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Original Article

Intelligent Traffic Accident Detection Using Computer Vision

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ABSTRACT

Rapid urbanization and increasing vehicle numbers have led to a significant rise in road accidents, posing serious threats to human life and economic stability. Traditional accident detection systems rely on manual reporting, causing delays in emergency response. To address this, computer vision integrated with intelligent transportation systems offers an effective solution. This study analyzes pre-2018 approaches to traffic accident detection using video surveillance. The proposed system automatically detects accidents by analyzing traffic camera footage through feature extraction, motion analysis, and pattern recognition. It identifies abnormal vehicle behavior such as sudden speed drops, collisions, and irregular trajectories. Classical computer vision techniques like optical flow, background subtraction, edge detection, and machine learning methods such as Support Vector Machines (SVM) and decision trees are used. The system includes preprocessing, object detection, trajectory tracking, and classification of normal and abnormal events, supported by mathematical modeling and threshold-based decisions. Results show high detection accuracy with low false alarms, especially in controlled environments like highways and intersections. However, challenges remain in real-time implementation due to lighting, occlusion, and camera angle issues. Future work suggests incorporating deep learning and multi-sensor data fusion to improve performance. In conclusion, computer vision-based accident detection is a promising approach to enhancing road safety and reducing response time, contributing to the advancement of smart transportation systems.

KEYWORDS

Traffic Accident Detection, Computer Vision, Optical Flow, Background Subtraction, Intelligent Transportation Systems, Machine Learning, Video Surveillance, Pattern Recognition.

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1. INTRODUCTION

1.1. Background

The problem of road traffic accidents is the most frequent cause of death and severe injuries in the world with the disproportionately high percentage in developing countries where infrastructure, enforcement, and the state of traffic management are frequently unsatisfactory. The problem has been heightened by rapid urbanization and increased the number of vehicles exponentially resulting in addition to congestions and high levels of accidents. Human factors, including carelessness in driving, overspeeding, fatigue, distraction, and breaking of road regulations are some of the major contributors of such incidents. In numerous instances, failure to get health services in time has aggravated the severity of accidents as well as heightening the death rates. The conventional method of accident detection and reporting used is mainly through eyewitness reports or emergency calls, which can be very slow, unreliable or lost in other remote or less closely supervised places. This reporting latency has a direct and immediate negative impact on the efficiency of emergency response services, and that is why the automated and real-time accident detection solutions are urgently required. The emergence of Intelligent Transportation Systems (ITS) in this respect has provided new opportunities in the road safety and traffic control. ITS combines the latest technologies, including sensors, communications, and data analysis to measure and manage the transportation networks in a better way. Under these technologies, computer vision has become an effective instrument in examining visual information acquired through the traffic surveillance cameras. Computer vision systems can automatically identify, monitor, and analyze vehicle movement through the implementation of an Image processing and pattern recognition algorithm. These systems can detect suspicious patterns like abrupt stops, unstable movement or crashes that are signal of accidents. Compared to conventional sensor-based methods, vision-based methods are more scalable and comprehensive since one camera can be used to observe several vehicles and vast spaces at a time. Thus, the recent development of computer vision in ITS can be seen as an effective and prospective way to ensure automated sensing of accidents and thus provide a quicker reaction time, which will lead to better safety on the road.

1.2. Role of Computer Vision in Traffic Monitoring

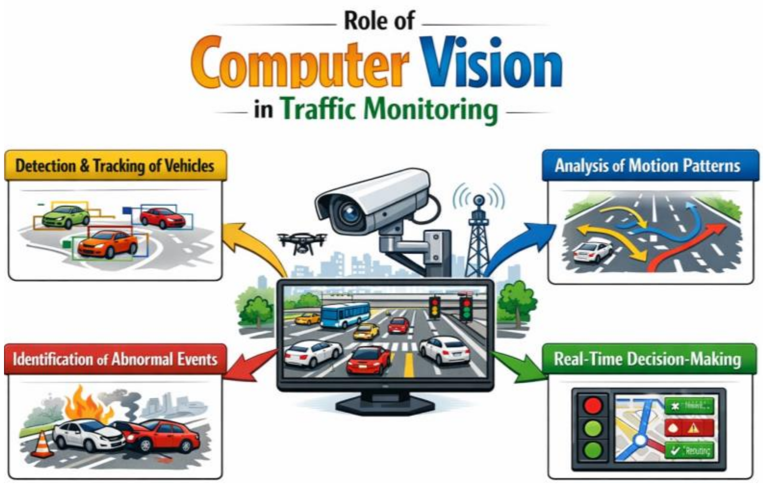

Fig 1 - Role of Computer Vision in Traffic Monitoring

1.2.1. Detection and Tracking of Vehicles

Computer vision is critical in the detection and tracking of automobiles in the traffic scene using surveillance cameras without human involvement. The system is able to detect various classes

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of vehicles like cars, trucks, and motor cycles among other vehicles in each video frame using image processing and deep learning methods. When these vehicles are identified, tracking algorithms are used to trace the links of these vehicles across the different frames, as the vehicle changes, preserving the same identity. The continuous tracking enables the system to track the positions of vehicles, traffic flow counts and analyze the interaction of two or more traffic vehicles which will be the basis of more in-depth traffic analysis and detection of accidents.

