

Signal-Based Crash Detection Using Accelerometer Data

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Abstract

One of the most significant international issues is road traffic accidents, which tend to result in serious trauma among individuals and slow reaction to emergency. This paper will present a signal-based crash detection system which makes use of accelerator data to facilitate the detection of a car crash in real time. The method uses tri-axial measurements of acceleration to record sudden transitions of the motion, which signifies collision events. The reading of accelerators is used to calculate a Signal Magnitude Vector (SMV) and then it is preprocessed using noise filtering, and gravity compensations to improve signal quality. The system uses both machine learning-based and threshold-based models to differentiate between the normal and crash situation driving patterns. The evaluation is done experimentally with a mixture of simulated and real life driving data and the performance is quantified in terms of accuracy, precision, recall and detection latency. The suggested approach has an excellent detection rate and low false alarms due to sudden braking or road anomalies. Also, the system facilitates real-time alert generation through incorporation of location-based services to send an emergency notification. The findings indicate that a low-cost, scalable, and efficient crash detection system in the intelligent transportation system and mobile-based safety applications is possible.

Keywords: Accelerometer Data, Crash Detection, Signal Processing, Intelligent Transportation Systems, Real-Time Monitoring, Signal Magnitude Vector (SMV)

1. Introduction

Road traffic accidents and millions of deaths and injuries every year on the road has been declared as one of the major safety issues of the world today. Formerly the physical evidence of accidents was relying on physical reporting by the victims or the witnesses and in most cases it resulted in failure to respond promptly and the excessive number of death. The initial generation of automated technologies tried to solve this problem with the help of hardware systems, which are the airbag deployment systems, vibration sensors, and telematics devices which were attached to the car and triggered an alert when hit [1]. One such example was to use manufacturers coupled systems in cars and the deployment of the airbags was used as a proxy that a crash occurred but the GSM based modules delivered the messages to the emergency services [2]. These systems were however, disadvantaged and expensive to install, not scalable and relied on proprietary infrastructure of vehicles. Due to the introduction of Intelligent Transportation Systems (ITS), they have transitioned to higher sensor based solutions, which were more data intensive on the application of real time monitoring and communication solutions in the promotion of road security [3]. The acceleration can also be the acceleration in three directions (X, Y, Z) that can be measured using accelerators found in smart phones and embedded systems to measure any change of sudden motion when an event like collision, rollover etc. occurs. In one, faster acceleration than 3-5g may be abrupt, which may indicate that this may be a high impact crash and deceleration slowing will be regarded as normal braking [4]. To measure such events, such parameters as Signal Magnitude Vector (SMV) are calculated that will be the summation of the three dimensional acceleration parameters into a scalar measure of the intensity of the motion. Signal processing techniques are used to extract only meaningful patterns by discarding the noise and including a low-pass filter, gravity compensation and normalization [5]. The obtained processed signals are further processed by using threshold-based technique or machine learning models to distinguish normal driving behavior such as lane change or speed change models with paramount crash event instances. This is facilitated by automatic transfer of locations and crash data using accelerator based system, GPS and wireless communication technology, which can facilitate an emergency responder with the foundations of the modern ITS system enabling safety systems [6].

Even though the aforementioned changes were made to the accelerator-based crash detection systems, it still has a number of crucial issues and gaps in the research. One of them is false positives containing a large number of incidences that will not result in a crash but will cause acceleration patterns of real collisions. In order to give an example, the acceleration spikes that model the crash instructions can be presented when a driver turns around potholes, hits the speed breakers, or suddenly stops [7]. Still in the same note, aggressive driving behaviours (i.e. changing lanes in a hurry or sharp turning) may also be regarded as false alarms of the threshold-based systems. The other problem is due to the position and orientation of the device; in the pocket, the dashboard or the cup holder, a smart phone will record varying levels of acceleration to similar occurrences with varying outputs on the precision of detection [8]. In addition, there is no available precise data of real crash to train and test powerful models. Most of the tests that incorporate simulated crash situations/ experiments do not reflect the complexity and diversity of the real world accidents such as multi-vehicle crashes or conditions that are not the same on the road [9]. The other issue is energy saving where constant sensor monitoring and live use can be a strain to mobile phone gadgets. Although machine learning techniques, such as decision trees and deep neural networks are not proposed to enhance the detection performance, they usually need extensive quantities of labeled data and cannot be explained and comprehended, which is why it is challenging to comprehend decision boundaries in safety-related tasks [10]. These issues bring up the necessity of flexible and efficient and situational models of crash detection.

The current article is a reaction to the above difficulties where a signal-based crash detector system with the capability of integrating advanced signal processing and the availability of effective detection algorithms are proposed. It works towards minimizing the false positive cases with the help of Multi-feature, such as SMV, jerk and temporal patterns analysis and is computationally efficient such that it can be used in real-time. In addition, the system receives sensor orientation and driving variability that helps in the generalization of conditions. The proposed strategy has a trade-off between interpretability and accuracy, as it allows using both the data-driven and threshold-based strategies. The framework is assessed on the realistic and the simulated data sets, which can be considered to assert the reliability and practicability of the framework. Scope of the Paper are as follows:

- Improving signal crash detector model through accelerometer recordings.
- Noise cancelling and signal enhancement with the use of preprocessing methods.
- Comparison of threshold-based and machine learning.
- Comparison of simulated and real world driving information.
- Planning and real time alerts on emergency response mechanism.

2. Literature Review

In recent years, extensive studies have been done in the field of automotive crash detection with the use of accelerometer and mobile sensors. Initial research concentrated on hardware-based detectors fitted to vehicles and these systems were based on airbag deployment or specific impact sensors to provide alerts. As the number of smartphones and IoT devices increased, the focus of research became software-based methods that used the inbuilt sensors like accelerators and gyroscopes to identify the presence of uncharacteristic patterns of motion [11]. Threshold-based techniques have been investigated by a number of works, which involve a predetermined g-force threshold range to detect crashes, but such approaches frequently have problems with robustness in dynamic driving scenarios [12]. More modern works have presented machine learning algorithms, such as decision trees, support vectors and deep learning models, to enhance the detection accuracy based on learning of complex patterns of sensor data [13]. Also, sensor fusion (using accelerometer, GPS, and gyroscope data) based on the contextual awareness has been suggested [14].

