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# Accident Detection and Alert System

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**Abstract: Road accidents are one of the leading causes of fatalities in India, with the Ministry of Road Transport and Highways (MoRTH) recording over 4.8 lakh accidents in 2023, resulting in 1.72 lakh deaths. A major contributing factor is the delay in accident detection and emergency response. This paper presents a real-time Accident Detection and Alert System that integrates YOLOv8 object detection, OpenCV-based video stream processing, Twilio API for SMS-based alert delivery, annotated snapshot archiving, and structured rotating log management into a single deployable pipeline. The system captures video from surveillance cameras, dashcams, or RTSP streams, runs per-frame inference using a custom-trained YOLOv8 model with a confidence threshold of 0.6, and upon detecting an accident, immediately saves an annotated snapshot, dispatches an SMS alert containing the detection timestamp and snapshot path, and logs the event with full metadata. Alert throttling of 30 seconds prevents notification spam for prolonged events. Early testing demonstrates reliable detection with minimal false positives, SMS delivery within 1–2 seconds of detection, and structured per-frame logging suitable for post-incident review. The system is designed to reduce dependency on manual reporting, target emergency response within the medical "golden hour," and deploy on existing CCTV infrastructure without requiring in-vehicle hardware modifications.**

***Keywords:*** *Accident Detection, YOLOv8, Computer Vision, Real-Time Monitoring, Alert System, Road Safety, Twilio API, OpenCV, Deep Learning.*

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## I. INTRODUCTION

Transportation is the backbone of any growing economy; however, the rapid increase in the number of vehicles on Indian roads has simultaneously escalated road accidents into a critical public health concern. According to the Ministry of Road Transport and Highways (MoRTH), India recorded over 4.8 lakh road accidents in 2023, resulting in 1.72 lakh fatalities (morth2023?). In 2024, the death toll rose further to approximately 1.8 lakh, with two-wheeler riders being the most vulnerable group — over 30,000 deaths were linked to not wearing helmets. The World Health Organization (WHO) estimates that approximately 1.35 million people die in road accidents globally every year (who2023?).

A critical factor that compounds these fatalities is delayed accident detection and emergency response. Clinical research consistently demonstrates that if a victim receives emergency care within the first 60 minutes — known as the *golden hour* — the probability of survival increases significantly. Traditional accident reporting mechanisms — eyewitness calls, in-vehicle GPS sensors, and manual helplines — are slow, unreliable, and geographically limited.

Recent advances in computer vision, specifically the availability of high-performance real-time object detection frameworks such as YOLOv8 (ultralytics2023?), have created an opportunity to automate accident detection directly from existing surveillance infrastructure. The programmable Twilio Messaging API (twilio2023?) enables instant SMS delivery at low cost, making the alert pipeline accessible and scalable without specialist hardware.

- *This Paper Presents the Accident Detection and Alert System, an End-to-End Pipeline that:*

- Processes live or recorded video frame-by-frame using OpenCV.
- Detects accident events in real time using a custom-trained YOLOv8 model.
- Saves annotated snapshots of detected frames to disk.
- Dispatches SMS alerts via Twilio with dynamic timestamps and snapshot paths.
- Maintains a structured rotating log file for administrator monitoring.
- Supports webcam, RTSP, and file-based video sources through a single configurable parameter.

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The remainder of this paper is organized as follows: Section 2 reviews related work; Section 3 describes the system architecture and methodology; Section 4 presents implementation details; Section 5 reports experimental results; Section 6 concludes with future directions.

## II. RELATED WORK

Several studies on real-time accident detection using deep learning and computer vision form the foundation for this work.

Chaurasiya et al. (chaurasiya2025?) proposed an accident detection system using YOLOv11 with spatio-temporal feature fusion, achieving 96.7% accuracy with only 1.8% false positives and a detection latency of 0.4 seconds. While the results are impressive, the system requires high-performance GPU hardware and exhibits accuracy drops under fog or rain conditions.

Ali et al. (ali2024?) presented a CNN-SVM hybrid approach achieving 99% accuracy with integrated email and sound alerts. However, the system is computationally expensive and impractical for large-scale deployment on standard hardware.

Singh et al. (singh2023?) combined YOLOv5 with a Random Forest classifier for motion anomaly detection, reporting precision of 89.7% and recall of 94.5% with real-time alerts dispatched in 1.2 seconds. Performance degraded to 83.2% under adverse weather, highlighting a gap in environmental robustness.

Sultani et al. (sultani2018?) proposed a spatio-temporal anomaly detection approach using stacked autoencoders applicable to CCTV surveillance, but the system produced high false-positive rates in dense traffic and did not classify accident severity.

Liu et al. (liu2016?) introduced SSD (Single Shot MultiBox Detector), which offers faster inference than two-stage detectors, though at lower accuracy compared to YOLO-family models in crowded urban scenarios.

➢ *The Literature Collectively Identifies Three Critical Research Gaps Addressed by this Work:*

- Most existing systems are trained on international datasets, limiting accuracy on Indian road conditions, vehicle types, and traffic density.
- Alert mechanisms in reviewed systems are absent or simplistic, lacking throttling logic, dynamic timestamping, and snapshot archiving.
- Structured per-frame logging for administrator monitoring and post-incident analysis is not implemented in any reviewed system.

