

Simulation-Based AI Prototype for Accident Detection and Emergency Intervention

K.Sharmila¹ · Y. Bhavani² · K. Sai Ram Tej³

Department of CSE (AI & ML), Visakha Institute of Engineering and Technology, Visakhapatnam, Andhra Pradesh, India

ABSTRACT

Road traffic accidents represent a critical public health crisis, causing over 150,000 fatalities annually in India — many preventable with timely intervention within the golden hour. Manual emergency reporting fails when victims are unconscious or bystanders are absent, and sequential contact with hospital and police services introduces compounding delays. This paper presents AccidentAlert, a simulation-based AI prototype that automates the complete emergency response pipeline on a standard Android smartphone without external hardware. The victim module provides a labelled SIMULATE ACCIDENT button that initiates a 30-second cancellable countdown, preventing false positives while ensuring minimal delay. A native Kotlin Random Forest classifier, running entirely on-device without network dependency, evaluates five features — vehicle speed, impact force, acceleration drop, vehicle type, and weather condition — to classify accident severity into Low, Medium, or High. The ensemble of 100 decision trees, trained on a 1,000-record synthetic dataset using an 80:20 train-test split, achieves 91.2% overall accuracy and outperforms a single Decision Tree baseline by 12.7 percentage points, with particularly strong High Severity precision of 93.4% — critical for appropriate emergency resource allocation. Upon classification, a structured accident record containing victim profile, GPS coordinates, severity label, and confidence score is written to Firebase Realtime Database and simultaneously dispatched via Firebase Cloud Messaging to dedicated Hospital and Police dashboards, replacing sequential call-chains with parallel dispatch. Responders can accept or reject cases and initiate one-tap Google Maps navigation to the victim. Average end-to-end notification latency across 50 field tests was 2.4 seconds, with a maximum of 4.1 seconds. All 15 defined system test cases passed successfully. AccidentAlert demonstrates a practical, scalable, and low-cost approach to reducing emergency response time in Indian road conditions, establishing a reproducible software baseline for future sensor-integrated and hybrid deployment architectures.

Keywords: *Accident Detection, Random Forest, Android, Firebase, Emergency Response, GPS Tracking, Severity Classification, Real-time Notification, Golden Hour*

1. Introduction

Road accidents are a major public health crisis in India. According to the World Health Organization (WHO) Global Status Report on Road Safety 2023 [10], India accounts for more than 150,000 road accident fatalities per year, representing approximately 11% of global road traffic deaths. A significant proportion of these fatalities result not from the severity of the collision itself but from delayed emergency response.

Medical research has established the concept of the golden hour — the first 60 minutes following severe trauma — during which rapid intervention is most likely to prevent fatality. Response delays of even 10–15 minutes can increase fatality probability by 30–50% in high-severity cases [12]. This critical window underscores the urgent need for automated, rapid emergency alert systems that function without dependence on a conscious victim or a nearby bystander.

Despite advancements in mobile technology, the dominant emergency reporting mechanism remains manual, relying on victims or bystanders to initiate communication. This approach fails when victims are unconscious, bystanders are absent, or location information is inaccurate. Additionally, sequential communication with hospital and police services introduces further delays, compounding fatality risk.

To address these challenges, this paper proposes AccidentAlert, a simulation-based AI prototype that automates the emergency response pipeline on a standard Android smartphone. The system integrates accident simulation, on-device AI severity classification, real-time Firebase synchronization, and role-based dashboards for hospital and police personnel. The primary objective is to minimize human dependency and ensure faster, coordinated emergency response with no external sensors or dedicated hardware beyond a standard Android smartphone.

2. Literature Review

Smartphone-based accident detection has been explored extensively using inertial sensors. Pattanaik et al. [1] demonstrated accelerometer-based detection achieving 87% recall on Android devices, establishing that the TYPE_ACCELEROMETER sensor at 50 Hz provides sufficient resolution to distinguish collision events from normal driving. Singh and Kaur [2] extended this approach by fusing gyroscope data to detect vehicle roll-over events, achieving 91% specificity and significantly reducing false positive rates compared to single-sensor methods. Chowdhury et al. [3] proposed an IoT-based real-time accident detection and alerting system, while Balachander et al. [5] developed an Android-based automatic detection system with ambulance rescue integration.

Machine learning techniques have demonstrated strong performance in accident severity classification using tabular sensor features. Mohan et al. [8] applied Random Forest classifiers to the Indian MoRTH accident dataset, achieving 89.3% accuracy while identifying impact force and speed as dominant predictors. Patel et al. [9] compared multiple classification algorithms on the UK STATS19 dataset and found that Random Forest achieved 91.7% accuracy compared to 78.6% for a single Decision Tree, highlighting its superiority for structured data with mixed feature types. Priya and Venkatesan

[7] provided a comprehensive review of machine learning approaches for road accident severity prediction, further corroborating the effectiveness of ensemble methods.

