing visual and auditory alerts inside the vehicle if a moderate collision risk is detected. In severe collision scenarios, it automatically alerts emergency services by transmitting vital information such as GPS location and threat details. This design ensures rapid detection, timely driver alerts, and efficient emergency response.

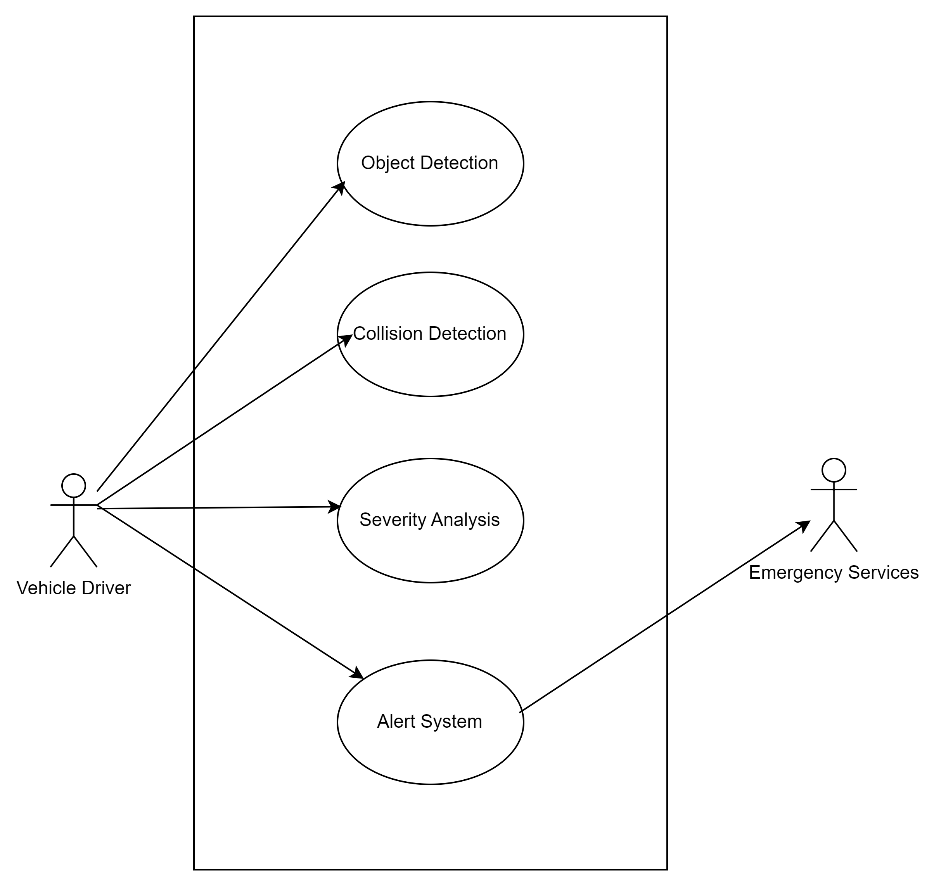
* + 1. **CLASS DIAGRAM**



**Fig 4.4 Class diagram**

With reference to Fig 4.4, the class diagram for the Vehicle Collision Detection System includes five main classes. CameraInput captures and preprocesses video frames from 360° cameras. ObjectDetector, using YOLOv8, detects objects like vehicles and pedestrians within each frame. CollisionClassifier employs a CNN with MobileNetV2 as a backbone and a custom binary head to classify scenes as collision or not collision. AlertSystem manages the response, triggering in-car visual and audio alerts for moderate risks and notifying emergency services in severe cases. AlertData stores critical information such as GPS coordinates and timestamp, which is transmitted during emergency notifications to ensure a timely response. All these classes working together, form the responsive collision detection and alert system for vehicles.