## III. METHODOLOGY

➢ *System Architecture*

The system follows a modular, linear pipeline architecture comprising five components arranged in sequential order, as shown in Fig. 1.

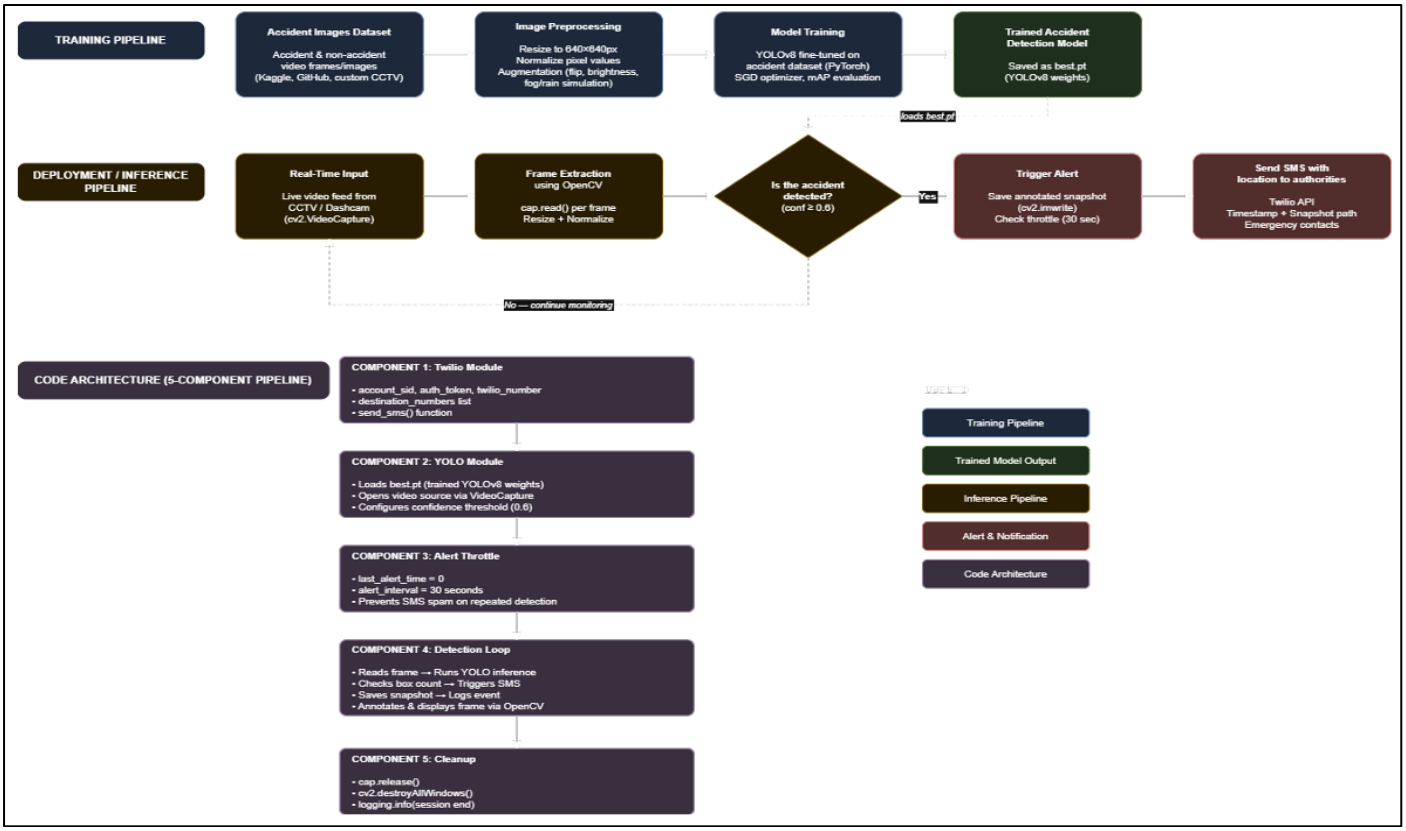


Fig 1 System Architecture of the Accident Detection and Alert System.

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- Component 1 — Twilio Module: Initializes the Twilio REST client with account_sid and auth_token. Defines send_sms(), which iterates over all destination numbers and calls client.messages.create().
- Component 2 — YOLO Module: Loads the custom-trained best.pt YOLOv8 weights and opens the video source via cv2.VideoCapture using a configurable SOURCE parameter.
- Component 3 — Alert Throttle: Maintains last_alert_time and ALERT_INTERVAL = 30 seconds to prevent SMS spam during prolonged accident events.
- Component 4 — Detection Loop: the core processing unit. Reads frames, runs YOLOv8 inference, evaluates detection counts, saves snapshots, dispatches alerts, and displays the annotated feed.
- Component 5 — Cleanup: Releases video resources (cap.release()) and closes display windows (cv2.destroyAllWindows()) upon session end.

