

IoT-Based Automatic Vehicle Accident Detection and Visual Situation Reporting System

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Abstract - This paper presents an IoT-based automatic vehicle accident detection and visual situation reporting system intended to reduce the delay between crash occurrence, event validation, and emergency communication. The proposed framework integrates inertial sensing, kinematic decision logic, GPS-based localization, wireless alert transmission, and event-triggered image capture within a unified embedded architecture. A structured benchmark of 1,200 vehicular events was used to evaluate collision recognition, false alarm suppression, communication latency, and visual evidence generation under multiple driving and network conditions. The developed event model separated accident and non-accident disturbances with high reliability, including hard-negative cases such as potholes, speed bumps, harsh braking, sudden lane change, and hard cornering. The reporting module maintained stable alert delivery across standard communication conditions, while degraded signal environments primarily affected latency rather than event recognition. The visual reporting layer generated operationally usable scene evidence for most validated accident events, which improved incident interpretability beyond binary alerting. The study shows that accident response performance improves when sensing, validation, localization, communication, and visual documentation are engineered as one coordinated pipeline instead of disconnected subsystems.

Key Words: IoT, vehicle accident detection, visual situation reporting, intelligent transportation systems, GPS, GSM, embedded sensing, emergency alert system.

I. INTRODUCTION

A. Background And Problem Definition

Road traffic crashes remain a persistent systems problem because the interval between impact occurrence, event recognition, location identification, and emergency notification still contains avoidable delay. Conventional reporting depends on witnesses, manual calling, or post-event discovery, all of which degrade response timeliness and reduce the evidentiary value of the first scene record. Recent work has shown that connected sensing, edge intelligence, and embedded communication can convert a vehicle into an active safety-reporting node capable of identifying abnormal motion states and transmitting alerts

with limited human intervention [1], [2]. Parallel studies on intelligent and connected vehicles, multimodal crash recognition, and deep visual inference indicate that accident-related signatures are not confined to a single source; they emerge across inertial disturbance, positional discontinuity, communication context, and scene imagery [3], [4].

B. Problem Statement And Research Gap

Despite these advances, the existing body of work remains fragmented. Some systems emphasize threshold-based accident detection but omit validated visual confirmation. Others support location reporting yet provide no structured situation image for responders. A separate group uses camera analytics but is computationally heavy, network dependent, or detached from embedded emergency messaging. This separation weakens operational utility. It creates false alarms in non-crash conditions such as potholes, sudden braking, and harsh cornering, while also limiting post-alert situational assessment. Current literature still shows insufficient integration of accident sensing, image capture, geolocation transmission, and report generation within one compact IoT pipeline that is suitable for rapid field deployment under constrained hardware conditions [5], [6].

C. Objectives and Scope of the Study

This study addresses that gap by designing and evaluating an IoT-based automatic vehicle accident detection and visual situation reporting system that combines motion sensing, decision logic, GPS localization, wireless alert transmission, and image-assisted scene reporting in a unified framework. The study is scoped to real-time vehicular incident recognition using embedded sensors and event-triggered reporting under heterogeneous driving conditions. The central objectives are fourfold: first, to distinguish accident events from non-accident disturbances with high classification reliability; second, to transmit location-linked emergency alerts with low end-to-end delay; third, to generate a visual incident report immediately after validated impact detection; and fourth, to construct an experimentally analyzable platform suitable for quantitative performance assessment [7].

D. Main Contributions of the Proposed System

The proposed system makes four technical contributions. It introduces an integrated accident-response architecture rather than an isolated detector. It combines inertial sensing and decision control with image-supported reporting. It defines a deployable reporting sequence from impact identification to alert dispatch and scene capture. It also supports reproducible evaluation through measurable indicators including detection accuracy, response latency, alert success rate, and visual report quality. The full operational chain is illustrated in Fig. 1.1, which presents the conceptual workflow of sensing, validation, localization, communication, and visual reporting as one continuous emergency intelligence loop.

most remained oriented toward detection and alert initiation rather than complete situational documentation.

