BVB Campus, Vidyanagar, Hubballi – 580031, Karnataka, INDIA.

SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

Minor Project Report

On

Safe Track: Real-Time Accident Detection and Emergency Response

submitted in partial fulfillment of the requirements for the award of the degree of

Bachelor of Engineering

IN

COMPUTER SCIENCE AND ENGINEERING

Submitted By

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SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

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CERTIFICATE

This is to certify that project entitled " Safe Track : Real-Time Accident Detection and Emergency Response " is a bonafied work carried out by the team members Ankit Kumar - 01FE21BCS241 , Gouri Vernekar-01FE21BCI058 , Pradeep Aryan-01FE21BCS235 , Rajat Singh Jakhar-01FE21BCS129 in partial fulfillment of the completion of 6th semester B. E. course during the year 2023 – 2024. The project report has been approved as it satisfies the academic requirement with respect to the project work prescribed for the above said course.

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ABSTRACT

The implementation of computer vision algorithms for real-time accident detection is extensively investigated to eliminate delays in post-crash response. Existing approaches generally struggle with accuracy, resulting to numerous false positives. This study attempts to boost accident detection precision while avoiding false alarms. Our technique offers a four-phase framework merging YOLO and ByteTrack for vehicle recognition and continuous tracking. We present criteria for identifying abrupt changes by assessing vehicle overlap and collision angles, significant indicators of possible accidents. Using Vision Transformer (ViT) in the final phase boosts accuracy by filtering out incorrect detections. This methodology blends different deep learning algorithms, transcending typical CNN-based approaches. Evaluation on varied real-world surveillance footage indicates higher performance compared to previous approaches.

Keywords :*Deep Learning, Accident Detection, Video Surveillance, Vision Transformer, CNN, Computer Vision 1 .*

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Chapter 1

INTRODUCTION

In recent years, traffic management has confronted a severe issue: a high global fatality rate due to the increasing incidence of traffic accidents. These accidents represent not just a traffic control difficulty but also a huge public health risk. Worldwide, traffic accidents have significant ramifications for public health, making them a main concern for healthcare organizations. Annually, over 1.35 million individuals either die or become crippled due to road accidents. In 2019, road traffic injuries accounted for the majority of these fatalities (93%).

The situation in India is extremely worrying. According to the Press Information Bureau (PIB), 2022 had an 11.9% increase in traffic-related mortality. Modern traffic management is plagued by delays in incident reporting. Manual reporting processes and eyewitness accounts often delay communication to emergency personnel, limiting the timely provision of medical treatment, worsening injuries, and lowering survival rates. Consequently, there is an increased demand for systems that can automatically detect accidents.

Recently, both industrial and academic professionals have been researching on automated detection systems employing computer vision and pattern recognition algorithms. However, accident detection approaches based exclusively on CNN and computer vision have proven ineffective. Traditional approaches may erroneously detect traffic bottlenecks as accidents. Our complete system combines deep learning approaches to enhance accident detection and drastically reduce false alarms.

Our technique is not exclusively data-centric, hence avoiding overfitting to specific real-life data. The distinctiveness of our system resides in its stepped processing scheme, where each phase plays a significant role, collectively impacting the ultimate outcomes. Our research surpasses the typical dependence on CNN-based approaches.

To overcome the inherent limits of previous systems, we have devised a holistic method that integrates several deep learning algorithms, resulting in a more reliable and precise accident detection system. In the initial step, we focus on recognizing and monitoring cars inside particular frames, preserving a constant record of their movements. In the second step, we utilize a proprietary standard to detect rapid changes within frames, rather of depending entirely on deep learning approaches to classify frames as accidents. Our criterion considers elements such as the degree of overlap between cars and the angle at which the vehicles collide. Frames satisfying these requirements are subsequently forwarded to the next phase for further processing.

In the third phase, we try to properly determine the precise site of accidents among frames that demonstrate abrupt changes. These localizations are then processed in the last step, where we employ the capabilities of Vision Transformer (ViT), an encoder-only model. This integration substantially decreases false positives by examining frames from the preceding step. This step functions as an extra safety to reliably detect real accidents, separating our method from earlier approaches. Our suggested method displays excellent precision in spotting accidents in real-life surveillance footage, reaching a Detection Rate of 94.4%.

The rest of the paper is organized as follows: Section 2 presents a comprehensive assessment of the current literature on accident detection. Section 3 describes our novel method. Section 4 explains the training and implementation phase of our methodology. Section 5 contains the empirical evaluations and outcomes. Finally, Section 6 considers future directions.

1.1 Motivation

The rising global mortality rate from traffic accidents offers a substantial challenge to traffic management and public health. Each year, over 1.35 million individuals are killed or disabled by road accidents, having a disproportionate impact on low- and middle-income countries. Traditional accident detection systems, which rely on manual reporting and eyewitness testimonies, result in considerable delays in emergency response, increasing injuries and reducing survival rates. There is an urgent need for automated and precise accident detection technologies to alleviate this issue. Recent improvements in computer vision and deep learning provide interesting solutions, however conventional CNN-based algorithms typically fail to discern between traffic congestion and actual accidents, leading to false alerts. Our research seeks to design a more reliable and precise accident detection system that integrates deep learning techniques, efficiently decreases false positives, and enhances real-time reaction, eventually saving lives and boosting public safety.