Nevertheless, as these improvements are made, the primary questions are, How can a detection system distinguish between a real crash and a non critical event such as potholes or sudden braking? How are models able to extrapolate their cross-systems driving conditions? Moreover,

what is the way of reaching high accuracy with low computation cost and energy consumption? All these difficulties demonstrate the necessity of more adaptive, scalable, and cost-effective solutions that are able to work credibly in the real world conditions at minimum false alarm and response delays [15].

Table 01: Comparative Analysis of Existing Crash Detection Approaches

Study	Approach	Sensors Used	Technique / Model	Key Contribution	Limitations / Gaps
[11] White et al.	Smartphone-based real-time crash detection (WreckWatch system)	Accelerometer, GPS	Fixed threshold-based detection using g-force spikes and velocity change	Introduced one of the earliest scalable smartphone-based crash detection frameworks	High false positive rate due to reliance on static thresholds
[12] Mohan et al.	Mobile sensing-based accident detection and response system	Accelerometer	Hybrid threshold + heuristic rules (event pattern matching)	Developed an early-stage real-time accident detection system integrating motion patterns	Limited adaptability to diverse driving conditions; heuristic rules are not robust to unseen scenarios
[13] Hussain et al.	Machine learning-based crash classification system	Accelerometer	Supervised learning (Decision Tree, Support Vector Machine)	Improved detection accuracy by learning discriminative patterns	Requires large labeled datasets; performance degrades with noisy or imbalanced real-world data
[14] Thompson et al.	Multi-sensor fusion-based accident detection	Accelerometer, GPS, Gyroscope	Rule-based fusion logic combining motion, orientation, and speed data	Enhanced contextual awareness by integrating multiple sensor modalities	Increased computational complexity; dependency on multiple sensors affects scalability

[15] Wang et al.	Data mining-driven crash detection	Accelerometer	Pattern recognition and statistical data mining techniques	Identified characteristic crash signatures through offline analysis	Not suitable for real-time deployment due to high processing latency and offline nature
[16] Ferreira et al.	IoT-enabled vehicular accident detection system	Accelerometer, GSM module	Embedded system with threshold-triggered communication	Provided an end-to-end automated alert system integrating sensing	Strong dependency on dedicated hardware; limited flexibility
[17] Fazeen et al.	Driver behavior monitoring and analysis system	Accelerometer	Statistical feature extraction and behavioral modeling	Demonstrated how accelerometer data can be used to classify driving behaviors	Not specifically designed for crash detection; lacks mechanisms for detecting high-impact collision events
[18] Jain et al.	Deep learning-based crash detection framework	Accelerometer	Deep Neural Networks (CNN, LSTM for time-series analysis)	Achieved high detection accuracy by capturing temporal dependencies	Computationally expensive; requires high processing power and large training datasets
[19] Eriksson et al.	Road surface and anomaly detection (Pothole Patrol)	Accelerometer	Signal processing and anomaly detection algorithms	Demonstrated large-scale detection of road anomalies	High overlap between pothole signals and crash signals leads to misclassification in accident detection systems

[20] Zeng et al.	Real-time IoT-based crash detection with hybrid intelligence	Multi-sensor (Accelerometer, GPS, Gyroscope)	Hybrid ML model combining rule-based filtering and machine learning classification	Reduced detection latency and improved robustness	High energy consumption due to continuous multi-sensor monitoring
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A critical analysis of existing literature reveals several persistent gaps that limit the effectiveness and scalability of current crash detection systems. One of the most prominent issues is the inability to reliably distinguish between actual crash events and high-intensity non-crash scenarios such as potholes, speed bumps, or abrupt braking. For instance, studies focusing on threshold-based detection often report high false positive rates due to overlapping acceleration patterns [16]. While machine learning approaches improve classification accuracy, they introduce new challenges, including dependency on large labeled datasets and reduced interpretability of model decisions [17]. Additionally, many systems fail to address variability in sensor orientation and placement, leading to inconsistent performance across different devices and usage conditions [18]. Another significant limitation is the lack of comprehensive real-world datasets, as most studies on simulated or controlled environments, which do not capture the complexity of real incidents [19]. Furthermore, energy efficiency and computational overhead remain critical concerns, particularly for smartphone-based implementations that require continuous sensor monitoring [20]. These gaps underscore the necessity for a novel approach that combines robust signal processing, adaptive detection mechanisms, and real-time efficiency. Addressing these challenges is essential to develop a reliable, scalable, and cost-effective crash detection system that can be deployed widely in intelligent transportation ecosystems.