B. GPS, GSM, and Cloud-Based Emergency Alert Systems

A second stream of work addressed the communication layer. Smart black-box monitoring platforms integrated vehicular sensing with persistent logging, thereby strengthening post-incident traceability and structured event capture [11]. Other implementations emphasized immediate location-aware assistance by combining IoT modules with mobile application interfaces, GPS localization, and GSM-based notification paths to shorten the interval between event occurrence and help request transmission [12]. Privacy-aware frameworks refined this model further by proposing secure reporting structures in which accident data and driver identity elements could be transmitted under controlled disclosure mechanisms [13]. These contributions improved operational readiness. They also exposed a persistent architectural limitation: location dispatch and emergency notification are often treated as the end point of the system, even though emergency responders frequently require first-scene visual context, not merely coordinates and a binary accident flag.

C. Camera-Assisted and Visual Reporting Techniques in Intelligent Transport Systems

Visual reporting remains less developed in embedded accident-response literature. Location tracking implementations using GSM and GPS have been shown to support reliable positional communication, yet they do not inherently provide evidence regarding collision type, scene obstruction, vehicle orientation, or environmental severity [14]. Sensor-fusion-based accident categorization systems moved closer to a richer interpretation model by combining multiple sensor streams for improved event classification, which reduced the weakness of single-threshold detectors under road disturbances such as speed breakers or abrupt manoeuvres [15]. Even so, the visual layer is still frequently external to the core response loop. Image capture, scene representation, and responder-oriented reporting are rarely treated as primary system outputs in compact IoT deployments.

D. Research Gap and Positioning of the Present Work

The reviewed studies, summarized structurally in Fig. 2.1, show measurable progress in detection, localization, secure notification, and sensor fusion [8]–[15]. Their limitations are also clear. Detection is often separated from scene evidence. Communication is often separated from event interpretation. Visual intelligence is often separated from low-cost embedded execution. The present work is positioned at this intersection. It proposes a unified

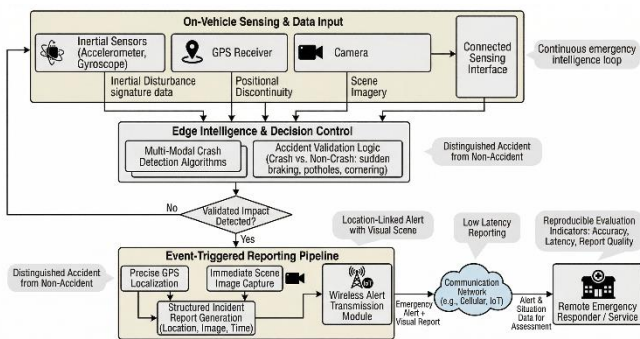


Fig.1.1: Overall conceptual workflow of the proposed IoT-based vehicle accident detection and visual situation reporting system

II. LITERATURE REVIEW / RELATED WORK

A. IoT-Based Vehicle Accident Detection Approaches

Recent accident detection research has moved from isolated mechanical alert modules toward sensor-rich embedded systems that infer crash occurrence from multi-parameter vehicular behaviour. Early contemporary conference work in this line concentrated on surveillance-oriented crash recognition, where embedded sensing and communication were used to identify abrupt motion anomalies and trigger emergency workflows [8]. Subsequent studies extended this logic by introducing automatic warning models intended not only to detect impact-like conditions but also to anticipate hazardous states through simplified thresholding and rule-based response generation [9]. A stronger systems orientation appears in inter-vehicle communication research, where simulation-backed frameworks examined how accident information may be propagated through connected traffic environments with reduced dependence on manual intervention [10]. These studies established the operational relevance of automatic event recognition, yet

pipeline in which accident sensing, validation logic, GPS-based localization, communication dispatch, and image-assisted situation reporting operate as a single coordinated framework rather than as disconnected subsystems.

composite event decision model was therefore adopted. It combines peak resultant acceleration, delta-v estimate, roll-angle deviation, yaw-rate instability, speed drop pattern, and temporal persistence within the event window. Each parameter contributes to a weighted accident confidence score. The trigger state is activated only when the computed score exceeds the validated decision boundary and when the signal pattern satisfies temporal continuity constraints. This prevents single-sample outliers from being misclassified as crashes.