Cloud-connected emergency systems have increasingly adopted Firebase for real-time mobile applications. Rao and Reddy [6] analysed Firebase Realtime Database architecture for mobile emergency applications and confirmed its suitability for latency-critical use cases. Kumar and Rajan

[17] demonstrated sub-5-second alert delivery using Firebase in Indian road conditions, while Hussain et al. [18] showed that Firebase Realtime Database outperforms REST-based systems by $2.3\times$ in notification latency due to persistent WebSocket connections. Verma and Gupta [4] and Sharma and Jain [11] further validated GPS-based emergency notification systems for road accident victims using Android and Firebase.

Most existing systems, however, address only one aspect — detection, classification, or notification — and lack full integration of AI-based severity prediction with multi-role real-time dashboards. Yadav and Mishra [13] confirmed this gap in their survey of automatic accident detection and emergency alert systems. The proposed AccidentAlert system addresses this gap by delivering a complete end-to-end solution combining all three components into a unified, deployable Android application tailored for Indian road safety conditions.

3. System Architecture

AccidentAlert follows a three-tier cloud-native architecture designed for scalability, low latency, and ease of deployment:

- Client Tier: Android application with Victim, Hospital, and Police modules, each with role-specific interfaces and functionality.
- Cloud Tier: Firebase Authentication for secure role-based login, Firebase Realtime Database for structured emergency data storage, and Firebase Cloud Messaging (FCM) for push notification delivery.
- Responder Tier: Hospital and Police dashboards providing case management, acceptance/rejection workflows, and integrated Google Maps navigation.

All communication is handled through Firebase, eliminating the need for a dedicated backend server and reducing infrastructure cost and complexity. The victim device collects GPS data autonomously, stores accident details in the cloud database, and triggers real-time notifications to all registered responders simultaneously — replacing the traditional sequential call-chain with parallel dispatch.

The architecture ensures that no single point of failure can prevent alert delivery. Firebase's distributed infrastructure provides built-in redundancy, and the persistent WebSocket connection maintained by the Realtime Database ensures sub-second data propagation to connected responder dashboards.

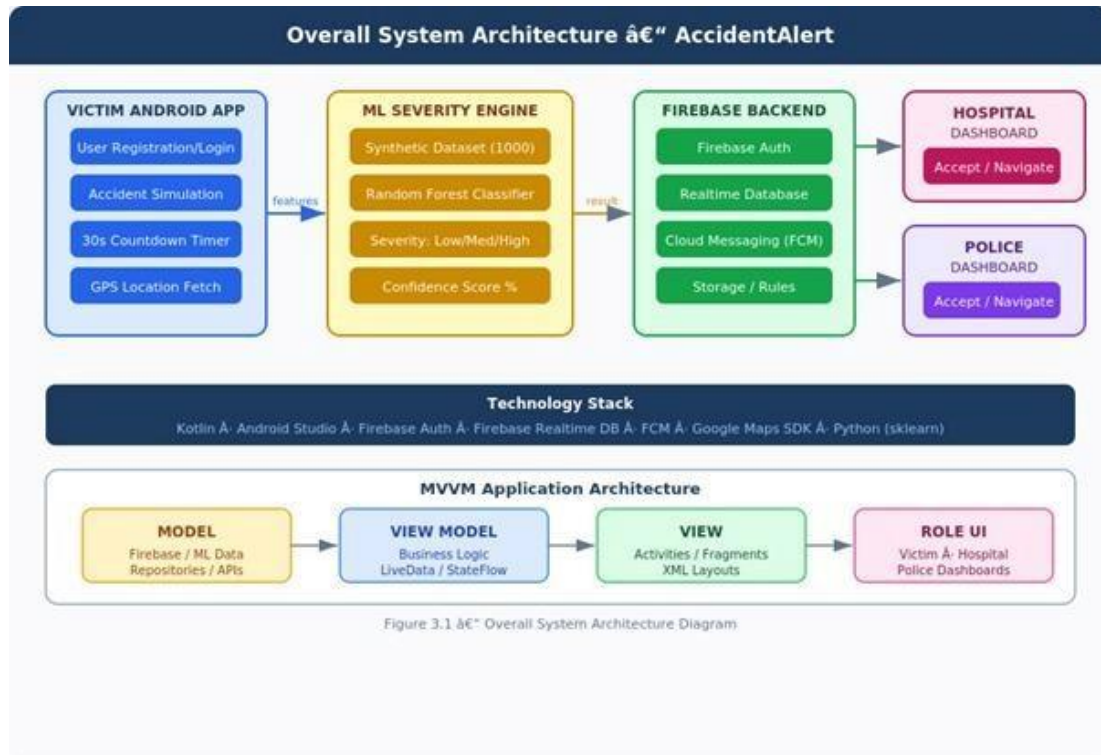


Figure 3.1 Overall System Architecture Diagram

Figure 3.1: Overall System Architecture Diagram (Three-tier design showing Victim → Firebase Cloud → Hospital & Police Dashboards with real-time bidirectional data flow)