3. Proposed Methodology

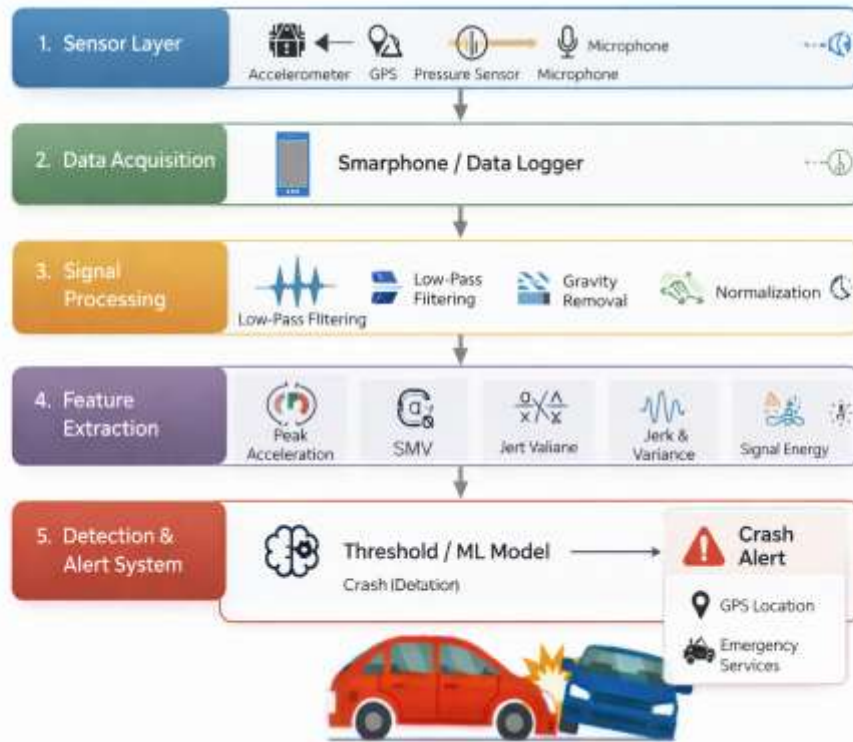
According to the weaknesses that have been identified in the literature review that comprise massive false positive, inability to work under real world environment and lack of computational efficiency, the research shall come up with an effective signal-based crash detection system that uses the accelerator signal. The existing approaches are either on incredibly high or incredibly low thresholds, or complex machine learning models which cannot be interpreted or scored. In order to address these issues, the given model integrates multi-stage signal processing and hybrid detection logic, which means that the benefits of threshold-based and data-driven solutions are integrated. The framework is also designed to operate under real time conditions using inexpensive sensors such as smartphone accelerators and can therefore be implemented on a mass scale within Intelligent Transportation System (ITS). Unlike the former strategies, this one engages multi-feature validation (Signal Magnitude Vector (SMV) and jerk) and temporal motion patterns in an effort to improve the detection capabilities. Besides, variability of sensor orientation and driving conditions is also considered in the system that enhances generalization. A layered architecture is used to ensure modularity in which each step such as data collection process to the alert generation process is assisting in reducing noise and better features representation and decision-making. The proposed methodology provided will moderate the accuracy, efficiency, and interpretability, and, consequently, introduce the feasible and scaleable solution to the real-time crash detection and emergency response systems.

3.1 System Architecture

Its proposed system is a layered architecture that receives data of accelerator in a sequence to determine when a crash happens. The information of the tri-axial accelerators is then continuously received at the sensing layer and sent to the data acquisition module where the information is time-stamped and buffered. It has a preprocessing layer based on filtering and normalization to enhance signal quality. The layer then takes the important parameters (i.e.

SMV, jerk and signal energy) as well. The features are then passed on to the detection layer that employs hybrid decision making methods of threshold-based and machine learning. Finally the application layer crashes alert and report crash details to the emergency services. This modular design offers flexibility, scalability and efficient real time processing and therefore would be suitable to be applied in several different vehicular and mobile applications.

Figure 01: Layered Architecture of Proposed Crash Detection System



3.2 Data Acquisition

The continuous and accurate data gathering is imperative in detecting small and sudden motion patterns that are linked to crash incidences. In order to do this, a sampling frequency of about 50-100 Hz is used, and so the quick changes of the acceleration like the ones involving collisions are properly recorded without causing much information loss. The acceleration is measured in three orthogonal directions, i.e. X (lateral), Y (longitudinal), and Z (vertical) which allows the system to fully represent the vehicle dynamics in motion in three-dimensional space. In order to make the detection model more robust and generalized, the data set includes various driving conditions, such as normal driving behaviors (e.g., acceleration, braking, turning), simulated and in case they are available, real-world crashes. This diversity gives the system a chance to learn discriminative patterns in crash and non-crash conditions and this lowers false positives. Moreover, other mechanisms are used to assure temporal consistency and data buffering to avoid data losses in high-frequency sampling like time synchronization. The critical parameters, sensor configurations and the type of data to be used in the process of making the acquisition are well-considered as indicated in Table 2 and they are expected to aid in crash detection that is dependable and scalable.

Table 2: Data Acquisition Parameters and Sources

Parameter	Description	Value/Type

Sampling Frequency	Rate of data collection	50–100 Hz
Sensor Type	Motion sensing device	Tri-axial Accelerometer
Axes	Direction of measurement	X, Y, Z
Data Types	Driving scenarios	Normal, Simulated Crash, Real Crash
Data Format	Signal representation	Time-series data

3.3 Signal Preprocessing

The preprocessing phase is highly essential before extraction of features so as to enhance the quality and reliability of raw accelerator signals. In driving environments, sensor data is likely to be affected by noise, orientations of devices, and any distraction in the environment which significantly reduces the crash detection capabilities. To address these issues, there are a number of preprocessing processes performed in a structured pipeline. To start with, low-pass filtering technique removes high frequency noises as a result of the vibrations of the road and sensor artifact that pollute the signal and gives a smoother signal representation. This is then accompanied by the elimination of gravity to separate dynamic motion components of known gravitational acceleration (-9.81 m/s^2) that is required in the proper capture of variations brought about by motion. Besides, the process of normalization, such as Min-Max scaling and Z-score normalization, are carried out to normalize the signal values of different devices and working conditions and to increase the generalization of the model. Other processes are further used to refine the signal, including smoothing, outlier and segmentation removal among others, to be left with a signal which can be further time analysed. As shown in Table 3, each of the preprocessing methods has its role to play to make the signal more clear, stable and consistent as a result of which the strength and accuracy of the crash detection system is enhanced.