1.2 Literature Review

The evolution of accident detection technologies has witnessed tremendous advancement over the years. Initially, emergency warnings depended on in-vehicle sensors like accelerometers and vibration sensors, relaying alerts over GSM modules. However, these technologies were limited to vehicle-centric applications. The switch to image-based detection constituted a significant leap, employing Convolutional Neural Networks (CNNs) to evaluate traffic and accident photos, thereby broadening the scope beyond individual automobiles.

Researchers have developed advanced algorithms that use supervised learning approaches in three stages to identify damaged autos from surveillance data. For instance, the integration of YOLOv3 algorithm with centroid-based tracking systems has greatly boosted accident detection capabilities in CCTV recordings. Real-time collision categorization utilizing CNNs and online applications underlined the criticality of quick data analysis. Techniques like merging YOLOv4 with Kalman filters for trajectory analysis have stressed the demand for real-time traffic monitoring systems.

In tough settings such as low-visibility conditions, advances like the integration of the Retinex algorithm, YOLOv3, and decision trees have proven useful in improving detection rates. Furthermore, approaches based on HFG (Histogram of Flow Gradients) and logistic regression models have showed promising results in forecasting accidents in traffic recordings. Recent improvements also include training systems to extract features directly from raw image data using denoising autoencoders and one-class support vector machines to assess accident risks.

Additionally, methods leveraging Gaussian Mixture Models and mean shift techniques have successfully separated foreground and background components, hence boosting the accuracy and efficiency of accident identification. These developments imply important strides towards more robust and reliable traffic surveillance systems, laying the way for future innovations in accident prevention and mitigation.

Moving forward, tackling technical problems such as the reliance exclusively on geographical distance as a criteria for controller placement and the necessity for more efficient algorithms will be critical. Future research and development efforts should focus on integrating these technological developments into complete frameworks that not only detect incidents immediately but also contribute to enhancing overall traffic management and safety.

Gaps identified/ technological challenges that would be addressed

- Considered only geographical distance as a parameter
- For controller placement efficient algorithm is not used

1.3 Problem Statement and Objectives

Problem statement: Monitoring automobiles using CCTV for checking accident occurrences and providing real time alert message if accident occurred.

1.3.1 Objectives

- To track the detected vehicle constantly using Byte track.
- To check accident occurred or not using CCTV video in real time.
- To generate a real-time alert message if accident occur to relevant authorities.

Chapter 2

REQUIREMENT ANALYSIS

A Software Requirements Specification (SRS) is a lengthy document that specifies the specific requirements for a software system. It generally comprises both functional and non-functional requirements. Functional requirements explain the system's features and operations, outlining how the program should perform in various contexts. Non-functional requirements focus on topics such as performance, security, and usability. The SRS also covers the system's architecture, interfaces, and data flow. To highlight the relationships between distinct components or modules, sequence diagrams are included, displaying the order of events in particular circumstances. Furthermore, the document specifies the necessary software and hardware requirements, including the tools, programming languages, platforms, and infrastructure needed for the system's construction and implementation. An SRS is crucial to software development, providing a precise specification of the project's scope and steering the development team throughout the software development process.

2.1 Functional Requirements

Functional requirements are particular criteria that a system or program must meet to achieve its intended purpose and serve the needs of users. These criteria outline the functionality, features, and capabilities that the system should contain. They specify how the system should respond to input, analyze data, and generate output, offering a clear grasp of the expected behavior. Functional requirements often involve topics such as user interfaces, data handling, calculations, and system interactions.

- **Automated Accident Detection:** The device should automatically identify accidents in real-time surveillance footage.
- **Accident Localization:** It should properly locate the exact site of incidents among frames exhibiting abrupt shifts.
- **Phased Processing:** The system should apply a phased processing strategy, including vehicle tracking, detection of rapid changes, and accident location.

  - **Integration with Vision Transformer:** Implementing Vision Transformer integration is required to minimize false positives and improve the accuracy of accident detection.
  - **Detection Rate:** The system should reach a detection rate of at least 94.4%.
  - **False Alarm Rate:** It should maintain a low false alarm rate, specifically less than 0.00631.
  - **Efficient Response:** The system should assist cut the response time for emergency services by rapidly recognizing and reporting accidents.