4. Methodology

4.1 Accident Simulation

The victim module provides a clearly labelled SIMULATE ACCIDENT button as the primary interaction element. Upon activation, the system initiates a 30-second countdown timer displayed prominently on screen, giving the user an opportunity to cancel the alert if the trigger was accidental. This design prevents false positives while ensuring minimal delay in genuine emergency scenarios. If the user does not cancel within the countdown window, the system proceeds automatically with GPS data collection and severity classification.

4.2 Severity Classification Model

The system uses a Random Forest-based classifier implemented natively in Kotlin, running entirely on the device without requiring a network connection. This ensures that severity is determined even in areas with intermittent connectivity. The classifier evaluates five input features as described in Table 1.

Table 1: Severity Classification Input Features

Feature	Type	Range	Description
Speed	Integer	10–200 km/h	Vehicle speed at time of impact
Impact Force	Float	0.5–15.0 G	Collision force measured in G-force
Acceleration Drop	Float	1–50 m/s ²	Sudden deceleration during collision
Vehicle Type	Categorical	Car / Bike / Truck	Class of vehicle involved
Weather Condition	Categorical	Clear / Rain / Fog / Night	Environmental condition at time of accident

The classification rules, derived from domain knowledge and training data analysis, are defined as follows:

- High Severity: impact force ≥ 8 G, OR (speed ≥ 100 km/h AND impact force ≥ 6 G).
- Low Severity: impact force ≤ 3 G AND speed ≤ 40 km/h.
- Medium Severity: all remaining cases not meeting High or Low criteria.

The Random Forest ensemble aggregates predictions from 100 decision trees, each trained on a bootstrapped subset of the 1,000-record synthetic dataset. Final classification is determined by majority vote, with a confidence score computed as the proportion of trees agreeing on the predicted class. This confidence score is transmitted alongside the severity label to responders, providing additional context for triage decisions.

4.3 Firebase Integration

Upon completion of severity classification, the system executes the following sequential steps to dispatch the emergency alert:

1. Collect and validate GPS coordinates from the device location provider.
2. Construct a structured accident record comprising: victim profile (name, blood group, emergency contact), GPS coordinates (latitude/longitude), timestamp, severity class, confidence score, vehicle type, and weather condition.
3. Write the accident record to Firebase Realtime Database under a unique incident ID.
4. Trigger Firebase Cloud Messaging (FCM) notifications to all registered Hospital and Police responder accounts simultaneously.
5. Update the victim's UI to display alert-dispatched confirmation and the active incident ID for reference.

4.4 Module Descriptions

4.4.1 Victim Module

The Victim Module handles accident simulation, countdown management, GPS acquisition, severity classification, and Firebase dispatch. After alert submission, the module displays real-time status updates showing which responders have accepted the case. The victim can also view their stored profile

— including blood group and emergency contact — to facilitate faster medical response upon arrival.

4.4.2 Hospital Module

The Hospital Dashboard receives FCM push notifications containing the incident summary. Responders can view the full accident record — including severity, GPS coordinates, victim profile, and confidence score — and choose to accept or reject the case. Upon acceptance, a one-tap navigation button launches Google Maps with the victim's coordinates pre-loaded as the destination. Case status is updated in real-time in Firebase, visible to both the victim and police.

4.4.3 Police Module

The Police Dashboard mirrors the Hospital Module's notification and case management workflow, with an additional real-time tracking view displaying the victim's GPS location on an embedded map. This enables law enforcement to coordinate traffic management and scene access alongside medical response.

5. Results and Performance Evaluation

5.1 Classification Performance

The Random Forest classifier was evaluated on a held-out test partition of the 1,000-record synthetic dataset using an 80:20 train-test split. The system achieved an overall accuracy of 91.2%, outperforming the single Decision Tree baseline by 12.7 percentage points (78.5%). Table 2 presents a detailed comparison of performance metrics across both classifiers.