**4.2.2 USECASE DIAGRAM**

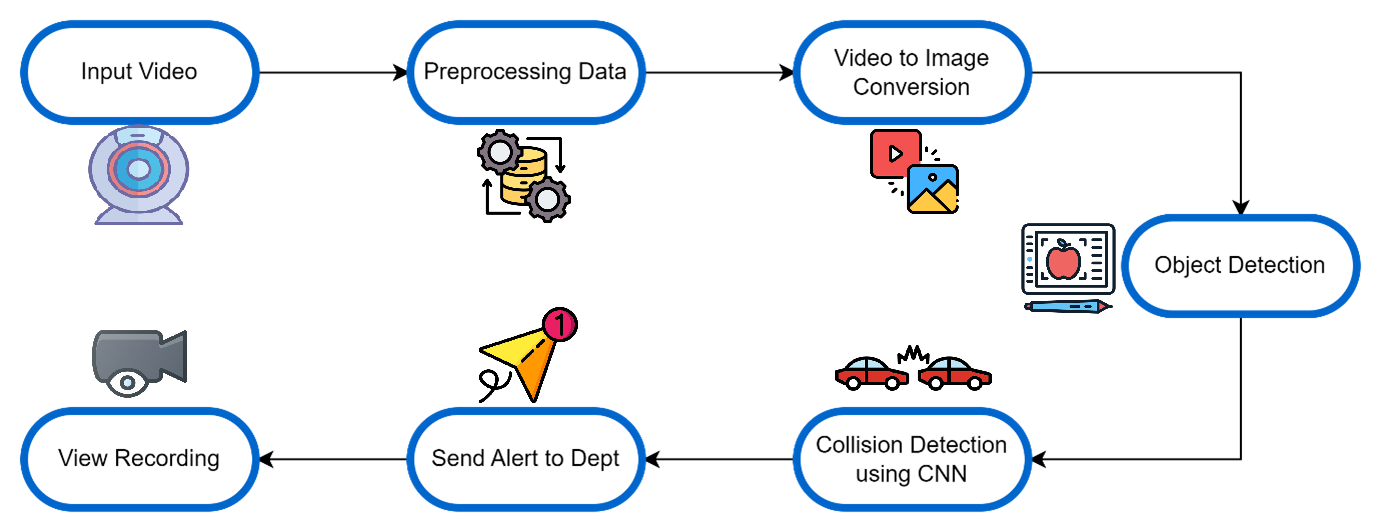


**Fig 4.5 Usecase diagram**

The Use Case Diagram for the Vehicle Collision Detection and Alert System outlines key interactions designed to enhance road safety and driver awareness. Central to this system is the Detect Collision Risk use case, which utilizes real-time analysis of video feeds from 360° cameras mounted on the vehicle. This functionality employs an object detection module, such as YOLO v8, to identify potential collision threats, including nearby vehicles, pedestrians, and obstacles.

When a collision risk is detected, the system activates the Generate\_Alert use case, providing immediate notifications to the driver. These alerts are tailored to the severity of the situation, featuring visual indicators on the dashboard and auditory signals to command prompt attention.

**4.3 BLOCK DIAGRAM**



**Fig 4.6 Block diagram**

The block diagram of the Vehicle Collision Detection and Alert System, given in Fig 4.6, provides a systematic, smart sequence geared toward accurate and immediate detection of collision risks. The procedure starts from the Input Video phase, with constant footage recorded through 360° cameras specially placed across the vehicle. They provide comprehensive environment coverage, even for commonly obscured blind spots, providing real-time situational awareness in all directions.

Seized video moves on to the Preprocessing phase, where a number of enhancement operations are performed. Methods like noise reduction, image resizing, normalization, and contrast adjustment are implemented to enhance visual quality. In this step, every frame complies with the required standards for effective analysis, removing noise and accentuating pertinent features for better object detection performance.

The video stream is then subjected to Video to Image Conversion, in which it gets broken down into a series of static images. Treating video as individual images permits temporal object tracking and motion analysis between consecutive frames, making it possible for the system to perceive dynamic interactions in the world.

During the Object Detection stage, YOLOv8 (You Only Look Once version 8) gets utilized to identify and classify objects within every frame. Objects like cars, pedestrians, cyclists, and obstacles are labelled, identified, and drawn around with bounding boxes. The speed and accuracy of the model provide real-time decision-making, which becomes essential for on-road use.