- **Accuracy:** The system must be exceedingly precise in recognizing accidents to reduce both false positives and false negatives.
- **Performance:** It should function effectively with little computational resources and swiftly respond to real-time inputs.
- **Scalability:** The system should be capable of scaling to manage more surveillance footage and big amounts of data.
- **User Interface:** A user-friendly interface should be offered for configuring, monitoring, and maintaining the system.
- Server: Deploy the system on a server infrastructure capable of handling the predicted load.
- Processing Power: Multi-core processors for parallel processing. Memory (RAM):8+GB RAM.
- Storage: Provide adequate storage capacity for the database, logs, and any machine learning models.
- Client Devices: Web browsers or mobile devices for issuing warnings

2.2 Software Requirements

- Operating System: The system should be compatible with major operating systems such as Windows, Linux, and macOS.
- Database Management System (DBMS): A relational database system like MySQL or PostgreSQL for storing and managing data relating to passenger numbers, cleanliness, and alerts.

- Programming Language: Programming language suited for the application. Python is preferred here.
- Machine Learning Framework: Adaptive learning algorithms frameworks like TensorFlow or PyTorch.
- Real-time Communication: Implement real-time communication libraries or frameworks

Chapter 3

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Chapter 4

SYSTEM DESIGN

System design is a vital phase in the software development lifecycle when the architecture and components of the system are rigorously developed and described. This phase comprises turning the requirements gathered in earlier stages into a detailed design, which outlines the system's structure, components, interfaces, and data flow. The idea is to provide a design that fulfills the specified objectives while insuring scalability, maintainability, and efficient execution. System design establishes the framework for the development process, providing developers with clear instructions to construct a strong and operating system.

4.1 System Model / Architecture Design

The system architecture diagram depicts the whole workflow and critical components involved in the video analysis process for accident detection. At a high level, the architecture is designed to scan input video frames, detect significant events, and classify occurrences of accidents. The process begins with the input video, which undergoes various rounds of processing. Initially, the video frames are examined to detect sudden shifts and limited occurrences. This initial stage features object detection techniques (ODT) that scrutinize each frame for notable adjustments. The detected features are then passed to a Transformer Encoder, which utilizes advanced machine learning algorithms to further process and enrich the data. The encoder is backed by patch and positional embeddings, ensuring that the spatial and temporal components of the video frames are appropriately treated. Following this, the system employs a Multi-Layer Perceptron (MLP) head, which takes the encoded input and classifies the occurrences into specified categories, such as 'Accident' or 'No Accident'. This last classification phase is crucial for determining the conclusion and generating alerts depending on the analysis. The architecture is designed to handle real-time video feeds, guaranteeing that mishaps may be discovered fast and correctly. Overall, this system represents a complex mix of computer vision and deep learning technologies aimed at enhancing road safety through automated video analysis. The Transformer Encoder appears to handle the video frame by dividing it down into patches and feeding them into a transformer architecture. Transformers are a type of neural network design that has proven popular for natural language processing applications, but are also being increasingly applied to computer vision challenges.

The Classifier module takes the output from the transformer encoder and classifies the

