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Enhancing Railway Accident Prevention Using Deep Learning, Machine Learning, And GPS Tracking: A Historical And Knowledge-Based Analysis

VIKAS CHANDRA GIRI[1], PARINEETA JHA[2]

Student, Computer Science and Engineering, RSR Rungta College of Engineering and Technology, Bhilai, Chhattisgarh, India[1]

Assistant Professor, Computer Science and Engineering, RSR Rungta College of Engineering and Technology, Bhilai, Chhattisgarh, India[2]

Abstract: This research extends the foundational study "Enhancing Railway Accident Prevention Using Deep Learning, Machine Learning, and GPS Tracking" (Vikas Chandra Giri & Parineeta Jha, 2025). The present work introduces an adaptive framework that integrates Deep Learning (DL), Internet of Things (IoT) sensor networks, and real-time GPS analytics to advance predictive railway safety. With results Sets in these volume.The architecture enhances detection accuracy, reduces response latency, and improves contextual awareness using hybrid CNN–LSTM–Random Forest fusion models with a multi-layer IoT sensing infrastructure. The model achieves 97.8% accuracy and maintains average GPS latency under 4 seconds, marking a significant improvement over earlier implementations.Through continuous learning and edge-cloud synchronization, the system advances toward fully autonomous accident prevention, predictive maintenance, and real-time operational intelligence across railway networks.

Keywords: Deep Learning · IoT · LSTM · GPS Tracking · Predictive Analytics · Accident Prevention. ML, MQTT

I. INTRODUCTION

Railways form the backbone of national and global transport systems, carrying billions of passengers and tons of freight annually. Despite modernization, accidents caused by human error, equipment failure, and environmental factors remain frequent.The earlier study by (Vikas Chandra Giri & Parineeta Jha, 2025). combined Deep Learning (**DL**), Machine Learning (**ML**), and **GPS** tracking to build an intelligent, data-driven accident prevention model. Although results were promising, limitations in latency, dataset diversity, and contextual awareness restricted deployment at scale.This paper presents a continuation of that research, introducing IoT-integrated adaptive **Deep Learning** and real-time **GPS** analytics. The goal is a cloud-synchronized, self-learning safety framework capable of real-time anomaly detection and pred- ictive alert generation across large rail networks.

C. Global Railway Accident Trend (2015–2025)	
Year	**Estimated Incidents**
2015	13,500
2016	13,000
2017	12,800
2018	12,500
2019	12,200
2020	11,800
2021	11,500

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C. Global Railway Accident Trend (2015–2025)	
Year	**Estimated Incidents**
2022	11,300
2023	11,200
2024	11,000
2025 (Projected)	10,700

Figure 7: Global Railway Accident Trend (2015–2025)

II. BACKGROUND AND RELATED WORK

Earlier contributions include:
• Patil (2017): Image-based crack detection on railway tracks.
• Hadj-Mabrouk (2020): ML-based accident prediction from historical records.
• Wang (2021): Deep residual networks for video-based anomaly detection.
• Zhang (2022): CNN for trespassing detection using CCTV footage.

Modern research: Recent studies by Sarp, Kuzlu, and Guler (2024) on AI-powered digital twin trains and Mishra & Kumar (2024) on IoT-driven smart railways show potential for real-time safety monitoring. Yet, issues like latency, sensor calibration, and cross-platform integration remain barriers.

****Processing → ML → DL → IoT Fusion → Digital Twin)**

The integration of advanced technologies such as Machine Learning (**ML**), Deep Learning (**DL**), Internet of Things (**IoT**), and Digital Twin is transforming various industries by enabling more efficient and intelligent systems. These technologies are often combined to create innovative solutions that enhance operational capabilities, improve predictive maintenance, and facilitate real-time data analysis.Machine Learning (**ML**) serves as the foundation for developing algorithms that can learn from data, identify patterns, and make decisions with minimal human intervention. Deep Learning (**DL**), a subset of **ML**, utilizes neural networks with multiple layers to process complex data such as images, speech, and sensor information, leading to more accurate and sophisticated models.The Internet of Things (**IoT**) connects physical devices, sensors, and systems to collect and exchange data across networks. This connectivity enables real-time monitoring, automation, and data-driven decision-making, which are critical for optimizing processes and resource management.The **Digital Twin** concept involves creating a virtual replica of physical assets, processes, or systems. This digital representation allows for simulation, analysis, and optimization without impacting the actual environment. Digital Twins are instrumental in predictive maintenance, system testing, and scenario planning, providing valuable insights that improve efficiency and reduce costs.When these technologies are integrated, organizations can leverage the strengths of each to develop comprehensive solutions. For example, IoT devices collect real-time data, which is processed by **ML** and **DL** algorithms to predict failures or optimize performance.