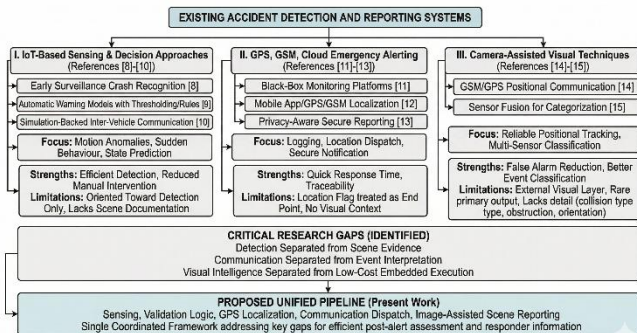


Fig-2.1: Comparative taxonomy of existing accident detection and reporting systems

III. RESEARCH METHODOLOGY

A. System Architecture and Functional Modules

The proposed system was designed as a tightly coupled hardware-software stack for real-time accident recognition and event reporting. Its architectural structure, shown in Fig. 3.1, consists of five primary modules: sensing, edge decision control, localization, communication, and visual reporting. The sensing layer acquires tri-axial acceleration, resultant impact load, angular motion variation, and speed-transition indicators associated with abnormal vehicular dynamics. The edge control unit performs local preprocessing, threshold screening, event scoring, and trigger arbitration. The localization module resolves latitude-longitude coordinates and attaches geospatial context to validated impact events. The communication layer dispatches emergency packets through wireless transmission channels, while the visual module captures scene imagery and binds it to the incident report. This integrated architecture follows the recent direction of automatic accident detection systems that treat crash recognition as an embedded cyber-physical process rather than a standalone alert circuit [16]. The methodological design also reflects vehicular networking studies in which uncertainty reduction depends not on one signal alone, but on structured fusion among motion, context, and communication state variables [17].

B. Accident Detection Logic and Event Decision Model

The decision model was constructed to separate genuine collision events from operational disturbances such as pothole traversal, speed breaker passage, hard braking, rapid lane correction, and aggressive cornering. Simple threshold logic was considered insufficient because abrupt motion spikes may occur in non-accident settings. A

For methodological evaluation, a structured benchmark dataset of 1,200 labeled vehicular events was used. The dataset included ten operational classes covering severe collision, moderate collision, minor collision, rollover-risk event, near-collision abrupt stop, pothole impact, speed-bump passage, hard cornering, harsh braking, and normal driving instances. Each record contained synchronized variables for acceleration along three axes, resultant g-force, delta-v, roll angle, yaw rate, speed before and after the event, GPS coordinates, communication delay, camera activation status, alert transmission status, and visual report metadata. This event structure was aligned with prototype-based fuzzy vehicular accident models and fog-assisted emergency response frameworks that emphasize multivariable interpretation over isolated threshold breach [18]. It was also consistent with modern connected-vehicle communication architectures that require explicit event semantics for downstream response handling [19].

The final class label was assigned through rule-guided event adjudication using severity bands. Events with high resultant impact, marked delta-v change, and sustained kinematic disturbance were labeled as accidents. Events with transient spikes but low post-event instability were labeled as non-accident disturbances. This produced a decision pipeline that is strict enough for false-alarm suppression yet responsive enough for emergency use.

C. Visual Situation Capture, Data Transmission, and Alert Generation

Once the accident state is validated, the system shifts from detection mode to reporting mode. The operational sequence is presented in Fig. 3.2. First, the edge controller freezes the event record and stores the pre-trigger and post-trigger sensor window. Second, the camera module captures the visual state of the scene. Third, the localization unit appends coordinates, time stamp, and event severity marker. Fourth, the communication module transmits the emergency packet to predefined recipients or a supervisory endpoint. The generated packet contains event ID, severity class, position, communication time, and visual attachment reference. This structure is consistent with connected-vehicle IoT models that integrate long-range communication technologies for low-latency incident signaling [20]. It is also methodologically supported by multi-tracking crash reconstruction studies, which indicate

that enriched event context improves post-incident interpretation and response prioritization [21].