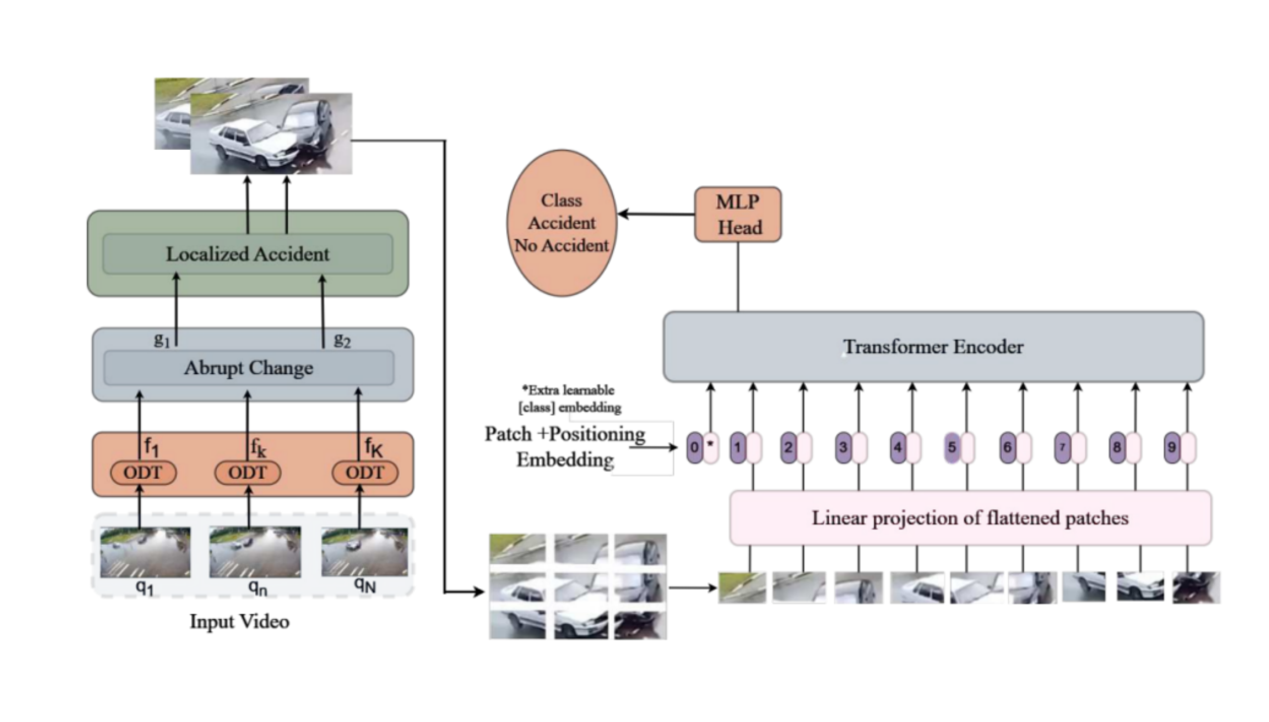

Figure 4.1: System Architecture

video frame as containing an accident or not containing an accident. The classifier makes use of a Multilayer Perceptron (MLP), a form of artificial neural network that can be applied for classification tasks.

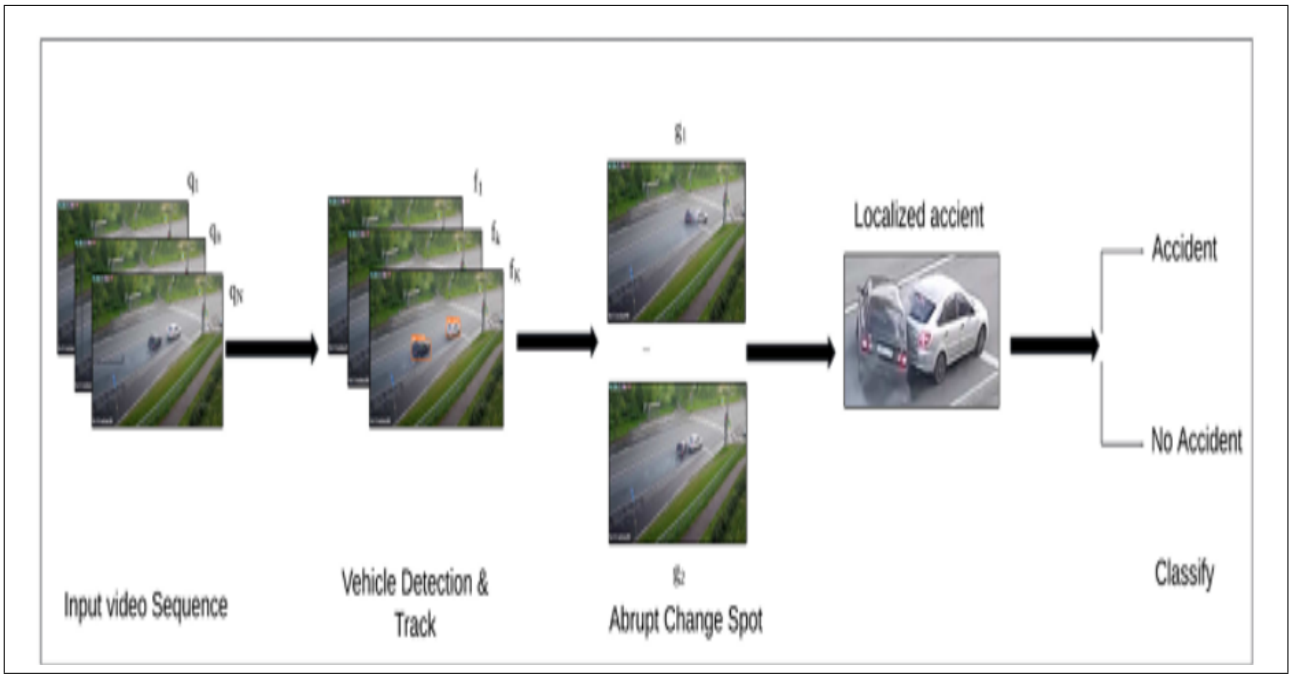

Figure 4.2: Abrupt Change Detection

4.2 Data Design

Roboflow datasets are collections of annotated pictures aimed to simplify computer vision tasks and machine learning model training. Each dataset often includes several photos with related annotations like bounding boxes, segmentation masks, or crucial locations. These annotations include specific information about items or regions of interest inside the photos, allowing developers and researchers to train and evaluate models for object detection, image classification, and semantic segmentation tasks. The datasets on Roboflow are often modified and preprocessed to promote diversity and quality, making them suited for different applications in fields such as autonomous vehicles, healthcare diagnostics, and industrial automation. Furthermore, Roboflow provides tools for dataset administration, augmentation, and interface with essential machine learning frameworks, facilitating the workflow from dataset creation to model deployment..