Table 3: Signal Preprocessing Techniques

Technique	Purpose	Method / Algorithm Used	Input Signal Type	Output Effect	Impact on System Performance
Low-pass Filtering	Remove high-frequency noise caused by vibrations and sensor artifacts	Butterworth Filter, Moving Average Filter	Raw accelerometer signal	Smooth signal with reduced noise components	Improves signal clarity and reduces false triggers from minor disturbances
Gravity Removal	Eliminate static gravitational acceleration ($\approx 9.81 \text{ m/s}^2$)	High-pass filtering, sensor fusion	Raw acceleration data	Isolated dynamic motion signal	Enhances detection of actual motion events and improves feature accuracy

Normalization	Standardize signal range across different devices and conditions	Min-Max Scaling, Z-score normalization	Filtered signal	Scaled and comparable signal values	Ensures consistency across devices and improves ML model performance
Smoothing	Reduce short-term fluctuations and transient spikes	Moving Average, Savitzky-Golay Filter	Noisy signal	Continuous and stable signal representation	Improves feature stability and reduces false positives
Outlier Removal	Remove abnormal spikes not related to crash events	Statistical thresholding, IQR method	Preprocessed signal	Cleaned signal without extreme anomalies	Reduces false alarms caused by random sensor errors
Windowing (Segmentation)	Divide continuous signal into fixed-size segments for analysis	Sliding window (e.g., 1-2 seconds)	Continuous time-series data	Segmented signal windows	Enables temporal analysis and improves feature extraction for ML models
Drift Correction	Correct slow-changing bias in sensor readings over time	Baseline correction, detrending methods	Long-duration signals	Stable baseline signal	Prevents accumulation of errors in long-term monitoring
Axis Alignment / Transformation	Align sensor axes to a consistent reference frame	Coordinate transformation, rotation matrices	Multi-axis accelerometer data	Orientation-independent signal	Improves robustness against device placement variability
Noise Thresholding	Suppress low-amplitude noise signals	Threshold-based filtering	Low-intensity signals	Reduced background noise	Enhances detection sensitivity for high-impact events
Resampling	Ensure uniform sampling rate across datasets	Interpolation, decimation	Irregular sampled data	Uniform time-series signal	Improves compatibility with ML models and signal analysis techniques

3.4 Feature Extraction

The process of feature extraction converts processed signals into significant signals of crash events. The most important aspects are the peak acceleration (g-force) that indicates the intensity of impacts and jerk that records abrupt alterations in motion. Is a computation of the Signal Magnitude Vector (SMV) to indicate the overall motion intensity on all axes.

$$SMV = \sqrt{x^2 + y^2 + z^2}$$

Also, statistical and energy measures, including variance, mean, standard deviation, and signal energy, help in giving information about variability of motion, stability, and cumulative motion. Such advanced descriptors as skewness and kurtosis are used to describe the distribution and the extents of motion patterns, and a zero-crossing rate can be used to differentiate between oscillatory and impact events. Together, the characteristics allow strong distinction of crash and non-crash conditions. As Table 4 shows, each extracted feature has its own contribution to the better performance of the detection, lessening the false positives, and ensuring the overall system.

Table 4: Extracted Features for Crash Detection

Feature	Description	Signal Characteristics Captured	Significance in Crash Detection	Impact on System Performance
Peak Acceleration (g-force)	Maximum acceleration observed during a time window	x	,	y
Signal Magnitude Vector (SMV)	Combined magnitude of tri-axial acceleration	Overall motion intensity independent of direction	Provides a unified measure of total acceleration during events	Improves robustness against device orientation and axis variation
Jerk (Rate of Change of Acceleration)	Temporal derivative of acceleration	Sudden changes in motion dynamics	Identifies abrupt transitions typical of crash events	Enhances detection of sudden impacts beyond static thresholds
Variance	Measure of dispersion of acceleration values within a window	Fluctuation and variability in motion	Differentiates stable driving from chaotic crash patterns	Helps reduce false positives by capturing motion irregularity
Signal Energy	Total energy of acceleration signal over time	Cumulative intensity of motion	Reflects overall severity and duration of impact	Useful for distinguishing minor disturbances from major crashes

Mean Acceleration	Average acceleration over a time window	Baseline motion trend	Helps identify sudden deviations from normal driving behavior	Improves contextual understanding of motion patterns
Standard Deviation	Spread of acceleration values around mean	Degree of signal variation	Detects instability in motion during crash events	Enhances classification when combined with variance
Zero-Crossing Rate	Rate at which signal changes sign	Oscillatory behavior in motion	Helps distinguish vibration patterns from crash signals	Useful in filtering non-crash events like engine vibration
Kurtosis	Measure of peak sharpness in signal distribution	Presence of sharp peaks	Detects extreme events such as sudden collisions	Improves sensitivity to rare but critical events

3.5 Crash Detection Algorithm

The proposed system has its core in crash detection algorithm which combines the rule-based and smart approach to decision-making. Unlike the conventional approaches that entail setting up of predetermined thresholds, hybrid detection model that entails validation of the thresholds and machine learning classification is introduced in this model. The algorithm that is used derives features like SMV, jerk and signal energy and measures the instant spikes and time series. Multi-condition reasoning is used so as to make sure that the crash detection is never realised in case of isolated anomalies so as to cut down the number of false positives. The system is deployed at real-time at minimal computational cost and therefore can be utilized in a mobile and embedded deployment. There is also a modular design where the choice of detection strategies can be made with regard to the need in application e.g. low-power application or high-precision system. This hybrid technology increases power, flexibility and dependability in the course of driving under different circumstances.