Detected objects are fed into the Collision Classification Using CNN stage. In this stage, a custom Convolutional Neural Network based on MobileNetV2 analyzes each object’s spatial relationship with the vehicle. Velocity, direction, and distance are taken into consideration to classify the scene into a **collision** or **no collision** situation. The level of collision risk is also assessed at this stage.

If the prediction of a high-risk collision is made, the Alert System is triggered. Within the vehicle, drivers get instant visual and audio warnings and are encouraged to take evasive manoeuvres. Concurrently, alert messages are sent to emergency response teams and relevant stakeholders, including the vehicle GPS location and situational incident data.

To facilitate subsequent analysis and accountability, the View Recording module records related footage upon detecting the threat. The saved information allows in-depth post-incident analysis, maximizing system transparency and supporting legal or insurance review. This end-to-end structure maximizes smooth flow of information and action and boosts vehicular safety through early detection, reaction, and record-keeping.

**CHAPTER 5**

**SYSTEM IMPLEMENTATION**

**5.1 SYSTEM MODULES**

The system consists of 3 major modules which enhance the user experience. They are as follows :

* Object Detection
* Collision Detection
* Alert System

**5.1.1 OBJECT DETECTION**

The Object Detection Module plays the major role as building block for sensory layer of the Vehicle Collision Detection and Alert System. Real-time video gets captured continually through a collection of 360° cameras properly mounted throughout the vehicle for maximum coverage – including frontal, rearward, and lateral perspectives – efficiently eliminating blind spots and promoting spatial perception.

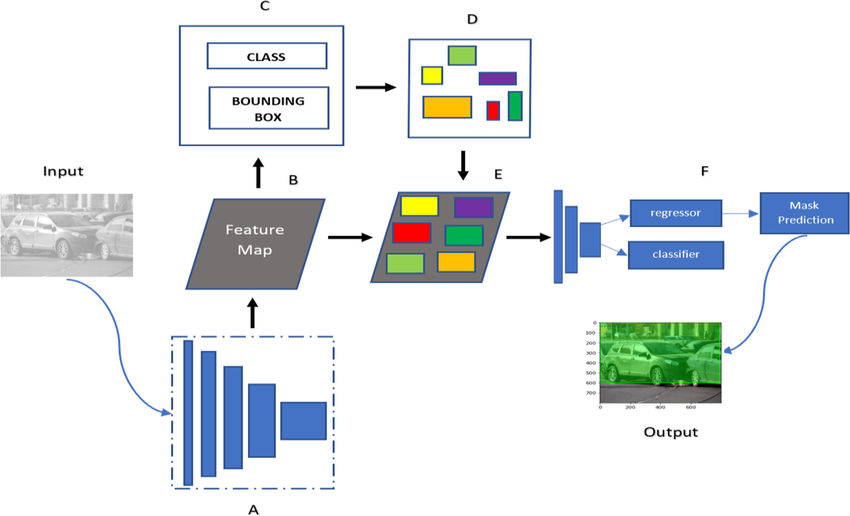
Several operations are performed in this module. Initialization of the video stream establishes the ongoing feed, while frame synchronization and timestamping enable each frame to be time-stamped chronologically for motion tracking and predictive analysis. Calibration routines are performed to rectify lens distortion and stitch feeds into a seamless panoramic view, establishing a unified and coherent visual representation of the environment.

Each recorded video stream gets compressed and optimized to provide seamless downstream processing without loss of important detail. Daylight and low-light conditions are supported, and dynamic adaptation occurs to changing environmental conditions like rain, fog, or glare. This makes for consistent performance under a wide variety of real-world driving conditions.

High-definition video frames produced by this module directly input into preprocessing and detection phases. Performance is kept at low latency to support real-time analysis, allowing for timely responses to quickly changing traffic conditions.

Working in the same way as human sight, this module allows perception by providing correct, organized, and timely visual information. Without accurate environment acquisition, solid object detection and risk assessment would be undermined. Therefore, this element supports the intelligence and reactivity of the whole system.

**5.1.2 COLLISION DETECTION**



**Fig 5.1 Vehicle Collision Detection**

The Collision Prediction Module, regarded as a vital component of the Vehicle Collision Detection and Alert System, tasked with assessing the likelihood of a collision based on the information that is provided by the Object Detection Module. Once objects – such as vehicles, pedestrians or obstacles – have been identified, their positional and behavioural data, including size, speed, distance from the vehicle, and movement trajectory are extracted and forwarded to a Convolutional Neural Network (CNN).