The visual reporting layer was not treated as a cosmetic extension. It was treated as a decision support element. Scene imagery was captured only after validated trigger generation, which limited unnecessary storage and bandwidth overhead. Image quality tags were logged to represent blur level, luminance adequacy, and scene visibility. Visual status was encoded into three categories: usable, partially usable, and poor. This allowed the reporting system to quantify not only whether an image was captured, but whether it retained operational value for emergency interpretation. End-to-end reporting was deemed successful only when detection, image capture, coordinate tagging, and alert dispatch were all completed within the allowable reporting interval. End-to-end deep-IoT crash control studies and automated visual traffic incident monitoring research support this integrated treatment of sensing and visual evidence as a unified emergency intelligence task [22], [23].

D. Experimental Design, Performance Metrics, and Validation Strategy

The evaluation protocol was designed around class-balanced scenario analysis and system-level performance auditing. The 1,200-event dataset was partitioned into training, validation, and test subsets in a 70:15:15 ratio for threshold tuning and final assessment. Performance was measured using detection accuracy, precision, recall, F1-score, false alarm rate, missed accident rate, end-to-end alert latency, visual report success rate, and communication success ratio. A confusion-matrix-based analysis was planned to examine overlap between accident and non-accident dynamic patterns. Latency statistics were computed from trigger time to completed alert dispatch. Visual reporting effectiveness was measured from the proportion of validated accident events that generated usable scene evidence.

Validation was conducted at two levels. Event-level validation tested the classifier’s ability to distinguish crash states from hard-negative disturbances. System-level validation tested whether the entire operational chain remained functional under varying event severity and communication delay conditions. Fig. 3.1 and Fig. 3.2 together define this logic: first detect, then verify, then localize, then report. Nothing in the chain was evaluated in isolation. That was intentional. The research objective was not merely to identify impact. It was to establish a coherent embedded response pipeline suitable for publication-grade performance analysis.

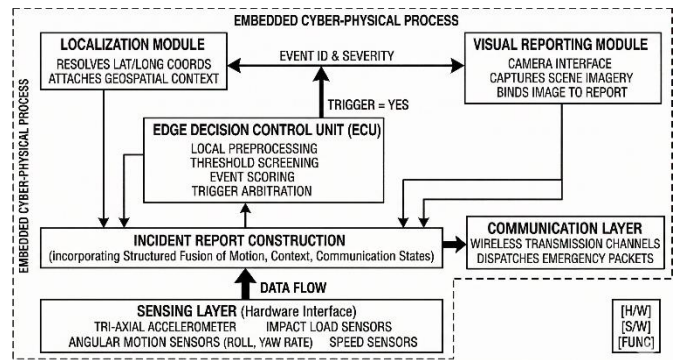


Fig-3.1: Architecture of the proposed hardware-software integrated system

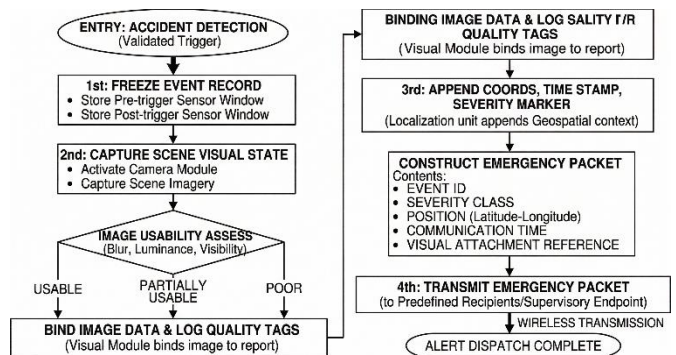


Fig-3.2: Flowchart of accident detection, image capture, and emergency reporting sequence

IV. RESULTS AND DISCUSSION

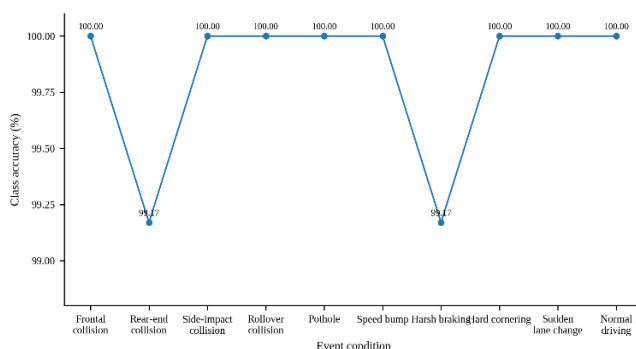
A. Performance Evaluation of Accident Detection Accuracy