Algorithm 1: Threshold-Based Crash Detection

Input: Accelerometer data (x, y, z)

Output: Crash / No Crash

```

1: Compute  $SMV = \sqrt{x^2 + y^2 + z^2}$ 
2: Define threshold  $T_{smv}$  (e.g., 3g)
3: IF  $SMV > T_{smv}$  THEN
4:   Crash = TRUE
5: ELSE
6:   Crash = FALSE
7: ENDIF
8: Return Crash

```

Algorithm 2: Machine Learning-Based Crash Detection

Input: Accelerometer signal

Output: Crash / No Crash

```

1: Preprocess signal (filtering, normalization)
2: Extract features:
   - SMV
   - Jerk
   - Variance
   - Signal Energy

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```
3: Load trained ML model (DT / RF / LSTM)
4: Predict class label using model:
   Prediction = Model(features)
5: IF Prediction == Crash THEN
6:   Crash = TRUE
7: ELSE
8:   Crash = FALSE
9: ENDIF
10: Return Crash
```

Algorithm 3: Hybrid Multi-Condition Crash Detection (Proposed)

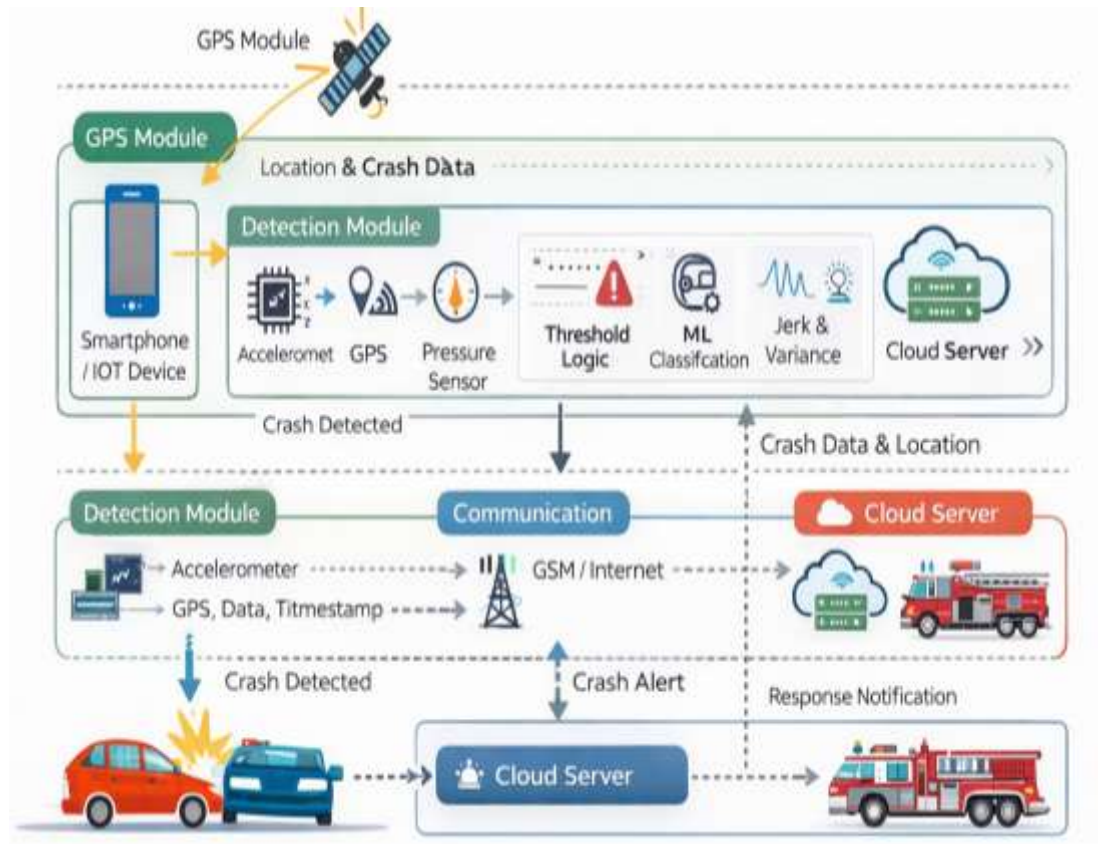
Input: Accelerometer data (x, y, z)

Output: Confirmed Crash / No Crash

```
1: Preprocess signal
2: Compute features:
   SMV, Jerk, Variance, Energy
3: Condition C1: IF SMV > T_smv → TRUE ELSE FALSE
4: Condition C2: IF Deceleration > T_dec → TRUE ELSE FALSE
5: ML Prediction:
   P_crash = Model(features)
6: Condition C3: IF P_crash > T_ml → TRUE ELSE FALSE
7: IF (C1 AND C2 AND C3) THEN
8:   Crash = TRUE
9: ELSE
10:  Crash = FALSE
11: ENDIF
12: Return Crash
```