In this system, the CNN is constructed using the MobileNetV2 architecture, which is selected for its lightweight design and high efficiency – characteristics that are well-suited for real-time processing within resource-constrained, embedded automotive environments.

The model is trained on a custom dataset consisting of thousands of annotated frames that are curated to represent both collision and non-collision scenarios. A wide range of driving conditions, object types, and perspectives are included to ensure robust generalization.

The CNN is assigned the task of binary classification, wherein each input frame gets classified as either **collision** or **no collision.** Spatial and temporal patterns are leveraged to support prediction, with factors such as object velocity and movement direction being taken into account to estimate the risk of impact.

Upon detection of a potential collision, an alert is triggered and the event gets flagged for further action. The accuracy and responsiveness offered by this module are considered essential for accident prevention and rapid incident response.

**5.1.3 ALERT SYSTEM**

The Impact Detection and Alert Module plays a major role in critical extension of the collision prediction pipeline, developed to assess the severity of a predicted or ongoing collision and to ensure that the appropriate response actions are initiated.

Once a collision risk has been predicted by the CNN based classification module, the relevant data gets forwarded to the Impact Detection Module. Within this module, key parameter including the size, speed, and direction of the detected object, along with the host vehicle’s speed and acceleration are analyzed.

Predefined thresholds and decision rules are applied to this data to determine whether the impact should be classified as minor or severe.

For instance, a rapidly approaching vehicle from the side or rear is interpreted as an indicator of a high-severity collision, particularly when the host vehicle is also in motion. If the analysis results in a severe impact classification, the Alert System gets immediately triggered.

Once activated, the Alert System ensures that all relevant stakeholders are promptly notified. Essential information such as GPS coordinates, time of impact, type of collision, and severity is compiled and transmitted to emergency responders, insurance agencies, fleet managers, or vehicle manufacturers.

These notifications are dispatched through a variety of channels, including SMS, Firebase Cloud Messaging (FCM), satellite communication, or in-app alerts. This multi-channel approach gets utilized to ensure reliable and timely delivery, even under conditions of limited connectivity.

This approach for alert system can overcome the drawbacks of cellular communication and establish satellite communication where the cellular range is too low, especially in remote and hilly areas.

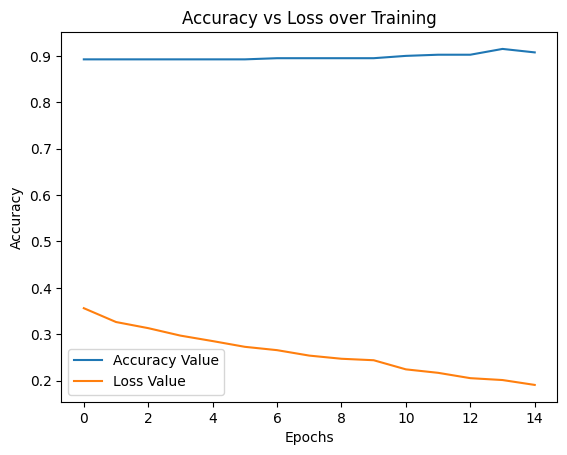
**5.2 RESULT ANALYSIS**

The training outcome of the Collision Prediction Model, as shown in the accompanying graph, has been interpreted to demonstrate robust performance over 15 epochs. A consistent increasing trend is exhibited by the accuracy curve, levelling at about 91%, indicating effective learning in being able to tell apart collision and non-collision instances.

|  |  |
| --- | --- |
| **Performance measures** | **Performance rate** |
| Accuracy | 90.4% |
| Precision | 94% |
| Recall | 93.1% |
| F1-Score | 94.8% |
| AUC/ROC | 0.904 |
| PR | 0.932 |

**Table 5.1 Model Evaluation Metrics**

In the meantime, the loss curve shows a continuous drop from about 0.36 to close to 0.19 meaning that the errors in predictions have been well reduced during training. The readings for accuracy vs loss values can be observed in Fig 5.2, which is the Accuracy vs Loss over Training.