Datasets column:

1. **img_id:** A unique identification assigned to each image in the dataset.
2. **img_width:** The width of the image measured in pixels.
3. **img_height:** The height of the image measured in pixels.
4. **img_file:** The filename or file path of the image.
5. **cat_id:** A numerical identifier indicating the category (kind) of the object tagged in the image.
6. **cat_name:** The name of the category (type) of the object marked.
7. **supercategory:** A higher-level category that groups comparable item kinds.
8. **ann_id:** A unique identification assigned to each annotation (segmentation) in the image.
9. **x:** The x-coordinate of a point in the annotation, presumably reflecting the location of the annotated object.
10. **y:** The y-coordinate of a point in the annotation, presumably reflecting the location of the annotated object.

Chapter 5

IMPLEMENTATION

5.1 Implemenation details

The implementation of the automatic accident detection system begins with the collecting and preparation of real-time surveillance footage gathered from traffic cameras strategically positioned throughout crucial sites. This initial phase comprises establishing scripts or apps to access and continually stream video data, ensuring it is optimized and of good quality for following processing phases. The core of the solution relies upon a staged processing methodology meant to boost efficiency and accuracy. Initially, computer vision algorithms monitor and track vehicles inside frames, followed by devices to detect unexpected environmental changes that may suggest accidents. Accurate localization of accidents inside these frames is done by complex algorithms specialized to determine precise accident locations.

Integrating Vision Transformer (ViT), an encoder-only model, plays a crucial role in boosting detection precision and lowering false positives. This integration entails designing adapters to smoothly add ViT into the existing processing pipeline, hence boosting the system's capabilities to evaluate and confirm identified occurrences. Performance measures such as detection rate and false alarm rate are key benchmarks, driving the evaluation and development of the system's effectiveness. A user-friendly interface is concurrently designed to simplify system configuration, real-time monitoring of issues, and visualization of performance indicators.

Throughout the installation process, comprehensive testing and validation ensure the system's resilience across varied environmental conditions and traffic scenarios. Comprehensive documentation covering installation, configuration, and usage guidelines is produced to assist flawless deployment and operational integration. Regulatory compliance and security safeguards, including data encryption and adherence to privacy standards, are incorporated within the system to preserve sensitive information and assure legal compliance. This holistic approach to implementation seeks to produce a robust, quick, and accurate automated accident detection system capable of greatly boosting traffic safety and emergency response efficiency.

Algorithm 1 Collision Detection Algorithm

Require: $V = \{f1, f2, ..., fN\}$ ▷ Input: Video sequence
Require: $\theta_{\text{threshold}}$ ▷ Input: Threshold angle
Ensure: g_i ▷ Output: Potential collision frames

Initialize g_i as an empty set
for $i = 1$ to N **do**
    $B_i \leftarrow \text{DetectBoxes}(f_i)$
    $O_i \leftarrow \text{CheckOverlap}(B_i)$
    if $O_i = \emptyset$ **then**
        for $(b1, b2) \in O_i$ **do**
            $(v1, v2) \leftarrow \text{CalcVelocityVec}(b1, b2)$
            if $\text{Angle}(v1, v2) > \theta_{\text{threshold}}$ **then**
                $g_i \leftarrow g_i \cup \{f_i\}$
                break
            end if
        end for
    end if
end for

5.2 Methodology

The methodology section details the systematic approach utilized to build and deploy the automated accident detection system. It encompasses defining project objectives, understanding stakeholder requirements, research and familiarization with current technologies, data collection and annotation, training and fine-tuning of deep learning models, integration into the system architecture, designing user interfaces, implementing an alerting and notification system, testing and validation procedures, deployment strategies, comprehensive training, and documentation, iterative improvement based on feedback, and a robust maintenance and support framework.

Define Project Objectives:

The project intends to develop an automated accident detection system utilizing deep learning and computer vision. It addresses the expanding global issue of traffic accidents by employing phased processing to monitor and pinpoint occurrences in real-time surveillance footage. Integration with Vision Transformer boosts accuracy, aiming for a high detection rate while decreasing false alarms.

Understand Stakeholder Requirements: Understanding stakeholder requirements entails comprehending the different needs of traffic management authorities, healthcare institutions, and the general population impacted by increased traffic accidents. It covers addressing safety concerns, improving reaction times, and deploying efficient accident detection systems that correspond with stakeholder expectations for increased public health and safety measures.

Research and Familiarization: Research and familiarization involve analyzing current trends and issues in traffic management, notably with the huge global issue of escalating traffic accidents. This includes comprehending the interaction of traffic control and public health concerns, evaluating the influence on mortality rates, and examining technical breakthroughs such as automated accident detection systems employing deep learning and computer vision.

Data Collection and Annotation:

- Data Sources: Acquire suitable datasets with annotated photos for training the YOLO V8 model.
- Annotation: Annotate datasets with bounding boxes and labels for vechiles.

Train and Fine-Tune YOLO V8 Model:

- Training: Train the YOLO V8 model using the annotated datasets.
- Fine-Tuning: Fine-tune the model to match it to the specific characteristics of traffic control.