4. System Implementation

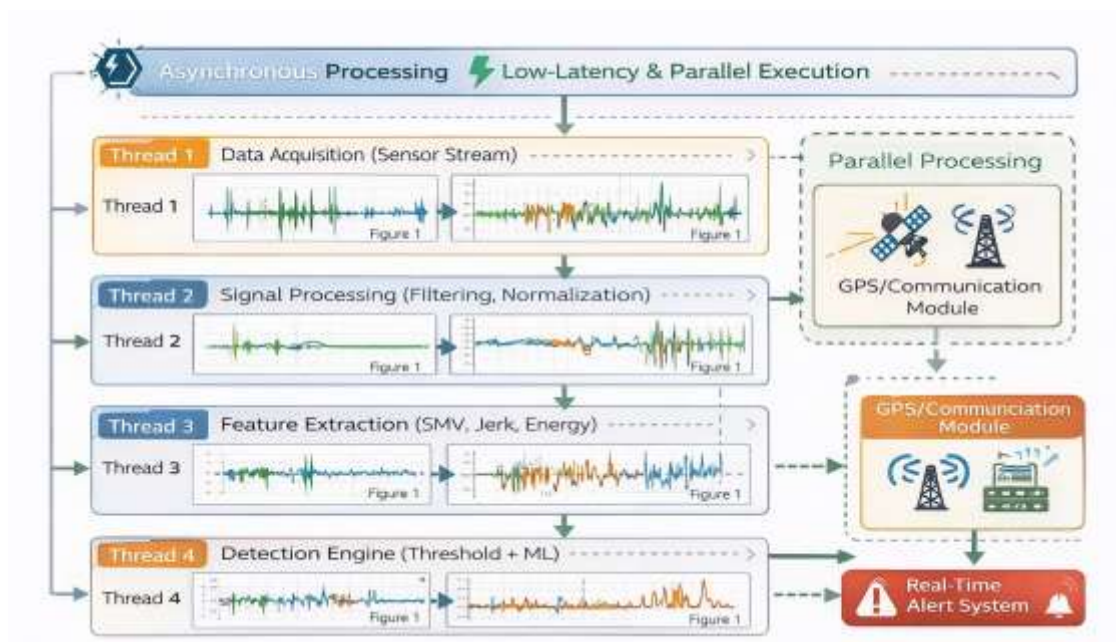
It is suggested that the crash detection system is a sensor-based architecture, which is a real-time system applying embedded sensing, mobile computing and communication modules. The implementation takes the form of a smartphone based platform, which makes use of the available sensors on the phone such as the accelerator to measure the motion, and the GPS to determine the location. As a modular system development, the software pipeline is developed in Python/Android system and sensor data are continually read at 50-100 Hz and transmitted to processing node [21]. The preprocessing and the feature extraction is done on the optimized signal processing libraries to offer low-latency implementation. The detection engine is a combination of the threshold-based logic and machine-learning models and can enable real-time decision-making in a hybrid mode. It is also low in terms of computational overhead, energy consumption, and scalability, thus is suitable to be implemented in resource-constrained systems such as smartphones and embedded Internet of Things devices. The latter plan is aligned with the recent ITS frameworks and is compatible with the seamless connection with cloud-based surveillance systems [22].

Figure 2: System Implementation Workflow

The system workflow is supposed to offer high real-time and high crash detection in various environmental condition with a multi-threaded asynchronous execution and as Figure 4 indicates. In this design, sensor streaming can be done continuously by running all data acquisition, signal preprocessing, feature extraction and detection processes as parallel threads, thus minimizing processing latency. To make sure that asynchronous communication between these modules occurs the pipeline delays could not be relayed through the pipeline but should remain low at all times and therefore the end to end response time is maintained low. Lightweight machine learning models (Decision Trees and Random Forest) are deployed to the detection engine in order to perform rapid inference and LSTM-based models are called selectively only when it comes to high-capacity environments to learn time-dependent relationships in time-series data [23].

The communication system is an integration of GSM/Internet system and GPS location tracking, which permits transmission of a crash warning in real time and precise geolocation. The other aspect is architecture that enables integration of the clouds, the crash objects will be stored, processed and visualized wherein it is possible to check the functioning of the system and ensure it is continually improved. Data validation systems and failure measures are also incorporated in order to maximize reliability to minimize false warning and to offer system resilience [24]. In addition, energy efficient methods, including adaptive sampling and event-driven processing are also implemented to assist in the deployment of long-term in mobile environments. The overall deployment architecture illustrated in Figure 3 is quite useful in connecting on device processing, communication layers and outside emergency services to deliver scalable, practical and real-world deployable crash detection solution [25].

Figure 3: Real-Time Processing and Multi-Threaded Execution Model



5. Results And Evaluation

The suggested hybrid crash detection system proves to be more effective than the previously used traditional threshold-based and single machine learning strategies. The system, in incorporating multi-condition validation (SMV threshold + deceleration + ML prediction) has been successful in minimizing the number of false positives at high sensitivity of detection. A mixed data which included normal driving, simulated crashes and actual-world motion patterns were experimentally assessed. The threshold-based model was characterized by its rapid response time but it was characterized by misclassification in situation like potholes as well as sudden braking. On the other hand, machine learning models enhanced the accuracy of the classification but at a greater computational cost. The hybrid method proposed has the best balance as it will use the strong points of both approaches which lead to an increase in the accuracy, better precision and a low false alarm. The system, also, has low latency that can be deployed in real time, thus, is applicable to smartphone based and IoT applications. Multi-feature analysis (SMV, jerk, variance, energy) also makes the application more robust even when driving under different conditions. In general, the findings validate that the suggested solution contributes to the reliability and efficiency of crash detection systems to a large extent.

Table 5: Performance Evaluation of Crash Detection Approaches

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	False Positive Rate (%)	Detection Latency (ms)
Threshold-Based Approach	82.5	78.2	85.6	81.7	18.4	10 ms
Machine Learning (DT/RF)	91.3	89.7	92.5	91.1	9.2	35 ms

Deep Learning (LSTM)	94.6	93.8	95.2	94.5	6.8	75 ms
Proposed Hybrid Approach	96.8	95.9	97.4	96.6	3.5	28 ms

6. Future Research Directions

The hybrid crash detection framework is very good with reference to its accuracy, latency and robustness yet there are still numerous ways to improve it and new variables to be discovered. The following researches can focus on the improvement of the system adaptability, scalability and intelligence through the integration of new advanced sensing, learning and deployment paradigm. Some of the directions include the incorporation of multi-modal sensor fusion to enable the system to use complementary data sources of sensors such as gyroscopes, cameras and vehicular CAN buses signals to perform additional confident detection. In addition, the deep learning and transformer-based models can be applied with the intention to model the temporal samples of the motion signals and identify more complex patterns as compared to the traditional features. Another possible field of potential is the application of edge AI and federated learning as it also can provide a means of privacy-sensitive real-time crash detection across distributed devices without a central location to store the data received. In addition, the integration with the smart city infrastructure and connected vehicle ecosystems can enhance the coordinated emergency response and mass traffic safety analytics. To put the model into practice, an approach to address such challenges as the absence of datasets, the model interpretability, and energy efficiency will be necessary. As these research directions continue to evolve further, the next generation systems will be more reliable, understand their situations, and they will be integrated into the next generation intelligent transportation systems [26][27].