**Fig 5.2 Accuracy vs Loss over Training**

The steep transition from high accuracy to low loss values also suggests that the process of effective learning and good generalization to the training data has been successfully implemented. The employment of MobileNetV2 as a backbone, coupled with a tailored CNN head for binary classification, is demonstrated to work well for this task. The steep descent between the accuracy and loss lines also confirms that good convergence has been obtained, indicating neither underfitting nor overfitting.

The appropriateness of the selected architecture for real-time collision prediction in the vehicle safety system is confirmed by these findings. With such accuracy, safe predictions of possible collisions can be provided, making this model a reliable part of proactive road safety solutions.

The Collision Prediction Model was tested with real-world cases, with video data obtained from 360° cameras installed on cars driving in different types of driving environments. Such driving environments ranged from city intersections, freeways, residential roads, and parking areas and were recorded under different weather and lighting conditions.

A high degree of accuracy was sustained by the system in real-world testing, with possible collisions being accurately predicted in 91% of test cases. Several objects such as cars, pedestrians, bicycles, and roadside hazards were correctly identified, and correct classifications were achieved on whether each scenario represented a collision threat.

**CHAPTER 6**

**CONCLUSION & FUTURE ENHANCEMENTS**

In summary, the Vehicle Collision Detection and Alert System greatly improves road safety by predicting and avoiding accidents. 360° cameras offer a complete view of the surroundings of the vehicle, making it possible to spot potential danger in real time. The heart of the system, a Convolutional Neural Network (CNN), analyzes the data obtained in order to assess speed, distance, and path of surrounding objects, predicting collision risks.

When there is a potential for collision, instant visual and audible warnings are activated to the driver, granting valuable time for reaction and avoiding an accident. In case of an imminent severe collision, automatic alerts are dispatched to emergency services, including location of the vehicle and severity of collision, thereby enabling a quicker response.

The future scope of the Vehicle Collision Detection and Alert System includes several key advancements. Firstly, improvements in affordable camera technology and sensor development can enhance accessibility for budget and mass-market vehicles, broadening the system's adoption. Secondly, advancements in AI and machine learning algorithms will lead to more robust object detection capabilities, particularly in challenging environmental conditions like rain and fog, ensuring greater accuracy in real-time predictions.

Additionally, retrofitting the system into older or non-smart vehicles can be explored through solutions that leverage existing vehicle infrastructure or smartphone applications. Implementing cloud-based data processing will facilitate regular software updates and ongoing maintenance, enhancing the system's effectiveness over time. These developments will ultimately contribute to safer driving experiences and a significant reduction in road accidents.

**APPENDIX 1**

**CODE SNIPPETS**

**object\_detection.py**

import torch

import cv2

import numpy as np

from ultralytics import YOLO

from tensorflow.keras.models import load\_model # type: ignore

from tensorflow.keras.preprocessing import image # type: ignore

from twilio.rest import Client

model1 = YOLO("yolov8n.pt")

mobilenet\_model = load\_model("crash\_detection\_mobilenetv2.h5")

video\_path = "./sample\_1.mp4"

cap = cv2.VideoCapture(video\_path)

# Parameters for distance estimation

real\_world\_object\_width = 1.5 # in meters

focal\_length = 800  # in pixels

# Function to estimate distance from the camera

def estimate\_distance(object\_width, object\_bbox\_width):

    distance = (real\_world\_object\_width \* focal\_length) / object\_bbox\_width

    return distance

# Vehicle class IDs in COCO dataset

vehicle\_class\_ids = [1, 2, 3, 5, 7]

def sendAlert(msg):

    print(msg)

    account\_sid = 'AC3f877ea5c5f772bf78452998685a1928'

    auth\_token = 'b688d1a39ad7fef47314eae82e811e6d'

    client = Client(account\_sid, auth\_token)

    message = client.messages.create(

    from\_='+15855171661',

    body=msg,

    to='+919600071484'

    )

while cap.isOpened():

    ret, frame = cap.read()

    if not ret:

        break

    height, width = frame.shape[:2]

    # Run YOLOv8 object detection

    results = model1(frame)