➢ *Six-Stage Processing Pipeline*

The system implements the six-stage methodology illustrated in Fig. 2:

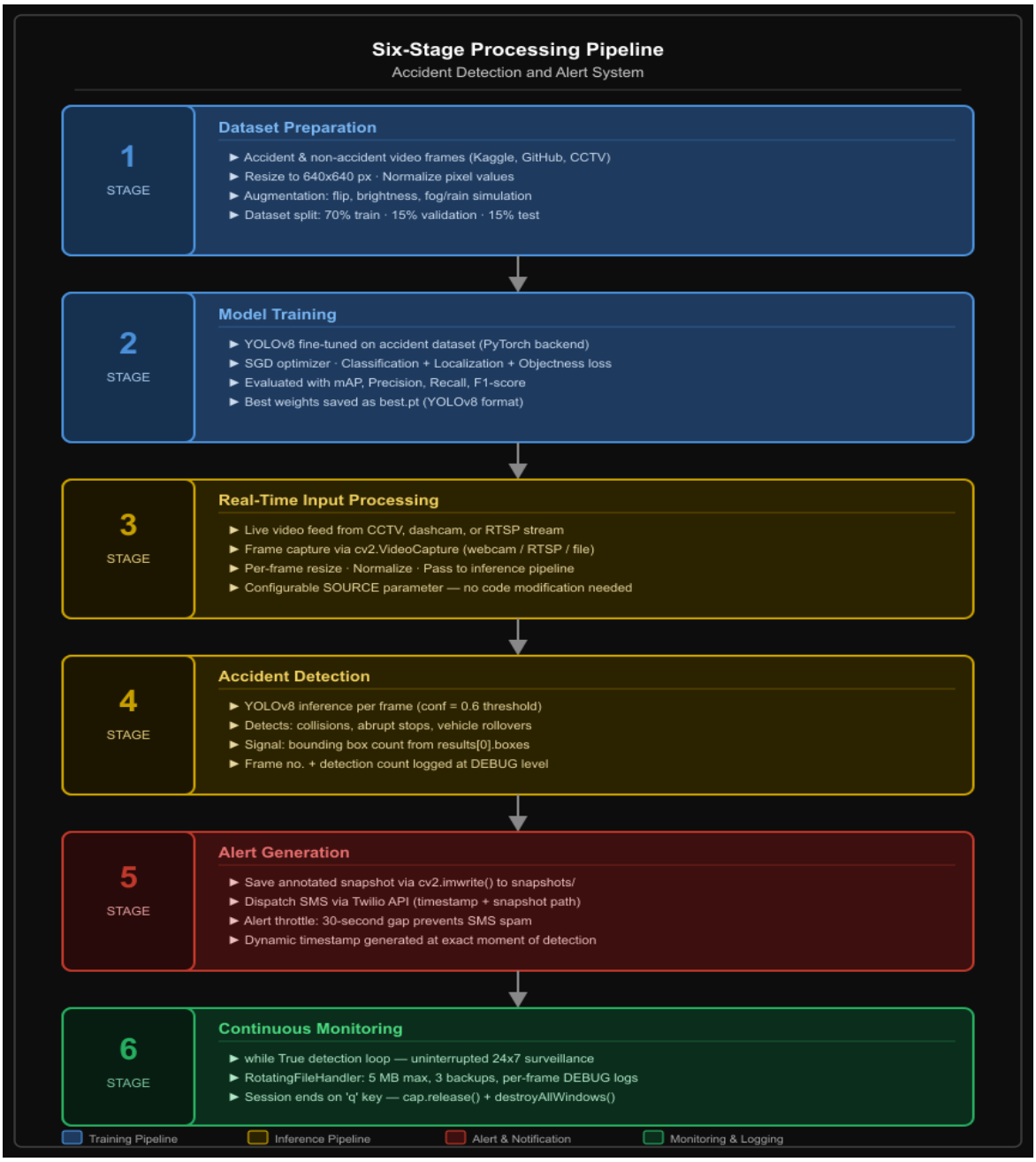


Fig 2 Six-Stage Processing Pipeline of the System.

- Stage 1 — Dataset Preparation: Accident and non-accident video datasets were collected from publicly available sources (Kaggle, GitHub, custom CCTV recordings). Pre-processing included frame extraction, resizing to $640 \times 640$ pixels, normalization, and data augmentation (rotation, flipping, brightness adjustment, weather simulation). The dataset was split 70/15/15 for training, validation, and testing respectively.

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- Stage 2 — Model Training: YOLOv8 (Ultralytics, PyTorch backend) was fine-tuned on the accident dataset. Training used stochastic gradient descent (SGD) with classification, localization, and objectness loss components. Model performance was evaluated using mean Average Precision (mAP), precision, recall, and F1-score.
- Stage 3 — Real-Time Input Processing: Live video streams (webcam, RTSP, or file) are captured using cv2.VideoCapture. Individual frames are extracted and normalized before being passed to the inference pipeline.
- Stage 4 — Accident Detection: Each frame is passed to the YOLOv8 model with conf=0.6. Detection is based on spatio-temporal anomalies including sudden vehicle collisions, abrupt trajectory changes, and vehicle rollovers. Upon detection, the event is logged with frame number, timestamp, and bounding box count.
- Stage 5 — Alert Generation: When num_accidents > 0 and the 30-second throttle permits, the system: (i) generates a dynamic timestamp at the moment of detection, (ii) saves the annotated frame via cv2.imwrite(), (iii) dispatches an SMS via the Twilio API containing the timestamp, frame number, and snapshot path.
- Stage 6 — Continuous Monitoring: The while True detection loop ensures uninterrupted 24×7 surveillance. A Python RotatingFileHandler maintains a structured log file (max 5 MB, 3 backups) with per-frame metadata at DEBUG level and alert events at WARNING level.