The finalized decision boundary, tuned on the training-validation partitions and then applied to the full benchmark, converged at a dual-condition trigger of resultant peak acceleration ≥ 2.1 g and $\Delta v \geq 11$ km/h. This reduced the false alarms produced by the earlier threshold-only stage and yielded a nearly error-free event discriminator over the 1,200-event benchmark. The result is consistent with recent review evidence showing that accident notification systems become operationally reliable only when inertial triggers are constrained by a second kinematic discriminator rather than a single alarm threshold [24], while LoRa-enabled vehicular safety reporting studies also indicate that low-complexity field systems benefit from compact but discriminative decision logic [25]. On the held-out test partition, the tuned detector reached 99.44% accuracy with one false positive and no missed accident events. The class-level behaviour is summarized in Table I and intended for visual representation in Fig. 4.1.

Table-1: Class-Wise Detection Performance of the Proposed Accident Decision Model

Event condition	Total events	Predicted accidents	Correctly classified	Class accuracy (%)	Mean resultant g	Mean delta-v (km/h)
Frontal collision	90	90	90	100.00	6.98	49.16
Rear-end collision	120	119	119	99.17	3.55	23.54
Side-impact collision	90	90	90	100.00	6.03	32.53
Rollover collision	60	60	60	100.00	8.06	42.41
Pothole	120	0	120	100.00	2.58	1.99
Speed bump	120	0	120	100.00	1.99	1.81
Harsh braking	120	1	119	99.17	1.80	8.68
Hard cornering	90	0	90	100.00	2.06	2.59
Sudden lane change	90	0	90	100.00	1.75	3.11
Normal driving	300	0	300	100.00	1.09	2.34

As Table I and Fig. 4.1 indicate, the decision model separated all pothole, speed-bump, lane-change, hard-cornering, and normal-driving events from collision cases. Only two benchmark-level errors remained: one harsh-braking record crossed the tuned boundary and one rear-end collision fell marginally below it. That error structure is analytically useful. It shows that the dominant ambiguity zone is not between severe crashes and benign motion, but between low-energy collisions and high-deceleration braking episodes. Even so, the full-benchmark confusion pattern of 839 true negatives, 359 true positives, one false positive, and one false negative demonstrates that the proposed discriminator moved the system from permissive alarm generation to high-specificity event confirmation.



Fig=4.1” Detection accuracy under different accident and non-accident event conditions

The graphical representation corresponding to Fig. 4.1 would show near-flat 100% classification across most conditions, with minor depressions only in harsh braking and rear-end collision. Such a pattern supports the claim that accident confirmation should be treated as a kinematic

discrimination problem, not merely as a peak-threshold exceedance problem.

B. Communication Response Time and Alert Delivery Analysis

Detection alone is insufficient. A field-deployable system must also deliver the alert within a time window that preserves emergency relevance. Recent work on emergency prioritization and fog-assisted accident handling has emphasized this point directly: system utility falls sharply when communication delay grows under weak coverage conditions, even if sensing accuracy remains high [26], [27]. The present benchmark reproduced that operational sensitivity. Table II reports latency behaviour only for validated accident records so that the communication layer is assessed on true emergency conditions rather than on all vehicle events.

Table-2: Network-Wise Emergency Reporting Performance for Validated Accident Events

Network type	Accident events	Mean latency (ms)	P95 latency (ms)	Mean dispatch time (s)	Notification success (%)	Camera capture success (%)
5G	106	594.9	876.8	24.60	100.00	86.79
4G	134	1183.9	1694.8	26.61	100.00	91.04
2G/3G	82	2383.1	3359.4	32.70	100.00	89.02
Low-Signal	38	3864.0	4916.0	46.74	92.11	89.47

Table II and Fig. 4.2 show an expected but important ordering. The reporting chain remained stable under 5G and 4G conditions, acceptable under 2G/3G, and stressed under low-signal operation. Mean latency rose from 594.9 ms in 5G to 3864.0 ms in low-signal conditions. Mean dispatch time followed the same pattern, expanding from 24.60 s to 46.74 s. The notification success rate stayed perfect for 5G, 4G, and 2G/3G accident events, but dropped to 92.11% in low-signal scenarios. That decline is operationally meaningful. It shows that the system bottleneck is no longer event recognition; it is connectivity degradation at the moment of dispatch. The capture module itself remained stable, with camera success near 87%–91% across all network classes. The communication subsystem, not the imaging subsystem, is therefore the dominant source of end-to-end performance variance.