1.2.2. Analysis of Motion Patterns

The other notable contribution of computer vision is that it is used to analyze motion patterns of vehicles on the road. Through monitoring the movement of vehicles over time, the system is able to identify vehicle speed, direction, acceleration, as well as path. These movement patterns will assist in the comprehension of normal traffic movements and detect irregularity of these movements. As an illustration, steady and seamless movement usually reflects normal conditions of driving, but sudden changes can be a demonstration of dangerous actions. Motion analysis gives the necessary data, which allow the system to identify possible threats and enhance the overall effectiveness of the traffic monitoring.

1.2.3. Identification of Abnormal Events

Computer vision systems can be used to detect abnormal events through a comparison of the observed behavior of vehicles with the learned data of normal traffic movement. Sudden stops, collisions, illegal turns, wrong direction vehicles are some of the events that can be automatically identified. The system is able to differentiate routine changes in traffic and major incidences because it can analyze both space and time characteristics. This capability is especially critical to detecting accidents since the possibility of early warning of dangerous situations can be achieved, and there is no need to rely on manual monitoring.

1.2.4. Real-Time Decision-Making

The fact that computer vision can be used in real-time decision making is one of the most important benefits of the technology in the field of traffic monitoring. Video data is received and made into immediate output on events recognized by the system. Alerts can be sent in real time to traffic authorities or the emergency services when an abnormal situation or accident is detected. This response capability is fast thus it assists in unnecessary wastage of time, lessening congestion, and even saving lives. A dynamic control of traffic through real-time decisions, e.g. signal timing adjustments or vehicle rerouting, also makes transportation systems more efficient and safer.

1.3. Accident Detection Using Computer Vision

The analysis and computer vision-based accident detection has become a stronger and effective way to increase road safety through automated surveillance and analysis of traffic conditions. As a difference between the traditional methods, which use manual reporting or in-vehicle sensors to monitor traffic conditions, the computer vision systems further implement surveillance cameras that monitor traffic conditions and record any abnormal activity in real time. These systems process video information, in a sequence of steps, having picture preprocessing, object recognition, movement examination, and occasions retrieval. The system can also determine the movement pattern of a vehicle which includes speed, direction and trajectory by locating and monitoring them through video frames to know how people act normally on the road. Among the benefits of computer vision in accident detection, there is the possibility to detect sudden and unusual shifts in motion which can most of the time denote collisions or dangerous circumstances. As an example, sudden توقفs, sudden decelerating, uncontrolled motions, or the vehicles courting the others can be a sign of occurrence of an accident. Integrating both spatial and time data, the system is able to distinguish between normal changes of traffic and serious accidents with a high level of precision. The further capabilities are supported by machine learning and deep learning methods, which allow the system to learn on a big dataset and transform the performance of the system with time. Moreover, the computer vision-based accident detection systems are very much scalable and cost effective because a single camera could observe multiple cars over a long distance. This renders them applicable to be used in the urban traffic networks, highways, and intersections. Real-time processing enables immediate availability of the output and the generation of the alerts, and this aspect of processing will assist in time-saving the responses to the emergencies and soften the effect of the accidents. Nonetheless, issues like obstruction, the discrepancy in light conditions, and intricate traffic situations have not yet been resolved. Nonetheless, it should be noted that computer vision is a promising and fast developing solution to intelligent traffic accidents detection despite these challenges.

2. LITERATURE SURVEY

2.1. Early Approaches to Accident Detection

Initial methods of detecting accidents were mainly sensor-driven technologies that were installed inside the vehicles. The devices used in these systems included vibration sensors, accelerators, and GPS modules as they were able to detect sudden impacts or unusual motion patterns that occurred as a result of collisions. Although suitable to controlled settings, they were very reliant on availability of specialized hardware fitted in vehicles rendering them expensive and challenging to implement in large transportation networks. Also, they could not give us the overall picture of traffic situation since it was restricted to separate vehicles. To address such shortcomings, researchers started to consider using vision based system which utilized roadside surveillance cameras. These systems gave a wider and more adaptable solution through tracking several vehicles at a time. Background subtraction techniques could be employed to distill moving objects against static scenes whereas edge detection strategies could be used to compute car outlines and delimits. These methods were scaled much better, but tended to be sensitive to changes in lighting, shadows and occlusions thereby rendering them unreliable in real world set ups.