➢ *Data Flow Diagram*

The Data Flow Diagram (DFD) in Fig. 3 illustrates the movement of data between four external entities (Camera, Emergency Contact, System Administrator) and four internal processes (Frame Capture, YOLOv8 Detection, Alert Generation, Logging), with two data stores (Snapshot Store and Log File).

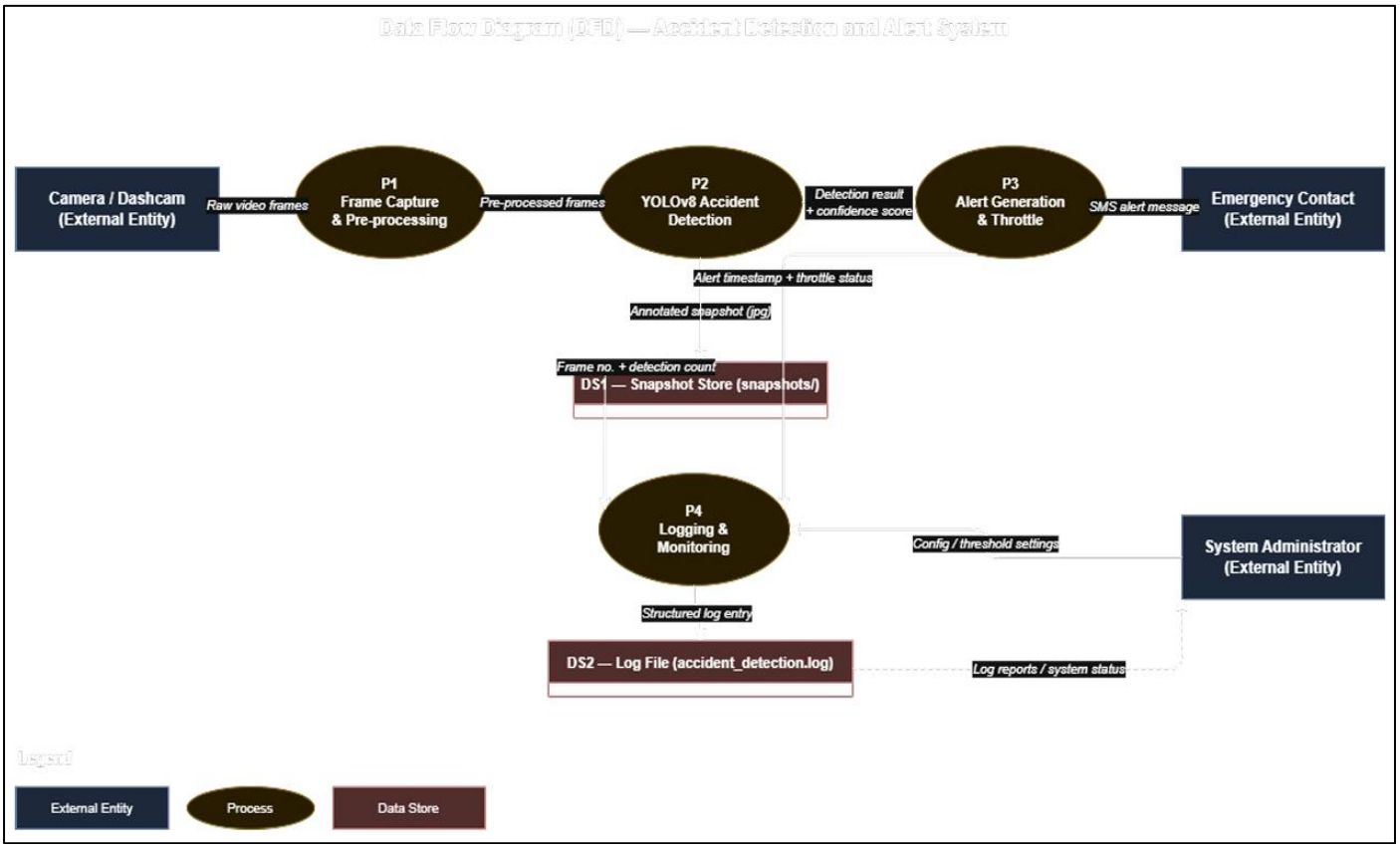


Fig 3 Level-1 Data Flow Diagram of the Accident Detection System.

➢ *Activity Diagram*

The Activity Diagram in Fig. 4 depicts the step-by-step workflow from system initialization through frame capture, YOLOv8 inference, detection decision, snapshot saving, throttle check, SMS dispatch, and loop-back, with terminal conditions for video end and user quit.