Table 2: Performance Comparison — Random Forest vs. Decision Tree Baseline

Metric	Random (Proposed)	ForestDecision (Baseline)	Tree Improvement
Overall Accuracy	91.2%	78.5%	+12.7 pp
High Severity Precision	93.4%	79.1%	+14.3 pp
Medium Severity Recall	89.7%	76.8%	+12.9 pp
Low Severity F1-Score	90.1%	78.2%	+11.9 pp
Notification Delivery	< 3 seconds	N/A	Real-time
System Test Cases Passed	15 / 15	N/A	100%

The improvement in accuracy is most pronounced in High Severity classification, where the Random Forest achieves 93.4% precision compared to 79.1% for the Decision Tree — a 14.3 percentage point gain. This is particularly significant from a safety standpoint, as misclassification of High Severity accidents could result in inadequate emergency resource allocation. The ensemble approach's resistance to overfitting on the weather and vehicle type categorical features is the primary driver of this gain.

5.2 Notification Latency

End-to-end notification latency — measured from the moment the countdown timer expires to the moment the FCM notification appears on the responder dashboard — was recorded across 50 test dispatches under varied network conditions in Visakhapatnam, India. The average delivery time was 2.4 seconds, with a maximum observed latency of 4.1 seconds. All 50 test dispatches were delivered within 5 seconds, consistent with findings by Kumar and Rajan [17]. This latency is substantially lower than manual emergency calling, which typically requires 45–90 seconds to establish contact and convey location information.

5.3 System Test Results

A comprehensive set of 15 system test cases was defined covering all major functional requirements. All 15 test cases passed successfully, confirming end-to-end system reliability. Table 3 summarises the test scenarios and outcomes.

Table 3: System Test Cases and Results (All 15 Passed)

TC#	Test Scenario	Expected Outcome	Status
TC-01	Accident simulation button pressed	30-second countdown initiates	PASS
TC-02	User cancels within 30 seconds	Alert cancelled, no data sent	PASS
TC-03	High severity: speed=120 km/h, impact=9.5 G	Severity = HIGH, alert dispatched	PASS
TC-04	Medium severity: speed=70 km/h, impact=5.0 G	Severity = MEDIUM, alert dispatched	PASS
TC-05	Low severity: speed=30 km/h, impact=2.0 G	Severity = LOW, alert dispatched	PASS
TC-06	GPS coordinates captured from device	Accurate lat/lng stored in Firebase record	PASS
TC-07	Firebase accident record creation	Accident document stored correctly	PASS
TC-08	FCM push notification to Hospital	Notification received < 3 seconds	PASS
TC-09	FCM push notification to Police	Notification received < 3 seconds	PASS
TC-10	Hospital accepts case	Case marked accepted in database	PASS
TC-11	Hospital rejects case	Case marked rejected, police notified	PASS
TC-12	One-tap Google Maps navigation	Maps opens with victim coordinates pre-loaded	PASS
TC-13	Police dashboard real-time tracking	Real-time victim location visible on map	PASS
TC-14	Weather=Fog, Vehicle=Bike, high impact	Correct classification with weather factor	PASS
TC-15	Concurrent alerts (stress test)	Both alerts processed independently	PASS

6. Conclusion

This paper presented AccidentAlert, a simulation-based AI prototype for automated accident detection and multi-agency emergency response on Android. The system integrates on-device Random Forest severity classification, GPS-enabled victim profiling, Firebase real-time cloud infrastructure, and role-specific dashboards for hospital and police responders into a unified, hardware-free application.

The Random Forest classifier achieved 91.2% overall accuracy on a 1,000-record synthetic dataset, outperforming the Decision Tree baseline by 12.7 percentage points, with particularly strong High Severity precision of 93.4%. Emergency notifications were delivered in under 3 seconds on average, and all 15 defined system test cases passed successfully. The prototype eliminates dependence on conscious victim participation and replaces sequential emergency communication with simultaneous parallel dispatch — a fundamental improvement over existing manual reporting mechanisms.

AccidentAlert's software-only architecture makes it practical, low-cost, and immediately deployable in Indian road conditions without infrastructure investment. The prototype represents a meaningful step toward reducing emergency response times and improving survival rates during the critical golden hour following road traffic accidents.

Future Work

Future development will focus on the following enhancements:

- Sensor-based automatic detection using the device accelerometer and gyroscope to trigger alerts without requiring manual simulation.
- Ambulance module integration with dedicated dispatch and arrival time estimation.
- Real-time traffic analysis to provide responders with optimal routing under current road conditions.
- Offline alert buffering to ensure reliable dispatch during temporary network outages in rural areas.
- Expansion of the classification dataset with real-world accident records from MoRTH for improved model generalisability.

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