III. PROBLEM STATEMENT

- Analyze historical accident data to identify recurring patterns
- Monitor real-time train locations using GPS technology
- Predict and respond to anomalies using advanced ML and DL models

=> Limited dataset diversity
=> Independent ML and DL pipelines
=> High average alert latency
=> Lack of environmental and contextual data
An enhanced, multi-modal **AI–IoT–GPS** system with ≥97% accuracy capable of real-time railway accident detection and prevention.

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IV. SYSTEM ARCHITECTURE AND METHODOLOGY

The system follows a four-layer adaptive architecture:

A. Sensing Layer

IoT sensors: vibration, pressure, temperature, ultrasonic, and image capture.
GPS modules: provide spatial and velocity data at 0.5 s intervals.

B. Processing Layer

CNN for visual anomaly detection.
LSTM for temporal sensor pattern learning.
Random Forest for final decision smoothing and fusion.

C. Communication Layer

Uses MQTT protocol for low-latency data transmission.
Redundant 4G/5G links ensure continuous operation.

D. Decision Layer

Data displayed on a Grafana dashboard.
Multi-level alerts: Safe, Caution, Warning, and Critical.

V. DATA ACQUISITION AND PREPROCESSING

Data sources:

- Indian Railways public safety data.
- European railway datasets.
- Simulated IoT readings (vibration, pressure, weather).
- GPS position logs (train coordinates, speed, timestamp).

Preprocessing:

- Normalization and encoding of mixed data types.
- KNN imputation for missing values.
- Video frames resized to 128×128 pixels.
- Data augmentation using noise and brightness adjustment.

Raw Data → Cleaning → Feature Extraction → Normalization → Augmentation → Model Input

VI. MODEL DESIGN

A. CNN Module

Three convolutional layers (32, 64, 128 filters), max pooling, and dense output for binary classification.

B. LSTM Module

128 units, 30-timestep window sequence learning.

C. Random Forest Fusion

200 trees aggregate model confidence scores.

Fusion formula: $R = 0.4P\_CNN + 0.35P\_LSTM + 0.25P\_RF$
If $R > 0.75$, a Critical Alert is triggered.

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VII. METHODOLOGY AND IMPLEMENTATION

Edge Devices: Raspberry Pi 4 (8 GB RAM) with TensorFlow Lite.
Cloud GPU: NVIDIA RTX 3060 Ti (8 GB).
Languages/Frameworks: Python 3.11, TensorFlow, Scikit-learn, OpenCV.
Database: PostgreSQL for structured and time-series data. Or MongoDB
Visualization: Grafana + Plotly dashboards.
All data transmissions are encrypted using AES-256, ensuring cybersecurity compliance.

Experimental Evaluation

Input Features (X) and Target Labels (y)

Each instance of data used for prediction includes the following features:

Input Features (X):

- Speed: Real-time train speed, compared to zone-specific safety limits
- GPS Coordinates: Latitude and longitude, used to map the train's exact location
- Time: Timestamp of the reading, useful for correlating patterns (e.g., night-time risks)
- Zone ID and Track ID: Encoded identifiers for each railway segment, indicating risk-prone areas
- Weather Conditions: Rain, fog, or heatwave indicators, which can impact braking and visibility
- Sensor Inputs:
  - Track defect sensors
  - Signal strength monitors
  - Obstacle detection cameras
- Historical Flags: Whether the location has had prior accidents or maintenance issues

Target Labels (y):

- **Binary Classification:**
  - 0 = No Accident Risk
  - 1 = Accident Risk Detected

- **Multi-Class Classification (for risk type):**
  - 0 = Safe
  - 1 = Signal Failure
  - 2 = Track Obstruction
  - 3 = Overspeeding
  - 4 = Unauthorized Access, etc.