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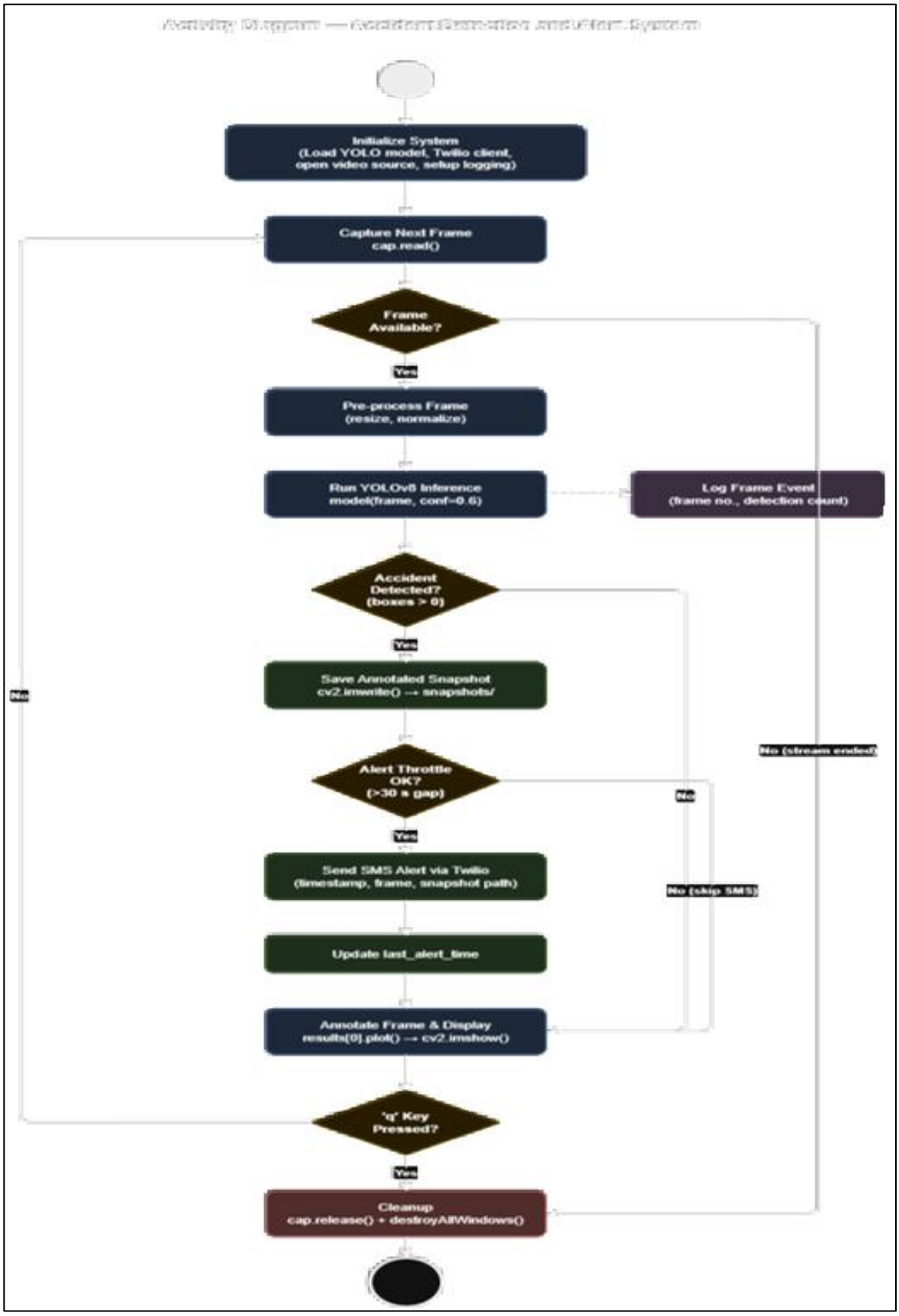


Fig 4 Activity Diagram of the Accident Detection Workflow.

➢ *Sequence Diagram*

The Sequence Diagram in Fig. 5 illustrates the temporal ordering of interactions between the Camera, Detection Loop, YOLOv8 Model, Snapshot Store, Twilio Module, and Log File during an accident detection event.