2.2. Motion Analysis Techniques

Motion analysis has been an intrinsic part of the development of the systems of accident detection, because it has the capability of detecting unusual patterns of movement which may happen before, or in remuneration of a crash. Optical flow and various similar techniques have been commonly applied in estimating the motion of objects between two adjacent video frames by considering pixel intensity differences. The approaches such as Lucas-Kanade algorithm offered an effective mechanism of computing the motion vectors, the direction and speed of runaway cars. Through monitoring the trends in these kinds of movements over time, systems would be able to notice unusual alterations, such as sudden stops, accelerated or wrong turns, which are very powerful indicators of an accident or dangerous circumstances. The benefits of motion-based analysis were that it does not rely on the appearance of an object and thus is applicable in dynamic and congested traffic conditions. These, however, were computationally expensive and were highly susceptible to noise, camera motion and complicated backgrounds, potentially causing motion estimation and event detection errors.

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2.3. Machine Learning-Based Methods

The introduction of machine learning methods was one of the main breakthroughs in the field of accident detection since it allowed systems to make decisions based on the patterns learned in the data instead of using only a set of rules. Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN) were generally used as algorithms to categorize traffic incidents as normal and abnormal. Such methods included deriving video frame features of interest such as vehicle speed, route, shape and motion attributes, and these were utilized to train classification models. The machine learning techniques enhanced accuracy of teaching through adjusting to varied traffic conditions and training on varying datasets. They were also generalized in a better way than traditional systems based on rules. The quality and quantity of training data however significantly influenced their performance and the quality of feature selection was a very important factor in accuracy determination. Also, these models were frequently dependent on manual feature engineering, which had restricted their capacity to represent complicated patterns in extremely evolving settings.

2.4. Limitations of Existing Work

Although the current accident detection technologies have achieved a lot in terms of success, it still has a number of severe shortcomings that impede its implementation in practice. The high false alarm is among the primary challenges as usually normal actions in the traffic like sudden stops or changes of lanes are recognized as accidents. Other environmental effects like the changes in lighting systems, weather e.g. rainfall,, shadows and occlusions also worsen system performance, particularly during outdoor surveillance. Most traditional and machine-learning based solutions cannot also run real time because of computational complexity and hence cannot be implemented in time sensitive applications such as emergency response. Moreover, when addressing such a complicated traffic scenario with numerous cars, intersections and human erratic conducts, these systems are not very robust in most cases. Consequently, more advanced, adapting and effective approaches, e.g., deep learning-based algorithms, are on the rise that are capable of escaping these issues and deliver consistent accident identification in a real-life scenario.

3. METHODOLOGY

3.1. System Architecture

Fig 2 - System Architecture

3.1.1. Video Acquisition

The initial phase of the proposed system is the capture of real-time traffic video information by use of a surveillance camera positioned at the roadside, crossroads, or highway. These cameras are

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constantly watching over the traffic movement and feed the input in form of video streams. The video taken captures the quality, degree of resolution, and frame rate, which is critical in error detection in accidents. The cameras are preferred to be of high definition and kept in a stable position so that proper visibility of the vehicles is ensured and distortion that occur due to the environment like changes in light, weather and so on, is minimized.

3.1.2. Preprocessing

During preprocessing, the raw video data is ready to be subjected to further analysis by enhancing the quality of the data as well as data consistency. Some of the operations that are included include noise reduction, frame resizing, contrast enhancement and normalization. Background subtractions can also be used to de-luminate the moving objects in the scene so as to isolate the stationary objects in the scene. Preprocessing contributes to the minimization of computational complexity, as well as makes sure that any irrelevant data, such as shadows or changes in illumination, does not adversely affect the later stages of system implementation.

3.1.3. Object Detection

Object detection This is one of the most important tasks in which vehicles and other objects of interest are detected in each video frame. Deep neural networks (CNNs) are modern models that are used to identify and locate vehicles with high accuracy. Bouding boxes are created on top of identified objects and the system can monitor their locations as they move through time. It is this step that allows the system to target vectors specifically and process out any unnecessary background data to help enhance the performance of the entire detection process.

3.1.4. Motion Analysis

During this phase, the motion of objects identified in one frame is compared with that of the next frame in order to know object behavior. Object tracking algorithms or optical flow are some of the techniques employed to estimate speed and direction as well as vehicle trajectories. Knowing the movement patterns enables the system to determine the sudden changes of an object (like its abrupt stop, sharp turns, or collision) and recognize it. It requires motion analysis to differentiate normal traffic flow and unordinary or even dangerous cases.