Integrate YOLO V8 with the System: Integrating YOLO v8 into the system demands a systematic process involving installation, data preparation, model integration, parameter adjustment, validation, and maintenance. Initially, YOLO v8 and its dependencies are installed and configured to align with the existing system architecture. Subsequently, real-time surveillance film is structured and preprocessed for input. YOLO v8 is then effortlessly integrated into the system's phased processing pipeline, with its output coupled to following analysis phases. Fine-tuning of model parameters maximizes its performance, followed by rigorous validation against various test data to assure accuracy and robustness. Continuous performance monitoring enables continuing optimization, while extensive documentation and maintenance plans assure the sustained effectiveness of the integrated YOLO v8 model.

System Architecture Design: The system architecture design entails creating a framework capable of efficiently processing real-time surveillance footage for automated accident detection. It incorporates numerous major components, including data gathering, phased processing, YOLO v8 integration, and result analysis. Data gathering systems capture and preprocess surveillance images from traffic cameras. Phased processing contains algorithms for car tracking, sudden change detection, and accident localization. YOLO v8 integration boosts detection accuracy. Result analysis examines detection performance and feeds back into the system for continual development. This design offers a sturdy and effective system for boosting traffic safety.

User Interfaces:

Design UI:

- Design user interfaces for police station and hospital.

• Include real-time dashboards indicating accident detected.

Alerting and Notification System:

Implementation:

• Implement an alerting mechanism to notify necessary staff in case of security concerns or cleaning issues.

• Integrate notification technologies such as emails, SMS, or push notifications.

Testing and Validation:

• Testing: Conduct extensive testing, including unit testing, integration testing, and system testing.

• Validation: Validate the accuracy and effectiveness of the YOLO V8 model in traffic management .

Deployment: Deployment requires implementing the automated accident detection system in real-world settings, guaranteeing smooth connection with existing traffic management infrastructure and surveillance systems. Monitoring covers regularly analyzing system performance, recognizing and correcting any errors promptly, and adjusting algorithms and parameters to maximize accuracy and efficiency over time.

Training and Documentation:

• Training Sessions: Training the automatic accident detection system requires multiple processes. Firstly, data gathering generates a diverse dataset of traffic surveillance film, annotated with accident instances. Secondly, this data is utilized to train the deep learning models, such as YOLO v8, through iterative processes, altering model parameters to enhance performance. Finally, validation ensures the trained models accurately detect accidents, attaining high detection rates while minimizing false positives.

• Documentation: Documentation for the automatic accident detection system comprises detailed instructions on installation, configuration, and usage. It offers thorough tutorials for setting up the system, configuring parameters, and integrating with existing infrastructure. Additionally, it gives troubleshooting suggestions, best practices, and references for further support, ensuring smooth implementation and maintenance of the system.

Feedback and Iterative Improvement: Feedback and iterative improvement are crucial to boosting the automated accident detection system's performance. Stakeholder input, system performance measurements, and real-world usage data inform continuing refinements. This iterative approach comprises assessing feedback, identifying areas for improvement, altering algorithms or settings accordingly, and validating changes through testing. Continuous iteration ensures the system changes to meet evolving needs and maintains optimal performance.

Maintenance and Support:

• Maintenance Plan: The maintenance plan for the automated accident detection system outlines measures to assure its continuing operation and effectiveness. It comprises regular monitoring of system performance, scheduled changes to software and algorithms, and proactive discovery and resolution of any errors or abnormalities. Additionally, it defines roles and duties for maintenance chores, develops communication routes for reporting and addressing concerns, and incorporates feedback mechanisms for continual improvement. This approach intends to maximize system reliability and durability, ensuring it stays a trustworthy tool for traffic safety enhancement.

• Issue Resolution: Issue resolution in the context of the automated accident detection system requires rapidly addressing any technical or operational challenges that occur. This method comprises finding the root cause of the issue, applying corrective measures or workarounds, and validating their effectiveness through testing. Communication channels are built to allow reporting and tracking of concerns, assuring fast resolution and minimizing system downtime. Additionally, documentation is updated to contain resolutions for typical difficulties, facilitating quick resolution in the future.