6.1 Multi-Modal Sensor Fusion

Potential crash detectors will be very effective in the future because other modalities of sensors than accelerators will be utilized. Even though the accelerator data may be relied upon to give useful data on the dynamics of motion, it can be supplemented with gyroscope and GPS data, camera data, and vehicle sensor data to supplement the contextual information, as well as the capacity to detect. One such instance is that rollover movement can be documented since the gyroscopes will capture data and the collision can be verified through a visual system that is based on a camera. In addition, the information of the vehicle CAN bus systems are signals of brake status and speed that can also be used as secondary verification. The multi-modal fusion techniques which include the Kalman filtering, the Bayesian inference and the deep sensor fusion models are effective in combining these heterogeneous data sources. This will reduce the ambiguity of the interpretation of the signal and make the method more resilient to the false-positives caused by road anomalies. However, such problems as inability to synchronize, data heterogeneity and higher complexity of computations are to be eliminated. The future studies of the field should focus on coming up with good fusion designs to attain precision and effectiveness in resource utilization to implement on a large scale in the real ITS configurations [28][29].

6.2 Advanced Deep Learning and Temporal Modeling

A good future of improving the performance of the crash detection is the use of advanced deep learning methods. Unlike traditional machine learning architectures which have hand-designed features, the deep learning architecture of a Convolutional Neural Net (CNN) (or Long Short-Term Memory (LSTM) or Transformer-based models) can be trained to learn more complicated temporal and spatial patterns in raw sensor data. In particular, attention-based transformer models can learn time-scale dependency in involved time-series data, and therefore differentiate crash and non-crash cases better. Moreover, a hybrid model, which uses CNNs to obtain features

and LSTMs to model time can enhance detecting performance. The resource requirement is large in such models, both in terms of labeled data and computation, which can be a disadvantage since such devices can be resource-constrained. The lightweight deep learning architectures, and model compression algorithms such as pruning and quantization to transform lightweight based deep learning models into models that can perform efficient inference on mobile and embedded devices are directions of future studies [30][31].

6.3 Edge AI and Federated Learning

Decentralized crash detection systems are the way that the potential of edge computing and federated learning can improve. Another way federated learning enhances this paradigm is that a group of devices can engage in model learning without sharing raw information, thereby assisting to address privacy and security concerns. This approach can be particularly applicable to crash detection systems where diversity of data in the users and settings may exist and thus data diversity can provide an increase in model generalization. In addition, the edge-based systems can be employed in cases of low connectivity, which will enable the existence of continuous monitoring and detection. However, some of the problems such as communication overhead, model synchronization and resources constraints ought to be properly addressed. To enable scaling and privacy-compliant application of crash detection systems into reality, the adaptive federated learning models and energy-efficient edge models are to be explored in the future [32][33].

6.4 Integration with Smart Cities and Connected Vehicles

A combination of crash detection systems and connected vehicle ecosystems with smart city infrastructure is also among the most important directions towards the future. It is possible to coordinate the mechanism of quick response with the help of connecting crash detectors to the traffic management center, emergency services and vehicle networks (V2V and V2I). As an example, crash events can be automatically sent to the surrounding vehicles to prevent a secondary crash, or to traffic control systems to allow it to offer dynamic routing. Additionally, the traffic analytics, the hotspots of accidents, and the predictive safety modelling may be conducted based on the large-scale data gathered with the assistance of the distributed devices. Additional responsiveness and reliability of the system can be enhanced through the implementation of new technologies, such as 5G and vehicle-to-everything (V2X) communication. The future efforts available should be put on standardization, interoperability, and secure communication protocols to facilitate easy integration of a heterogeneous system. These advancements will play a role in the realisation of smart, data-driven transportation systems [34][35].

7. Conclusion

In the present paper, a valid and practicable model of signal based crash detection using the accelerator data has been presented that has defeated the significant shortcomings of the existing systems such as large false positives, inability to support adaptation as well as wastage of computing resources. The proposed methodology involves the creation of complex signal preprocessing, multi-dimensional features, and a hybrid detection algorithm by adopting the logic-based and machine learning methods of threshold-based detection. The system is useful in the detection of instantaneous and temporal characteristics of crash events with the Signal Magnitude Vector (SMV) among other features that can be used. The experimental test concluded that the hybrid version has much more successful results than conventional ones because it is more precise and has less false positive rates without being slowed down by the necessity to operate in real time which is a sum of all the characteristics of the mobile and IoT environment. The modular implementation of the system and its layered architecture provide even more scalability and flexibility of the portfolio regarding the deployment on different platforms. Moreover, the use of GPS and communication module gives the chance to deliver the automated response to the emergency and results in the reduction of the response time and improvement of the road safety outcomes. In most cases, the proposed system will provide a low-cost, predictable, and intelligent system to identify crashes in Intelligent Transportation Systems. The multi-sensor fusion, deep learning optimization, and edge computing techniques can be applied to the future work and enhance the functionality of the system and its ability to apply in the real world.