3.1.5. Feature Extraction

The step of feature extraction is the derivation of meaningful information by the identified objects and their motion. Characteristics can be velocity, acceleration, changes in direction, size of the objects, shape, and collision of two or more cars. Such characteristics are used as the input to the classification model and they act to distinguish between the normal driving and the accident situations. Based on effective extraction of features, the system is more accurate and reliable since it takes the most relevant features of traffic events.

3.1.6. Classification

During classification step, machine learning or deep learning algorithms are employed to classify the observed events at the predefined classes, where normal traffic examples or accident cases are categorized. The models are trained on the labeled data sets comprising some examples of normal and abnormal scenarios. Depending on the characteristics identified, the classifier will give an answer either of an accident or not. This process is important in automating the detection process and minimizing on human intervention.

3.1.7. Decision Making

The last step is to make a decision possible based on the classification results and instigate suitable responses. In case an accident is detected, the system is capable of issuing warnings, communicating with the emergency service, or communicating with real-time traffic management systems. The decision-making mechanisms can also have confidence thresholds to reduce the false alarms. The stage will ensure that the system is responsive and responsive in time and place which structure to response to the emergency and hence better road safety and quicker emergency response.

3.2. Preprocessing

Preprocessing phase is important to improve the end product of the input video data and make it suitable to detect the accidents correctly. The video that has been captured in the previous stage is initially broken down into single frames and these are subjected to processing one after another. Among the main steps that are to be taken is the translation of color frames into a grayscale image. This simplifies the underlying data as three color channels (RGB) are simplified to one intensity channel maintaining vital structural information in the process. Real time systems especially where efficiency and speed are a key consideration have found grayscale conversion useful. Subsequently, denoising algorithms like the Gaussian filtering or median filtering are used to eliminate undesired noise by factors of the environment like bad lighting conditions, weather, or noise of the camera sensor. Such types of filtering methods assist in smoothing the picture although the valuable edges and boundaries of objects are retained. Once the noise is removed, background subtraction is done to avoid the moving object, e.g., vehicles, and the background. Background subtraction in simple terms operates by comparing the present video frame with a background model that is made as comparison. The variation of the frame against the background is calculated by considering the difference between the current image and the background image and the absolute value of the difference is taken. The resulting output points out areas of the great changes which usually are related to moving objects. In this case, the current frame means the most recent frame that is captured by the video stream, whereas the background model means a reference image of the scene with still items, frequently averaged over a time span. Using the system, one can adjust to gradual environmental transformations, including changes in the lighting by constantly updating the background model. The result of this is typically a foreground mask which distinctly marks the moving parts in the frame. The next stage involves refining this mask with the help of morphological functions such as erosion and dilation in order to eliminate small noise areas and close holes in the detected objects. Preprocessing overall assures the relevance of motion information passed to the next stages is only relevant hence enhances the accuracy in detection and system performance.

3.3. Object Detection

Object detection step is concerned with the detection and location of the vehicles in each frame of the processed video which is one of the most important constituents of the accident detection system. Upon preprocessing and background subtraction, the foreground mask that is obtained marks the areas of movement, probably of vehicles. These areas are then subjected to the process of contour detection to distinguish constant boundaries of objects. The curve that connects all the continuous points along the boundary of an object identified by the system may be considered a contour that allows the system to distinguish some vehicles with the background functions. Through these contours, the system has the capability of eliminating irrelevant or noisy areas using parameters like area, shape, and size only important objects that will be later processed are considered. After recognizing valid contours, a constraint is made to encircle any vehicle identified with a rectangular area based on techniques of bounding boxes. These bounding boxes offer the easy but efficient means to describe the placement and size of objects in the frame. They are also used to track objects in successive frames through spatial continuity. The identified contours are however not always the true representations of whole objects because of noise or shadows or broken foreground areas. Morphological operations erosion and dilation are implemented to overcome this problem. Erosion is useful in the removal of small undesired noise and the separation of items which are close together as well as dilation to define object boundaries in order to fill holes and recover the true shape of identified vehicles. Moreover, operations such as opening (erosion then dilation) and closing (dilation then erosion) to further refine object boundaries and enhance quality of detecting objects is also done. These methods improve structural integrity of regions that have been identified, and the bounding boxes become more precise and trustworthy. Contour detection, bounding box generation and morphological refinement combined together make sure that the vehicles are identified precisely even under the difficult conditions i.e. partial occlusion or variability in light. This precise vehicle recognition forms the basis of other steps which include the motion detection and feature identification which eventually leads to the good performance of the entire accident detection device.