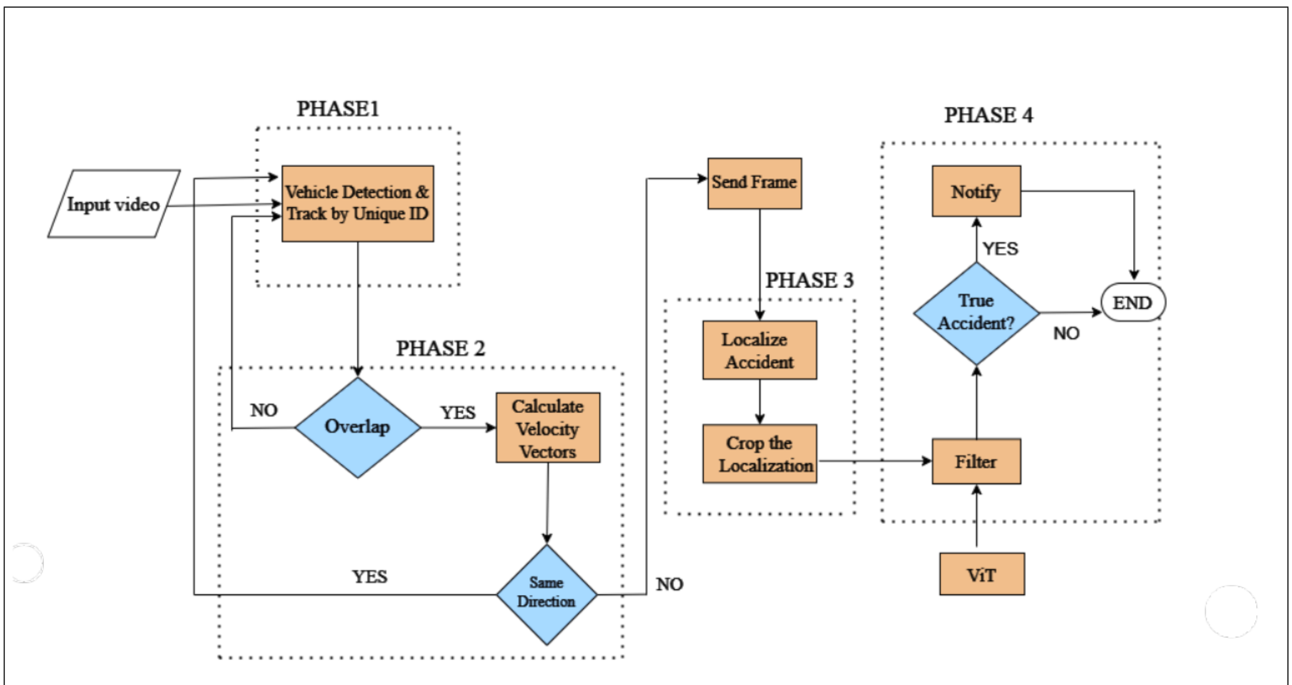

Figure 5.1: Flowchart

Chapter 6

RESULTS AND DISCUSSIONS

6.1 Experimental Setup

Our approach used a phased analysis of video frames to recognize and filter out accident scenarios marked by quick, significant changes. Out of the 31 videos studied, our algorithm effectively recognized accidents in 17 out of 18 relevant videos. Only one false alert occurred among the 13 films indicating typical traffic. The model earned an F1-score of 94.4 percent, indicating strong performance, however further rigorous testing is necessary to evaluate its resilience and applicability fully. The restricted sample of 31 videos offers obstacles for measuring performance across varied settings. Future studies should prioritize increasing the dataset to incorporate multiple accident kinds, lighting and weather conditions, and camera views for a more comprehensive evaluation under real-world situations. Additionally, studying the introduction of additional features or modifying the model architecture could potentially boost accuracy and reduce false positives.

6.2 Results Analysis

The examination of our accident detection algorithm offered important insights into its performance measures, emphasizing its potential for real-world implementation. One of the crucial metrics utilized to assess the model's usefulness was the F1-score, which balances precision and recall to produce a single measure of performance. Our model achieved an exceptional F1-score of 94.4%, indicating its skill in reliably identifying accidents while avoiding missed detections.

The Detection Rate (DR) was calculated to be 94.4%. This high detection rate reflects the model's capacity to accurately identify a vast majority of actual accident incidents in the dataset, indicating its practical application in real-time traffic surveillance scenarios. Another key indicator is the False Alarm Rate (FAR), which estimates the proportion of non-accident incidents that were wrongly categorized as accidents. Our model revealed an extremely low FAR of 0.00631%, proving its robustness in limiting false positives and ensuring that alarms are sent only when a genuine accident happens.

The results from these evaluation metrics collectively show that our model is very effective and reliable for real-world applications. The high detection rate, along with low false alarm