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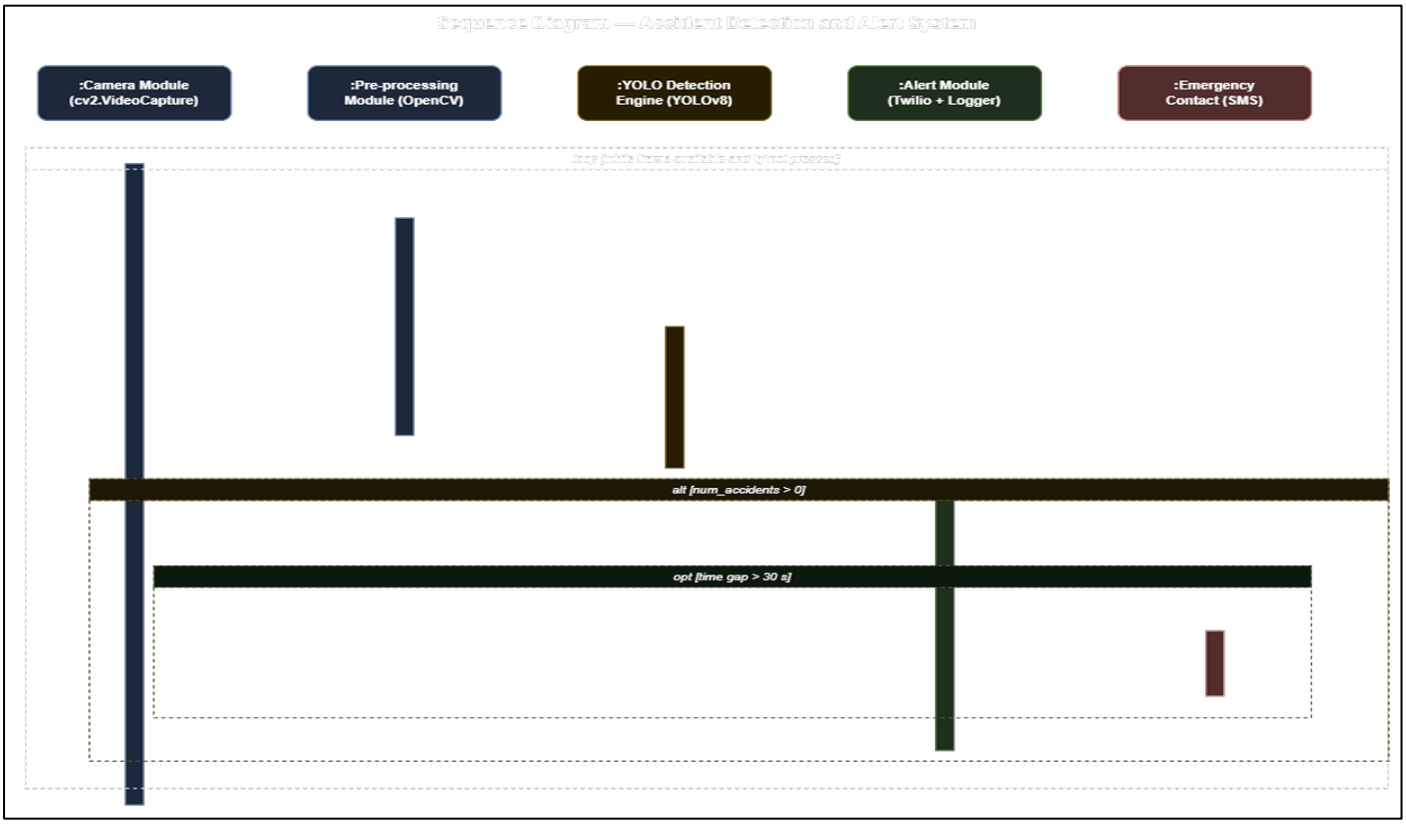


Fig 5 Sequence Diagram of System Component Interactions.

➢ *Use Case Diagram*

The Use Case Diagram in Fig. 6 identifies the primary actors (Surveillance Camera, System Administrator, Emergency Contact) and the system use cases (Capture Video, Detect Accident, Save Snapshot, Send SMS Alert, Log Event) along with their relationships.