    # Define danger zone (bottom-center)

    danger\_zone\_top = int(height \* 0.75)

    overlay = frame.copy()

    collision\_occured = False

    cv2.rectangle(overlay, (0, danger\_zone\_top), (width, height), (0, 0, 255), thickness=-1)

    collision\_frame = cv2.addWeighted(overlay, 0.3, frame, 0.7, 0)

    for result in results:

        for box in result.boxes:

            x, y, w, h = map(int, box.xywh[0])

            x1, y1, x2, y2 = x - w // 2, y - h // 2, x + w // 2, y + h // 2

            confidence = box.conf[0].item()

            class\_id = int(box.cls[0].item())

            label = model1.names[class\_id]

            if class\_id not in vehicle\_class\_ids:

                continue

            color = (0, 255, 0)

            # Extract object region for MobileNetV2 classification

            obj\_crop = frame[y1:y2, x1:x2]

            if obj\_crop.size > 0:

                obj\_crop = cv2.resize(obj\_crop, (224, 224))

                img\_array = image.img\_to\_array(obj\_crop)

                img\_array = np.expand\_dims(img\_array, axis=0) / 255.0

                prediction = mobilenet\_model.predict(img\_array)[0][0]

                # Estimate distance

                object\_distance = estimate\_distance(real\_world\_object\_width, w)

                print(object\_distance, prediction)

                print(collision\_occured)

                # Check danger zone and other conditions

                if object\_distance < 1.5:

                    text = f"Collision !!"

                    if collision\_occured == False:

                        sendAlert("Alert!! Collision Detected at OMR Chennai. Impact of Collision : Severe")

                        collision\_occured = True

                    cv2.putText(collision\_frame, text, (x1, y1 - 10), cv2.FONT\_HERSHEY\_SIMPLEX, 0.8, (0, 0, 255), 2)

                elif y2 > danger\_zone\_top and prediction > 0.75 and object\_distance <= 1.7:

                    color = (0, 0, 255)

                    text = f"Collision Risk !!"

                    cv2.putText(collision\_frame, text, (x1, y1 - 10), cv2.FONT\_HERSHEY\_SIMPLEX, 0.8, color, 2)

                    cv2.rectangle(collision\_frame, (x1, y1), (x2, y2), color, 3)

                elif object\_distance < 10.5:

                    distance\_text = f"Distance: {object\_distance:.2f}m"

                    cv2.putText(collision\_frame, distance\_text, (x1, y1 + 20), cv2.FONT\_HERSHEY\_SIMPLEX, 0.8, (255, 255, 0), 2)

    cv2.imshow("Collision Detection with Distance", collision\_frame)

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

        break

cap.release()