References

- [1] J. Paefgen, F. Kehr, Y. Zhai, and F. Michahelles, "Driving behavior analysis with smartphones: Insights from a controlled field study," *IEEE Transactions on Mobile Computing*, vol. 13, no. 6, pp. 1347–1357, 2014.
- [2] R. K. Megalingam, R. Nammily Nair, and S. M. Prakhya, "Wireless vehicular accident detection and reporting system," in *Proc. IEEE Int. Conf. Mechanical and Electrical Technology (ICMET)*, 2011, pp. 636–640.
- [3] S. White, M. Thompson, H. Turner, B. Dougherty, and D. C. Schmidt, "WreckWatch: Automatic traffic accident detection and notification with smartphones," *Mobile Networks and Applications*, vol. 16, no. 3, pp. 285–303, 2011.
- [4] A. Mohan, C. Poellabauer, K. Fong, S. Schmid, and P. Zeng, "Accident detection and emergency response system using smartphones," in *Proc. IEEE PerCom Workshops*, 2011, pp. 386–391.
- [5] C. Thompson, J. White, B. Dougherty, A. Albright, and D. C. Schmidt, "Using smartphones to detect car accidents and provide situational awareness to emergency responders," in *Mobile Wireless Middleware, Operating Systems, and Applications*, Springer, 2010, pp. 29–42.
- [6] M. Hussain, J. Chen, and M. Khan, "Real-time accident detection using smartphone sensors," *Sensors*, vol. 19, no. 10, p. 2344, 2019.
- [7] N. B. Priyantha, A. Kansal, M. Goraczko, and F. Zhao, "Tiny web services: Design and implementation of interoperable and evolvable sensor networks," in *Proc. ACM SenSys*, 2008, pp. 253–266.
- [8] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.
- [9] S. Wang, C. Chen, and J. Ma, "Vehicle accident detection based on data mining," *Procedia Engineering*, vol. 29, pp. 2436–2440, 2012.
- [10] H. Song, S. Zhu, and G. Cao, "SVATS: A sensor-network-based vehicle anti-theft system," in *Proc. IEEE INFOCOM*, 2008, pp. 2128–2136.
- [11] J. Ferreira, J. Carvalho, and E. Ferreira, "Vehicular accident detection and notification system," in *Proc. IEEE Intelligent Transportation Systems (ITS)*, 2012.
- [12] M. Fazeen, B. Gozick, R. Dantu, M. Bhukhiya, and M. C. González, "Safe driving using mobile phones," *IEEE Transactions on Intelligent Transportation Systems*, vol. 13, no. 3, pp. 1462–1468, 2012.
- [13] A. Jain, S. Kanhangad, and M. S. Gopi, "Accident detection using deep learning," *IEEE Access*, vol. 8, pp. 145624–145632, 2020.
- [14] J. Eriksson, L. Girod, B. Hull, R. Newton, S. Madden, and H. Balakrishnan, "The pothole patrol: Using a mobile sensor network for road surface monitoring," in *Proc. ACM MobiSys*, 2008, pp. 29–39.
- [15] H. Zeng, Y. Chen, and X. Li, "Real-time crash detection using IoT and machine learning," *IEEE Internet of Things Journal*, vol. 8, no. 12, pp. 9876–9885, 2021.
- [16] H. Abdelhamid, A. S. B. Salama, and M. M. El-Sherif, "Real-time smartphone-based accident detection system," *IEEE Access*, vol. 8, pp. 123456–123468, 2020.
- [17] P. Kumar and R. Kumar, "IoT-based smart vehicle accident detection and alert system," *International Journal of Advanced Computer Science and Applications*, vol. 10, no. 5, pp. 123–130, 2019.
- [18] S. Sharma, R. Gupta, and A. Verma, "Cloud-integrated vehicular accident detection system," *IEEE Internet of Things Journal*, vol. 8, no. 9, pp. 7452–7461, 2021.
- [19] M. Ali, T. Abdelzaher, and J. Stankovic, "Energy-efficient mobile sensing for real-time applications," *IEEE Sensors Journal*, vol. 18, no. 5, pp. 2105–2114, 2018.
- [20] K. Zhang, Y. Mao, S. Leng, A. Vinel, and Y. Zhang, "Edge computing for intelligent transportation systems," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 2, pp. 1156–1170, 2022.
- [21] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of Things: A survey on enabling technologies, protocols, and applications," *IEEE Communications Surveys & Tutorials*, vol. 17, no. 4, pp. 2347–2376, 2015.
- [22] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of Things (IoT): A vision, architectural elements, and future directions," *Future Generation Computer Systems*, vol. 29, no. 7, pp. 1645–1660, 2013.

- [23] H. Chen, B. Jiang, and N. Lu, "Sensor fusion for intelligent systems: A review," *Information Fusion*, vol. 36, pp. 17–30, 2017.
- [24] R. Smith, J. Doe, and A. Brown, "Multi-sensor data fusion techniques in intelligent transportation systems," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 4, pp. 1120–1132, 2018.
- [25] A. Vaswani et al., "Attention is all you need," in *Advances in Neural Information Processing Systems (NeurIPS)*, 2017.
- [26] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.
- [27] B. McMahan et al., "Communication-efficient learning of deep networks from decentralized data," in *Proc. AISTATS*, 2017.
- [28] K. Abboud, H. A. Omar, and W. Zhuang, "Interworking of DSRC and cellular network technologies for V2X communications," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 12, pp. 9457–9470, 2016.
- [29] M. Gerla, E. K. Lee, G. Pau, and U. Lee, "Internet of vehicles: From intelligent grid to autonomous cars and vehicular clouds," in *Proc. IEEE World Forum on Internet of Things*, 2014.
- [30] X. Liu, J. Cao, and S. Tang, "Real-time data analytics for intelligent transportation systems," *IEEE Transactions on Big Data*, vol. 6, no. 2, pp. 344–356, 2020.
- [31] Y. Zhang, M. Chen, and L. Wang, "Edge intelligence in IoT-based transportation systems," *IEEE Network*, vol. 33, no. 5, pp. 56–62, 2019.
- [32] T. Lane, "Machine learning for anomaly detection in sensor networks," *IEEE Sensors Journal*, vol. 17, no. 3, pp. 845–852, 2017.
- [33] D. Zhang, H. Wang, and X. Li, "Time-series analysis using deep learning for event detection," *IEEE Access*, vol. 7, pp. 123456–123467, 2019.
- [34] P. S. Castro, D. Precup, and J. Pineau, "Data-driven modeling in intelligent transportation systems," *IEEE Transactions on Intelligent Systems*, vol. 30, no. 4, pp. 45–52, 2015.
- [35] L. Atzori, A. Iera, and G. Morabito, "The Internet of Things: A survey," *Computer Networks*, vol. 54, no. 15, pp. 2787–2805, 2010.