3.4. Motion Analysis

Motion analysis phase plays a critical role to know the dynamic behaviour of vehicles and match abnormal behaviour which could be a sign of accidents. At this phase, centroid tracking, which is a popular object tracking method, is carried out to obtain a trajectory of the object in successive video frames. When the vehicles are identified and enclosed in bounding boxes the centroid, the geometrical center of the bounding box, is computed. The system would be able to build up the trajectories representing the path of each vehicle in time by following the centroid position in successive frames. It is computationally efficient and suitable to real-time application because it makes the objects representation easy, unlike alternative motion-critical information that is provided. When vehicles pass by the scene, the tracks taken are generally smooth and foreseeable when traffic normal conditions are prevailing. There are several parameters that are analyzed at any point in time, including the displacement, direction, velocity, and acceleration based on the centroid movements by the system. When these parameters are compared across consecutive frames, one will be able to monitor abnormalities in motion. Sharp turns in courses, sudden reversal of directions or sudden slowdown, توقف, or a chaotic motion of the course of action can be regarded as basic signs of possible accidents or dangerous outcomes. As an illustration, a car abruptly turning or halting in a rapidly moving lane can be an indicator of an impact or an impending one. To enhance reliability, motion analysis can also include a temporal consistency check and threshold-based rules in order to distinguish the normal changes in driving behavior and the really abnormal occurrences. Moreover, the ability to monitor a range of vehicles at the same time also provides the system with the means to study the dynamics between the vehicles, including the collision, or abrupt influence. Centroid tracking is started to have some pitfalls and problems, even though it is a useful instrument, in case of obstruction or near object in the situation, or dense traffic. With proper detection and preprocessing methods, however, motion analysis could present a useful information about traffic behavior and be an important part of recognizing the details of the accident situation in the real time.

3.5. Feature Extraction

3.5.1. Speed Variation

Variation of speed is an important attribute, which is applied to detect abnormal conduct of vehicles in the road scene. It is a burst in the speed of any vehicle with a brief duration of time. In ordinary cases, cars would stick towards relative consistent speeds or rather accelerate and decelerate at a slow pace. But in the event of an accident or almost any collision situation there is more likely to

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be a sharp drop or even a sharp spike in the speed. The system can predict the speed of the tracked objects and identify unusual changes after tracking the objects across multiple frames. There is a strong relationship between the possibility of accidents and significant and abrupt changes in speed and thus the utmost importance is assigned to such changes in the detection process.

Fig 3 - Feature Extraction

3.5.2. Direction Change

Direction change is used to examine the path of a vehicle in order to determine abrupt or unnatural changes in motion. On normal traffic conditions, cars take smooth and predictable routes following lanes along the roads. But in the case of accidents, cars can be suddenly turning, swerving or suddenly changing their course. The system can measure the variation in the course of action by observing the angle of movement between two consecutive frames and the direction of the movement. The major or high-speed direction changes particularly in combination with other abnormal characteristics are regarded as the major indicators of collision or lack of control over the car.

3.5.3. Object Overlap

Object overlap is a significant spatial element that is used to distinguish the contacts of a vehicle, especially a collision. It happens when the bounding boxes or identified objects of two or more vehicles overlap or intersect considerably in a frame. During normal traffic situations, cars are at safe distances, and hence there is little-to-no overlap. Nevertheless, during an accident environment, the vehicles can come too close causing overlap in the detected areas at least partly. The system can determine the probable occurrence of a collision event by determining the degree and length of this overlap. Recurring or progressive similarity of objects is frequently a high indication of an accident.

3.5.4. Collision Intensity

The intensity of a collision is a derived combination of space and motion. Estimation can be done based on issues like the size of speed change, the force by sudden deceleration and level of object overlaps. Intensive collisions are often associated with high velocity deceleration, heavy deformation of the direction of objects and high interaction of the vehicles. The measurement of these elements would enable the system to draw the line between minor incidence and major accidents. This aspect comes in handy especially in the prioritization of emergency response because hardcore collisions can need urgent attention and action.