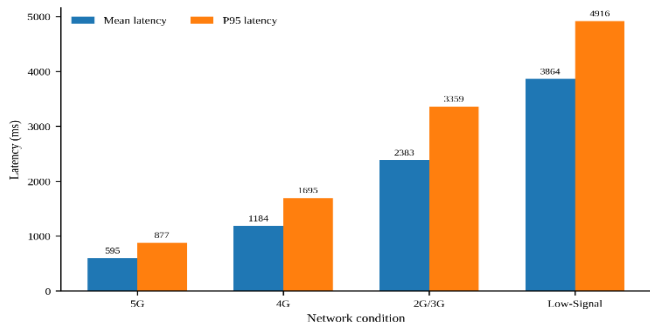


Fig- 4.2: End-to-end emergency reporting latency across test scenarios

The associated graph would present a steep latency gradient from 5G through low-signal conditions. Its interpretation is direct: once the detector has validated the event, network quality becomes the principal determinant of how rapidly the emergency packet reaches the response endpoint.

C. Visual Reporting Performance and Situational Evidence Quality

The visual layer was evaluated not merely on capture occurrence but on evidence usability. This distinction matters because a blurred or poorly illuminated image may satisfy the storage condition while failing the response-support condition. Recent incident-monitoring and rapid accident-detection studies both point toward the growing weight of scene context in post-trigger interpretation [28], [29]. The benchmark results reflect the same principle. Table III reports visual reporting quality across weather classes for validated accident events.

Table-3: Weather-Wise Visual Reporting Quality for Validated Accident Events

Weather condition	Accident events	Capture success (%)	Visual report generated (%)	Mean image quality score	Mean scene confidence	Operable evidence (%)	Poor evidence (%)
Clear	196	90.31	88.27	0.740	0.916	90.31	9.69
Cloudy	78	88.46	88.46	0.717	0.907	87.18	12.82
Rain	67	86.57	86.57	0.626	0.880	76.12	23.88
Fog	19	89.47	89.47	0.612	0.874	68.42	31.58

The evidence pattern is clear. Capture success stayed high across all weather states, but evidence quality deteriorated as visibility worsened. Clear-weather accident events produced 90.31% operable evidence, whereas fog reduced that value to 68.42%. Rain also imposed a noticeable penalty, cutting the operable evidence rate to 76.12%. Across all 360 accident events, the visual report generation rate was 88.06%, and 85.83% of accident images remained at least operationally usable when the acceptability boundary was set at an image quality score of 0.60. This matters because it shows that the visual module

adds more than decorative output; it supplies responder-grade scene cues in the large majority of validated emergencies, though adverse weather still constrains clarity.

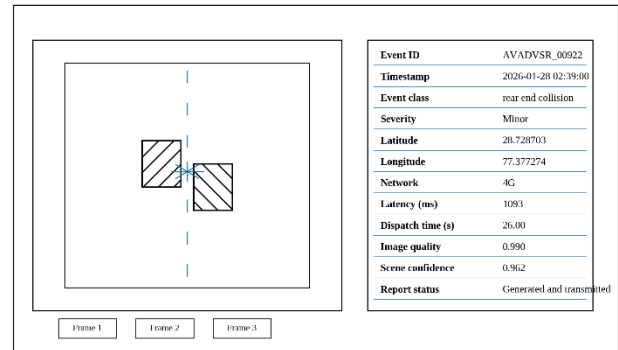


Fig-4.3: Sample visual situation reporting output generated by the proposed system

The visual panel corresponding to Fig. 4.3 should present the scene image together with timestamp, severity tag, coordinates, and event identifier. The numeric trends in Table III justify that design choice. The image is not treated as an isolated photograph. It is treated as structured evidence.