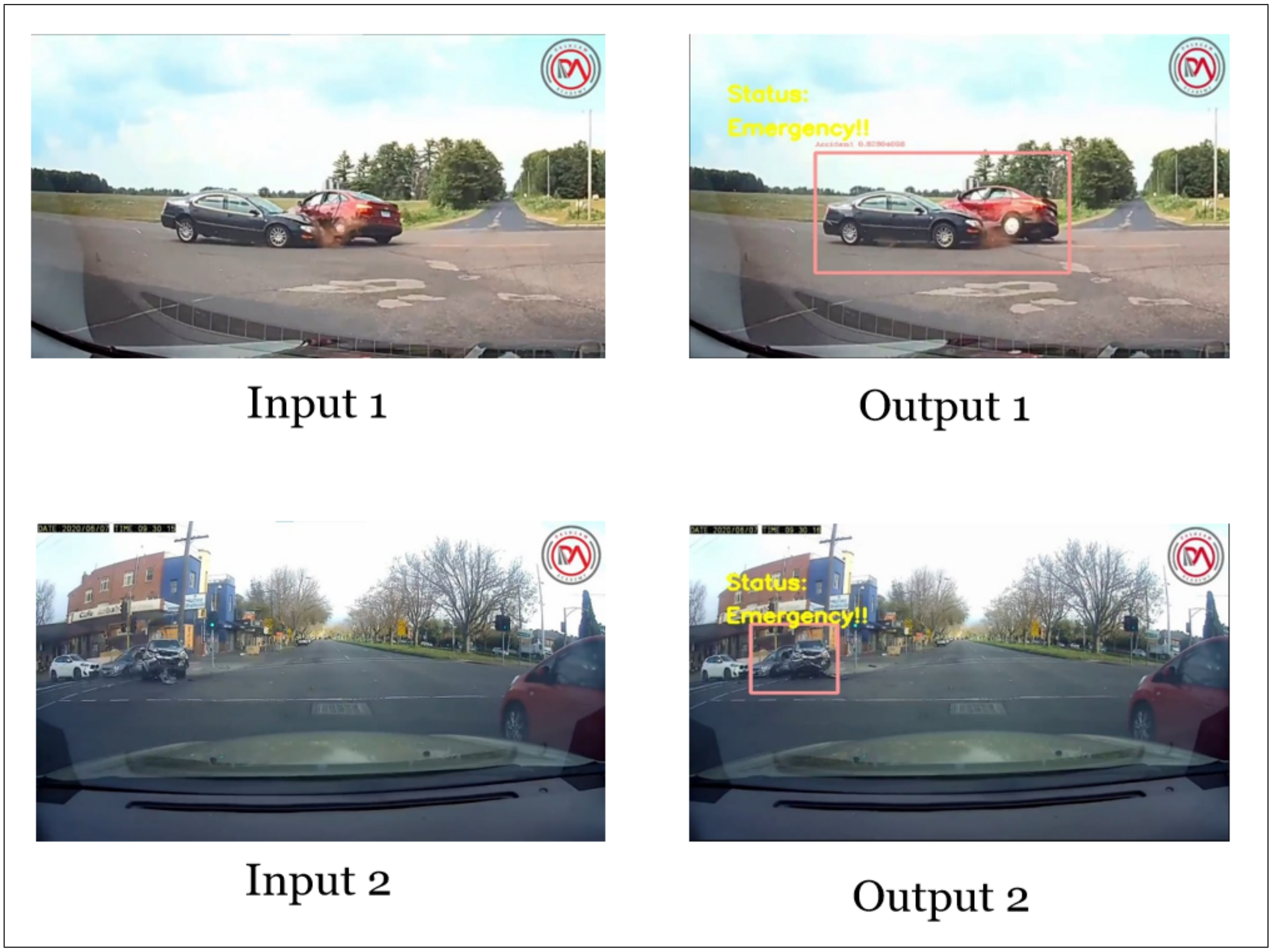

Figure 6.1: Visual output

instances, implies that the model may be feasibly employed in surveillance systems to promote traffic safety. The resilience of the model was further validated through rigorous testing on numerous video sequences, including various camera angles and lighting conditions, reaffirming its application in varied situations. We have expressed the scores in the table below to provide a clear and comprehensive overview of the model's performance measures.

Metric	Value %
F1-score	94.4
DR	94.4
FAR	0.00631

Figure 6.2: Performance Metrics Overview

Chapter 7

CONCLUSIONS AND FUTURE SCOPE

7.1 Conclusion

Our novel method indicates a considerable step forward in accident detection inside surveillance recordings, straying from standard methodologies. Our strategy consists of four phases: employing YOLOv8 for accurate vehicle detection, implementing ByteTrack for reliable tracking, identifying sudden environmental changes indicative of accidents, and precisely localizing accidents using selected frames processed with YOLOv8 and Vision Transformer (ViT) to minimize false positives. This methodology outperforms dependence primarily on CNN-based methods by incorporating a number of deep learning algorithms, establishing new norms for accuracy in video surveillance accident detection.

7.2 Future Scope

However, we realize the issue faced by the restricted availability of video data exclusively dedicated to accidents. To solve this issue, our phased architecture methodically processes frames progressively to enhance effectiveness. Future attempts should prioritize the construction of a dedicated dataset focused entirely on accidents to investigate more creative ways. Moreover, there is potential to extend our methodology by establishing more powerful modeling frameworks that surpass present sequential frame processing techniques. This investigation could involve leveraging 3D convolutions to better capture the temporal dynamics of accident events. Looking ahead, our aims include increasing dataset efforts and improving our approach to attain more computational efficiency and efficacy beyond the existing frame-by-frame processing approach.

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Appendix A

A.1 Description of Tools and Technology used

Our system performs inferencing tasks on a desktop featuring an Intel Core i7-6700 CPU, 32GB of RAM, and an NVIDIA GeForce GTX 1650 GPU. Model training occurs on Google Colaboratory, utilizing a Tesla T4 GPU and a minimum SSD storage capacity of 256 GB. On the software side, we rely on Google Colab for collaborative development and utilize VS Code. These specifications collectively ensure optimal performance, graphical capabilities, and software compatibility, providing a robust foundation for our applications