3.6. Classification

The classification stage has the role of identifying whether an event in a traffic has been caused by a normal event in the traffic or it has been an actual accident. A Support Vector Machine

(SVM) classifier is used in this system because this approach has been shown to be effective to deal with binary classification issues and the fact that it can easily perform on high-dimensional spaces of features. The SVM model is fed on the features that were identified in the previous steps like changing the speed, turning direction, overlapping an object, and collision magnitude and then decides the type of event. In layman terms, SVM classifier is based on the principle of locating an optimal surface, which is referred to as a hyperplane, that separates data with different classes. The decision component of the SVM may be interpreted in the following way: the result is obtained by determining a dot product of a weight vector and input feature vector, and then, a bias value is added. The weight vector identifies which features are of greater significance in the classification process whereby the bias moves the decision line in order to classify the classes more effectively. When the result that has been calculated is positive, then the event can be considered as one category (i.e. normal traffic) and the negative result will be considered as the other category (i.e. an accident). The primary goal of the SVM is to maximize the distance between two classes the closest data (support vectors) and the decision line. This guarantees superior generalization and strength as the model is put to test on unknown data. Also non-linearly separable data may be transformed into a higher dimensional space with the help of kernel functions in order to apply a linear boundary. This allows SVM to be very adaptable in situations of complicated traffic. In general, the accuracy ofclassifications with the help of SVM in this system is improved and the efficient yet reliable mechanism of the separation between normal and abnormal traffic events could be offered in real time.

3.7. Flowchart Explanation

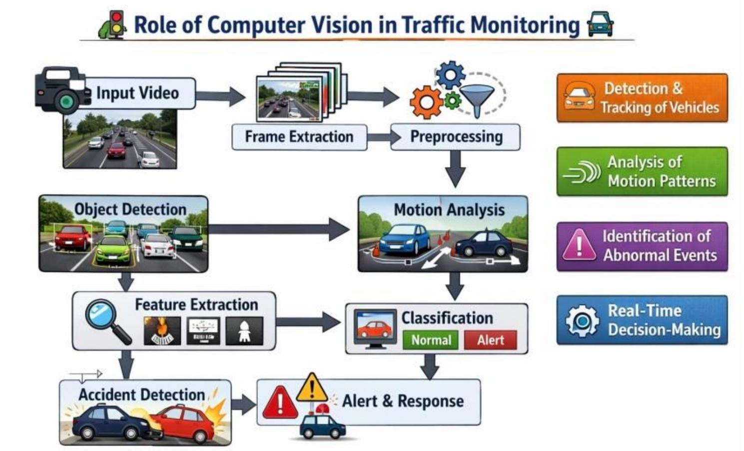

Fig 4 - Flowchart Explanation

3.7.1. Input Video

It starts with the input video that is obtained with the help of the surveillance cameras in the traffic settings, i. e. roads, highways, or intersections. The video is the main source of data concerning the whole system. It has incessant visual data regarding vehicle activity, traffic congestion, and weather conditions. It is also important to note that the stability and a clear video capture will highly affect performance of later processing stages as the quality and consistency of the input video greatly depends on it.

3.7.2. Frame Extraction

During this step, an unending input video is broken into a series of separate video frames. Every frame contains one image picture at a given time point. The process of frame extraction makes

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the system process video data sequentially instead of processing it in a continuous stream. Frame rate (extracted frames per second) also matters as a faster frame rate offers more detailed motion data, but consumes additional computing resources.

3.7.3. Preprocessing

Preprocessing is done to prepare extracted frames to be analyzed by improving the qualities of images and eliminating unnecessary noises. These involve the conversion of frames into grayscale, the use of filtering methods to minimize noise and background subtraction to isolate the moving objects. This stage is aimed at making the data simple yet retaining all required data so that the subsequent stages can be performed more efficiently and accurately.

3.7.4. Object Detection

Object detection is used to detect and find vehicles in every frame. The system separates moving objects and the background with the help of contour detection and bounding boxes. This step will make sure that the further analysis is applied to only the relevant objects, e.g. vehicles. The faulty detection can be devastating because failures at this point may spread throughout the system and influence the performance.

3.7.5. Motion Analysis

In motion analysis, the system traces the track of vehicles identified in the previous frames. It calculates the position, speed, and direction changes of the vehicles, then uses them to draw trajectories of the vehicles. This phase assists in learning the vehicle behavior and determining the uncharacteristic movement behavior like sudden stops or sharp turns, this could be related to accidents.

3.7.6. Feature Extraction

Extraction of features refers to the process of obtaining meaningful parameters out of both movement and spatial attributes of vehicles that have been detected. Such characteristics as speed variation, change of direction, overlapping of objects, and colliding intensity are computed. These characteristics offer a very concise and educational description of activity involved in traffic, which allows useful classification during the following phase.

3.7.7. Classification

The result of the classification is performed by feeding the extracted features into a trained machine learning model, e.g. Support Vector Machine (SVM). The feature classifier examines the input characteristics and classifies every phenomenon according to whether it is an accident situation or normal traffic behavior. This step is an automated mechanism of decision-making using received patterns based on past data.