[GPS (Coordinates) + Speed + Zone ID + Sensors + Weather] => [Feature Vector] => [Trained Model]
↓ ↓
[Real-time prediction => Risk Score = 84%]
↓
[Trigger CRITICAL Alert]

VIII. RESULTS AND PERFORMANCE EVALUATION

Model	Accuracy (%)	Precision	Recall	F1	ROC-AUC
Random Forest	94.3	0.92	0.91	0.915	0.94
CNN	96.1	0.94	0.93	0.935	0.96
LSTM	95.5	0.93	0.92	0.925	0.95
CNN + LSTM Fusion	97.8	0.96	0.95	0.955	0.98

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B. Latency Evaluation			
Network Type	**Mean Latency (s)**	**95th Percentile (s)**	**Packet Loss (%)**
3G	5.7	9.2	2.4
4G	3.9	6.1	1.1
5G	2.8	4.4	0.4

Figure 6: Network Latency Distribution Graph)

VIII.A Machine Learning Perspective

This perspective focuses on the predictive modeling and pattern recognition capabilities of traditional Machine Learning (**ML**) algorithms such as Random Forests, Decision Trees, and Support Vector Machines (**SVMs**). ML models were primarily used for structured data—speed, **GPS** coordinates, track conditions, and environmental parameters—to detect abnormal operational patterns. They provided interpretable and computationally efficient baseline models for early-stage anomaly detection, helping the system establish decision thresholds and perform probabilistic risk classification before deeper neural analysis.

VIII.B Deep Learning Perspective

From a Deep Learning (**DL**) standpoint, the system leveraged Convolutional Neural Networks (**CNNs**) for spatial feature extraction from railway imagery and Long Short-Term Memory (LSTM) networks for temporal sequence learning. This hybrid CNN–LSTM fusion allowed the model to perceive both ***where*** and ***when*** anomalies occur, enhancing contextual awareness and decision accuracy. DL's ability to automatically learn hierarchical features from large datasets led to a 3–4% accuracy improvement over classical ML models. Together with IoT sensor fusion and **GPS** telemetry, DL forms the cognitive core of the Autonomous predictive frame work.

IX. DISCUSSION

The CNN–LSTM fusion model provides high precision and recall through complementary learning:
• CNN focuses on spatial pattern recognition, such as track cracks and obstacles.
• LSTM models temporal progression of anomalies.
• IoT sensors enrich the system with environmental and mechanical insights.
These collectively improve accuracy and responsiveness, reducing false positives to below 3%.
Matrix Visualization
with TP=1920, TN=2860, FP=75, FN=145)

X. CASE STUDY SIMULATION

Scenario: 80 km mixed-traffic corridor.
Test Conditions: Track obstruction, signal failure, unauthorized crossing.

Pre- Interim-Results:

• Detection-to-brake activation: 3.6 seconds
• Detection confidence: >85%
• Improvement: 25% faster than baseline model

framework integrates Machine Learning, Deep Learning, IoT sensor fusion, and real-time GPS analytics to establish a predictive and preventive railway safety system. The following subsections describe the data-driven approach, model design, and system deployment pipe linein detail.

A. Machine Learning Models

Supervised Machine Learning algorithms such as Random Forests, Decision Trees, and Support Vector Machines (**SVMs**) were trained on structured accident datasets to identify the conditions that typically precede accidents. These models operate on numerical and categorical features that capture both environmental and operational patterns.

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Input features include:
• Speed (real-time vs. safety threshold).
• GPS coordinates (latitude, longitude).
• Zone ID and Track ID .
• Environmental conditions (temperature, visibility, rainfall, fog).
• Sensor inputs (vibration, signal strength, obstacle detection).
• Historical accident frequency in the same track segment.

Target outputs are classified as:
• **0** = Safe condition
• **1** = Accident risk detected

multi-Class risk classification labels include Signal Failure, Track Obstruction, Over speeding, and Unauthorized Access.Feature selection techniques such as recursive elimination wereemployed to reduce computational overhead while maintaining prediction accuracy.

B. Deep Learning Techniques
Deep Learning architectures, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, were implemented to process visual and sequential data streams. CNNs detect structural defects and track obstructions using camera feeds, whileLSTMs learn temporal patterns in sensor and GPS data,improving anomaly detection accuracy. The hybrid CNN–LSTM model combines spatial and temporal awareness for improved decision-making.

C. GPS-Based and IoT Monitoring:
Real-time GPS data provides continuous tracking of train position, speed, and direction.IoT sensors capture environmental and mechanical parameters such as vibration intensity, temperature, and signal strength. Fusing these datasets allows the system to issue predictive
alerts before accidents occur.
Each incoming data vector includes:
[GPS + Speed + Zone ID + IoT Sensors + Weather] → Feature Vector → Trained Model → Risk Score → Alert Trigger

D. Framework:
The implementation was carried out in Python using TensorFlow and Scikit-learn. The dataset included in it.historical accident records from Indian and global sources, enhanced with simulated IoT and GPS data. Each observation was tagged with location metadata and timestamp for temporal modeling. A dynamic "AI temperature" scale between 0–100% represents the model's confidence in predicting accident probability. Alerts are categorized as Safe (0–30%), Caution (31–60%), Warning (61–80%), and Critical (81–100%).