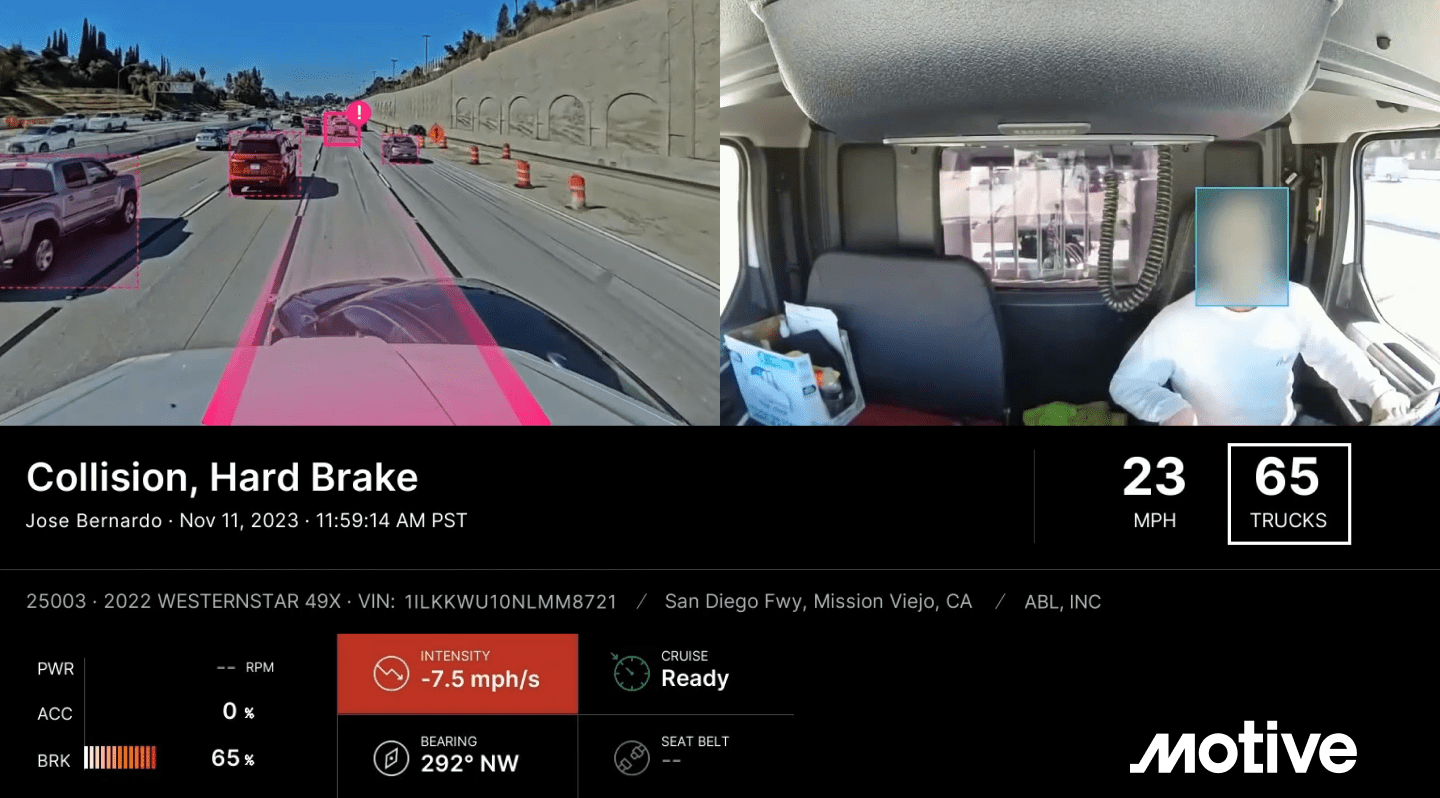
cv2.destroyAllWindows()

**APPENDIX 2**

**SCREENSHOTS**



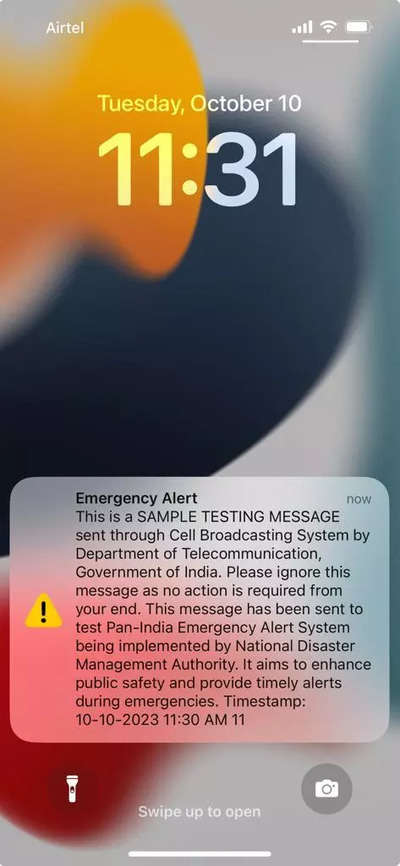
**A.2.1 Vehicle Front Footage**

z

**A.2.2 Distance Evaluation**



**A.2.3 Collision Detection**



**A.2.4 Sending Alert**

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**CERTIFICATE OF PRESENTATION**

**Conference Name :** AUTOMATION AND MACHINE LEARNING USING ROBOTS AND ARTIFICIAL INTELLIGENCE METHODS (AMLURAIM)-SERIES: 1

**Authors :** Viswanathan Krishnan, Dr. R. Elavarasan

**Conference Date :** 12/02/2025