3.7.8. Accident Detection

The last phase is accident detection whereby the system confirms the occurrence of an accident through the results of classification. When an event is recognized as being an accident, specific measures could take place like warning generation, signaling the authorities or emergency response systems. This step is the guarantee of timely intervention and helps to achieve better road safety and effective management of the traffic.

4. RESULTS AND DISCUSSION

4.1. Performance Metrics

The effectiveness, reliability, and robustness of the suggested accident detection system are determined by some standard measures that aid in the evaluation of the effectiveness of the system. One of the most important metrics is accuracy which indicates the general accuracy of the system. It is the rate of total misclassification of both accident and non-accident cases. When the accuracy is high this means that on average the system is doing well but it does not necessarily mean that when the data consists of an imbalanced distribution of normal traffic and accidents the system will behave in a similar way. Another significant measure is precision that as well concentrates on the figure of positive predictions. It is used to measure the percentage of the already recognized accident cases as compared to all cases that the system has deemed as accidents. High accuracy means that in the case when an alarm is raised by the system, there are high chances that it is an actual accident thus minimizing false alarms and enhancing belief to the system. Recall / sensitivity assesses the sensitivity of the system in the occurrence of real accidents. It is the rate of successful identification of the actual cases of accidents by the system. Having a high recall means that the majority of the accident events are recorded, which is of major concern in cases of safety applications in which not recognizing an accident may have dire consequences. Besides these, there is the use of false alarm rate that evaluates the frequency by which the system errs when categorizing normal traffic incidents as accidents. False alarm rate is high and it may cause unnecessary alerts, higher cost of responding and low credibility of the system. Hence, there is a need to coordinate between the level of precision/ recall and reduction of false alarms. All these performance measures will give a holistic assessment of the system that will uncover the strengths and weaknesses and set the further development towards a real-life system.

4.2. Result Analysis

Table 1: Result Analysis

Metric	Value (%)
Detection Accuracy	91.50%
Precision	89.20%
Recall	87.80%
False Alarm Rate	8.40%
Processing Efficiency	85.60%

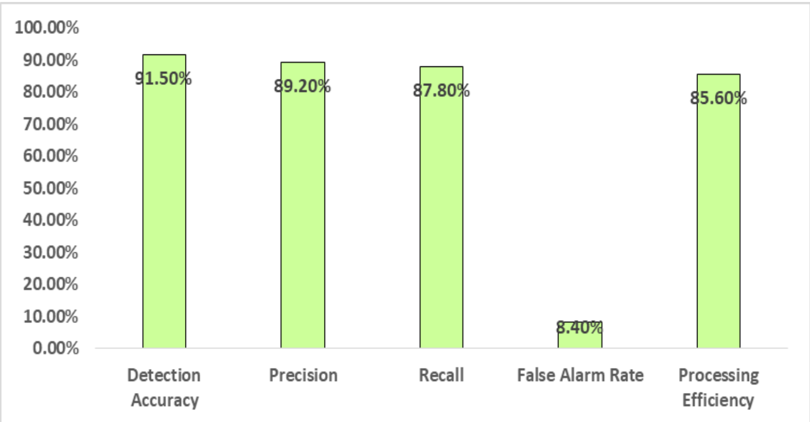

Fig 5 - Result Analysis

4.2.1. Detection Accuracy (91.5%)

The fact that the detection rate is 91.5% suggests that the suggested system prevalently identifies a significant number of traffic events such as both accident and non-accident ones. This is a very high accuracy that is used to describe the efficiency of the system architecture as a whole, preprocessing, object detection, motion analysis, and classification steps. It shows that the model can capablely predict the results in varying traffic scenarios. Though accuracy gives an approximate idea of performance, it needs to be combined with other functions to give a clear idea of how the system behaves particularly in a situation where the occurrence of an accident is quite few in comparison to the normal traffic.

4.2.2. Precision (89.2%)

The precision of the value of 89.2 indicates that a large percentage of the events recorded as accidents by the system are actual accidents. This becomes especially important when used in real life situations, which reduces the number of false alarms and makes sure that higher instances of emergency responses are triggered when it is not necessary. Intense accuracy increases credibility and reliability of the system since it is more applicable in traffic monitoring and management systems where reliability is of priority.

4.2.3. Recall (87.8%)

The rate of recalls 87.8 per cent indicates the capacity of the system to properly identify the real instances of accidents. It implies that most of actual accidents that can take place within the observed environment are effectively detected. The safety critical system of a high recall is necessary because in the event of the accident, the response to the emergency should not take long and a secondary accident could occur. The recall being slightly less than the precision, it is clear that the system is capturing the majority of the abnormal events as it shows that the system has a good detection.