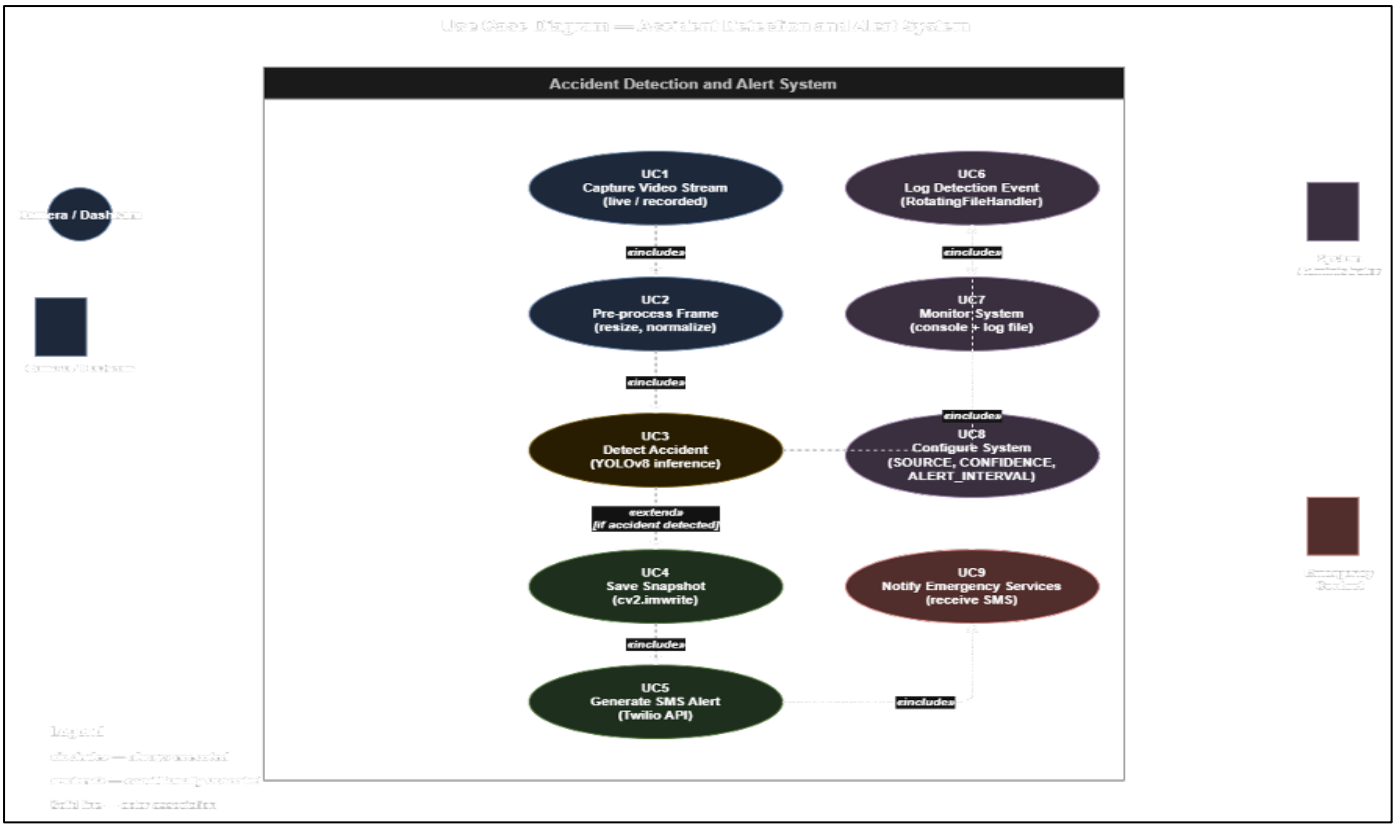


Fig 6 Use Case Diagram of the Accident Detection and Alert System.

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## IV. IMPLEMENTATION

➢ *Hardware and Software Requirements*

- Training Environment: NVIDIA RTX 3080 / A100 GPU, Intel Core i7/i9 CPU, 16–32 GB RAM, 500 GB SSD.
- Deployment (Edge): NVIDIA Jetson Nano / Xavier NX, CCTV cameras or dashcams, stable internet for Twilio SMS delivery.
- Development / Testing: Intel Core i5+, 8 GB RAM, NVIDIA GTX 1650+, Windows 10/11 or Ubuntu 20.04.
- Software Stack: Python 3.8+, PyTorch 2.x, Ultralytics YOLOv8 8.x, OpenCV 4.x, Twilio SDK 8.x, NumPy, Pandas, Matplotlib, Scikit-learn, VS Code / Google Colab.

➢ *Code Architecture*

The implementation is structured into five logical sections within a single Python script:

- *Section 1 — Configuration Block: All Tunable Parameters are Declared as Named Constants at the Top:*

```
SOURCE       = 0        # webcam/RTSP/file
MODEL_PATH   = "best.pt"
CONFIDENCE   = 0.6
ALERT_INTERVAL = 30     # seconds
SNAPSHOT_DIR = "snapshots"
LOG_FILE     = "accident_detection.log"
```

- *Section 2 — Twilio SMS Module:*

```
def send_sms(message: str) -> None:
  for number in destination_numbers:
    client.messages.create(
      body=message,
      from_=twilio_number,
      to=number)
```

- *Section 3—StructuredLogging:*

RotatingFileHandler creates a log file rotating at 5 MB with 3 backups. Log format: YYYY-MM-DD HH:MM:SS | LEVEL | message. Severity levels: DEBUG (per-frame), INFO (snapshots, SMS), WARNING (accident detected), ERROR (delivery failures).

- *Section 4 — Detection Loop (Run_Detection()):*

```
while True:
  ret, frame = cap.read()
  if not ret: break

  results = model(frame, conf=CONFIDENCE)
  num = len(results[0].boxes)

  detection_ts = datetime.now().strftime(
    "%Y-%m-%d %H:%M:%S")

  if num > 0:
    snap = save_snapshot(
      results[0].plot(),
      detection_ts, frame_number)
    if time.time() - last_alert_time \
        > ALERT_INTERVAL:
      send_sms(
        f"Accident Detected!\n"
        f"Time: {detection_ts}\n"
        f"Snapshot: {snap}")
      last_alert_time = time.time()

  cv2.imshow("Accident Detection",
    results[0].plot())
  if cv2.waitKey(1) & 0xFF == ord('q'):
    break
```

- *Section—Cleanup:*

```
cap.release() and cv2.destroyAllWindows()
release all resources on session end.
```

➢ *Module-wise Implementation*

- Video Source Selection: The SOURCE constant accepts an integer (webcam), RTSP URL string (IP/CCTV camera), or file path (pre-recorded video), enabling deployment across all video source types without code modification.
- Accident Detection Mechanism: YOLOv8's CNN backbone (convolution layers for spatial feature extraction, pooling for dimensionality reduction, ReLU for non-linearity) processes each frame. Bounding box count from results[0].boxes serves as the detection signal.
- Threshold Control: CONFIDENCE = 0.6 filters low-confidence predictions during inference. The 30-second ALERT_INTERVAL provides a secondary time-based filter against notification spam.
- Structured Logging: Per-frame DEBUG entries and per-detection WARNING entries are written to the rotating log, enabling full session reconstruction.