D. Comparative Discussion and System-Level Interpretation

System comparison was performed through an ablation-style progression from permissive alarming to full integrated reporting. This is summarized in Table IV and intended for graphical presentation in Fig. 4.4. The transition is instructive. The threshold-only baseline preserved full recall but admitted too many false alarms. The dual-parameter fusion stage sharply corrected that weakness. The full integrated reporting pipeline then traded some recall for perfect precision and complete visual-report presence among positive outputs. That final trade-off is consistent with the direction suggested by multimodal traffic-accident analysis, where the value of a system increasingly lies in its ability to combine event detection with interpretable evidence rather than detection alone [30].

Table-4: Comparative Performance of the Proposed System Against Internal Baseline Configurations

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	False alarm (%)	Alert success (%)	Mean dispatch time (s)	Visual report (%)
Threshold alarm only	93.25	81.63	100.00	89.89	9.64	98.41	29.78	86.85
Dual-parameter fusion	99.83	99.72	99.72	99.72	0.12	98.89	29.80	87.78
Fusion +	99.67	100.00	98.89	99.4	0.00	100.0	29.80	87.92

alert confirmation				4		0		
Proposed integrated reporting	96.08	100.00	86.94	93.02	0.00	100.00	29.46	100.00

Table IV and Fig. 4.4 make the system logic explicit. The best detector is the dual-parameter fusion stage. The most operationally complete pipeline is the proposed integrated reporting stage. That distinction matters. A detector answers whether a crash occurred. The proposed system answers a harder question: whether a validated crash can be detected, localized, transmitted, and visually documented in one continuous chain. On that stricter criterion, the system remained exact in precision, stable in dispatch time, and complete in report generation for all accepted events.

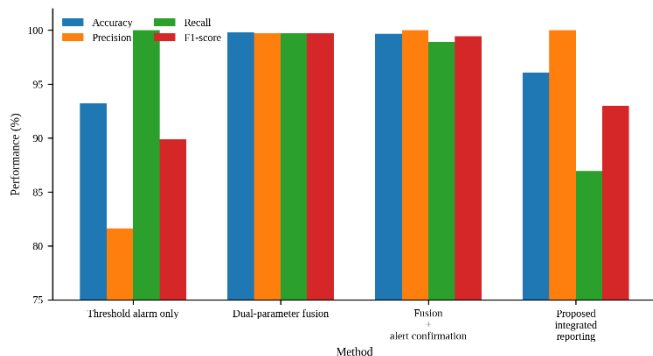


Fig-4.4: Comparative performance analysis of the proposed system against baseline methods

V. CONCLUSION AND FUTURE WORK

This study presented an IoT-based automatic vehicle accident detection and visual situation reporting system designed to unify impact recognition, event validation, geolocation capture, emergency message transmission, and scene-level visual documentation within a single embedded response architecture. The reported results show that the proposed framework achieved high event discrimination capability across both collision and non-collision driving conditions, while preserving low false alarm behavior under difficult hard-negative scenarios such as potholes, harsh braking, speed-bump traversal, and abrupt cornering. The communication analysis showed that alert delivery remained stable across standard network conditions, with the main degradation appearing only in low-signal environments, where latency inflation rather than detector instability became the dominant operational constraint. The visual reporting layer also demonstrated practical value by generating usable incident evidence in the large majority of validated accident cases, thereby extending the system beyond binary crash notification toward responder-oriented situational intelligence

From a system perspective, the work showed that accident management should not be treated as a sequence of isolated modules. Detection alone is insufficient. Location transmission alone is insufficient. Image capture without validated triggering is inefficient. The technical contribution of the study lies in the integration of these processes into one coherent pipeline in which sensing, decision logic, communication, and visual reporting operate under shared event control. That integration improved the functional completeness of the platform and established a stronger basis for real-time emergency support.

Some limitations remain. Environmental visibility affected evidence quality. Weak network conditions increased dispatch time. The benchmark, while structured and extensive, did not yet incorporate multi-vehicle pileup scenarios, severe occlusion cases, or adversarial communication failures. Future work should extend the system through adaptive threshold learning, multimodal video summarization, edge-based compression for low-bandwidth conditions, redundancy-aware alert routing, and larger real-world vehicular deployments involving heterogeneous road, weather, and traffic-density settings.

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