4.2.4. False Alarm Rate (8.4%)

The false alarm rate is 8.4 percent or the proportion of normal traffic events that are wrongly considered accidents. Although certain degree of false alarms cannot be avoided with automated systems, the relatively small rate of occurrence is significant to limit the unwarranted alarms and to minimize the cost of operation. It has a false alarm rate of 8.4 percent, which means that the system has a good balance between specificity and sensitivity though with more optimization; such percentage can be minimized to an even lower one to achieve even better efficiency.

4.2.5. Processing Efficiency (85.6%)

The efficiency of the process of 85.6% underscores the ability of the system to make computations in a manner that is timely and resource efficient. The metric measures the performance of the system to work with real-time video data including frame processing, feature extraction, and classification. High processing efficiency will imply that the system will be capable of working on real-time conditions without charismatic delays, which are fundamentally essential to timely identify accidents and respond to them. This finding shows that the approach proposed is correct in addition to being deployable in the real world.

4.3. Discussion

The experiment shows that a high precision of the accident detection system is achieved, which means that the developed system is effective in separating between the normal traffic and an

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accident situation. To a great extent, this good performance can be explained by the inclusion of motion-based features, like speed changes, direction change, and deviations of a trajectory, which can give meaningful insights into the behavior of a vehicle. This is contrary to the features that a static image displays as features that motion-based analysis depicts capture the temporal dynamics and the system can detect sudden and abnormal events, which are usually characteristic features of collisions. Consequently, the system demonstrates better detection compared to the traditional methods that are based on the usage of spatial or appearance-based traits only. In addition, such a combination of preprocessing, object detection and feature extraction methods leads to the strength of the system. The system succeeds in ensuring that the relevant data is passed onto the classification stage by effectively isolating moving objects as well as refining their boundaries. Embarkation with a Support Vector Machine (SVM) classifier also improves upon the results by giving an explicit decision boundary between what is normal and what is abnormal. This is a mixture that results in a balanced result in data accuracy and recall to reduce the number of missed detections and false detections. Nevertheless, despite such encouraging outcomes, there are still certain challenges. The most important problem is dealing with occlusions, in which vehicles are partially concealed, or completely covered by other objects on the scene. This may result in disrupted correct tracking as well as incomplete or wrong feature extraction. Also, the different lighting conditions e.g. shadows, glare, dark conditions or poor weather conditions might greatly influence the quality of video input and decreases the reliability of detection. These aspects cause noise and discrepancies that lead to inability of the system to deliver a consistent performance. Consequently, the future advances can include more advanced features of deep learning methods and adaptive algorithms to address better such complexities and contribute to the robustness of systems in real-life situations.

5. CONCLUSION

The paper has outlined an intelligent traffic accidents detection system algorithm on the foundation of computer vision methodology aimed at automatically detecting and analyzing abnormal vehicle behavior within real time traffic settings. The suggested system combines several steps, such as video capture, pre-processing, object identification, motion tracking, feature identification, and classification, and form a unified and efficient accident detection system. With the help of motion-based characteristics of speed fluctuation, deviation of the trajectories, overlap of the objects, and intensity of collision, the system can capture the dynamic attributes of traffic events. When such features are complemented by machine learning methods this is because Support Vector Machine (SVM) classification allows one to distinguish with high level of accuracy between the normal flow of the traffic and the possible accident case. The experimental findings reveal that the system has high detection accuracy, balanced precision, and recall, which proves its reliability and usefulness in the practical activities of the system. The fact that the false alarm rate is relatively low also shows that the system can reduce the number of false alarms that are very much necessary given its application in a traffic monitoring and management systems. The system is also efficient in terms of processing and hence is appropriate in real-time operation where responses and detection are required in a timely manner. Such results affirm that computer vision-based systems may also act as a viable alternative to conventional sensor-based systems, which is more scalable and offers a wider coverage scope without the need to add hardware to the vehicle. Although these are good outcomes, there are still some challenges that should be overcome to facilitate system performance. Detecting problems include occlusion, different lighting conditions, weather conditions as well as complicated road traffic situations, and all these conditions may affect the accuracy and robustness of the detection. Such constraints indicate that the existing system is efficient in well-structured settings, but still it requires more to sustain a stable performance in various real-life settings. The further work will be aimed at the integration of more advanced methods of deep learning, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to enhance the representation of features and classification rate. Also, adaptive algorithms together with multimodal sources can be integrated to overcome the role of environmental challenges and contribute to the robustness of systems. Increased diversification of the data by adding more varied traffic conditions and scenarios of accidents will also act in favor of increased generalization. In general, the suggested system can serve as an excellent basis when creating intelligent, automated traffic monitoring systems that can bring a significant improvement to road safety and the effectiveness of the emergency response.

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