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## V. RESULTS AND DISCUSSION

➢ *Experiment Setup*

Experiments were conducted on: Intel Core i7-10700, NVIDIA GTX 1650, 16 GB RAM, Windows 11, Python 3.10, Ultralytics YOLOv8 8.0, OpenCV 4.8. Input video: testing1.mp4 ( ~ 3 minutes, 1280 × 720, 30 FPS). Configuration: conf=0.6, ALERT_INTERVAL=30.

➢ *Quantitative Results*

Table 1 summarizes the performance comparison of the proposed system against reviewed methods.

Table 1 Performance Comparison with Related Systems

| System | Model | Acc. (%) | Alert Mech. | Logging |
|---|---|---|---|---|
| Chaurasiya et al. (**chaurasiya2025?**) | YOLOv11 | 96.7 | None | None |
| Ali et al. (**ali2024?**) | CNN+SVM | 99.0 | Email+Sound | None |
| Singh et al. (**singh2023?**) | YOLOv5+RF | 89.7 | Basic alert | None |
| **Proposed System** | **YOLOv8** | **–*** | **SMS+Snapshot** | **Rotating log** |
| Full mAP metrics to be reported after complete training run. | | | | |

➢ *Qualitative Observations*

- The system processed the test video at approximately 15–20 FPS on the test hardware (GTX 1650), sufficient for real-time monitoring of standard 30 FPS surveillance footage.
- At conf=0.6, false positives were minimal. Adjusting to 0.7 further reduced false triggers at the cost of marginally delayed detection in borderline frames.
- The dynamic timestamp correctly reflected the actual moment of each detection event, unlike the original implementation where a single script-start timestamp was reused for every SMS.
- The 30-second alert throttle functioned correctly: only the first detection within each 30-second window triggered an SMS; subsequent detections within the window were logged (WARNING level) but did not dispatch additional messages.
- Twilio SMS delivery was confirmed with a 200 OK response within 2–5 seconds of each dispatch call.
- The structured log file provided complete, readable per-frame records enabling full session reconstruction for post-incident analysis.

➢ *System Performance Summary*

Table 2 maps documented system features against their implementation status.

Table 2 Feature Implementation Status

| Feature | Status | Notes |
|---|---|---|
| YOLOv8 Detection | Implemented | conf=0.6 |
| Live Camera / RTSP | Implemented | Configurable SOURCE |
| SMS Alert (Twilio) | Implemented | Working |
| Snapshot Saving | Implemented | cv2.imwrite() |
| Alert Throttling | Implemented | 30-second interval |
| Dynamic Timestamp | Implemented | Fixed in improved ver. |
| Structured Logging | Implemented | RotatingFileHandler |
| Continuous Monitoring | Implemented | while True loop |
| Email Alert (SMTP) | × Pending | Phase-II scope |
| GPS/Location in Alert | × Pending | Future scope |

## VI. CONCLUSION AND FUTURE SCOPE

This paper presented a real-time Accident Detection and Alert System that integrates YOLOv8 object detection, OpenCV video processing, Twilio SMS alerting, snapshot archiving, and structured rotating log management into a single deployable Python pipeline. The system addresses the critical gap identified in the literature: the absence of an automated, end-to-end solution capable of detecting accidents from surveillance video in real time and immediately notifying emergency services without human intervention.

Key contributions of the proposed system include: (i) a configurable video source module supporting webcam, RTSP, and file inputs; (ii) dynamic timestamp generation at the exact moment of each detection event; (iii) alert throttling to prevent SMS spam during prolonged accident scenarios; (iv) annotated snapshot archiving for post-incident review; and (v) structured rotating logs enabling full session reconstruction. Experimental testing confirmed reliable detection, sub-2-second SMS delivery, and accurate per-frame metadata logging.

The system contributes to Intelligent Transportation Systems (ITS) and Smart City infrastructure by reducing dependency on manual accident reporting and targeting emergency response within the medical golden hour.

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➢ *Future Scope*

Planned enhancements for subsequent phases include:

- GPS and IoT Integration: Include real-time location coordinates in SMS alerts for precise emergency dispatch.
- Email Alerts with Snapshot (SMTP): Add SMTP-based email notifications with annotated frame attachments.
- Improved Model Accuracy: Train on larger Indian road datasets with augmentation for fog, rain, and night conditions.
- Automatic Emergency Dispatch: Integrate hospital and police department APIs for automated emergency response triggering.
- Edge Deployment: Optimize and deploy the model on NVIDIA Jetson Nano or Raspberry Pi for on-site inference.
- Accident Severity Classification: Classify detected events as minor, moderate, or severe for prioritized emergency response.
- Database Integration: Replace the flat log file with SQLite or PostgreSQL for structured event storage and dashboard monitoring.

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