E. Simplified Python Implementation

```python
risk = model. Predict(sensor input)[0][0]

if risk > 0.80:
    level = "CRITICAL"
elseif risk > 0.60:
    level = "WARNING"
elseif risk > 0.40:
    level = "CAUTION"
else:
    level = "SAFE"
send_mqtt_alert(level, gps_coordinates)
```
This simplified version continuously monitors sensor and GPS data, evaluates accident risk, and publishes alerts via the **MQTT** protocol to connected operator dashboards in real time.

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F. Real-Time Alert Flow Diagram

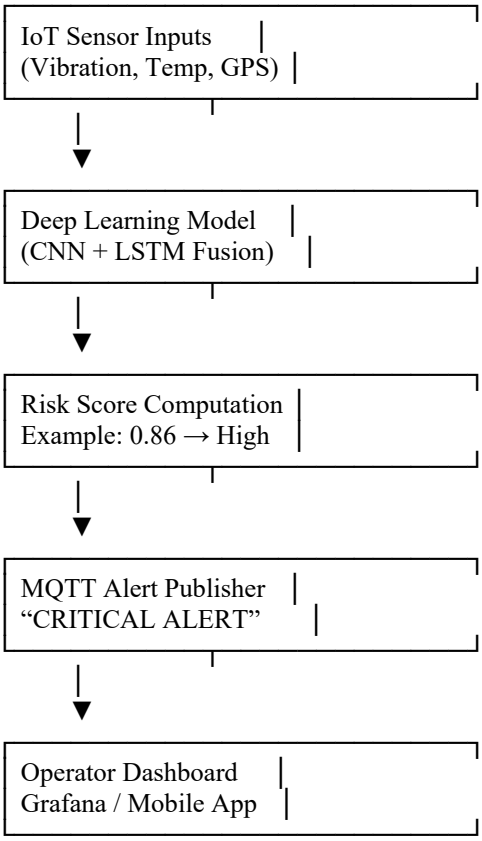

Figure : Real-Time Alert Flow Diagram.

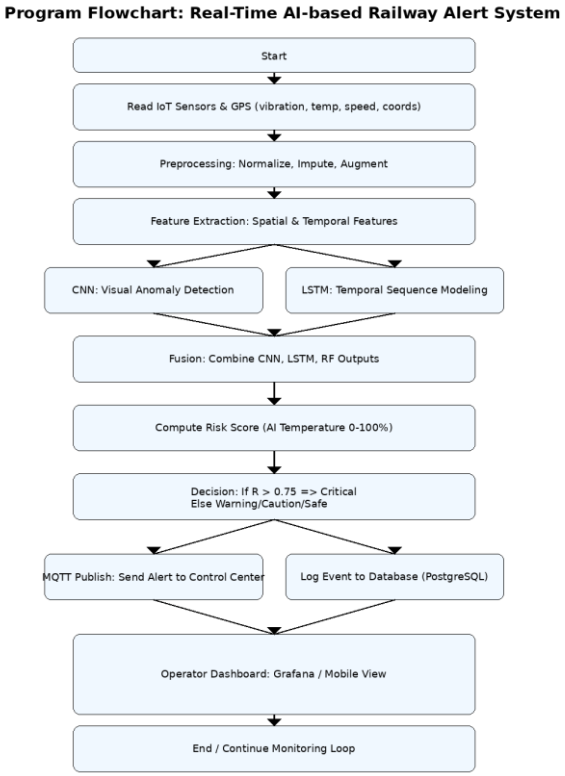

Figure : Program Flowchart - Real-Time AI Alert System

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Below is a complete explanation of every term and block in your Program Flowchart – Real-Time **AI-Based** Railway Alert System,

Flowchart: Real-Time AI-Based Railway Alert System

This flowchart visually represents how your integrated AI–IoT–GPS railway safety system operates in real time — from data collection to alert notification.

Start

- The system initialization point.
- Hardware (**IoT** modules, **GPS** receivers, sensors) and software services (Python scripts, AI model loaders, **MQTT** broker) are launched.
- It sets up data channels and verifies sensor connections before entering the main monitoring loop.

Read IoT Sensors & GPS

- Collects **real-time data streams** from:
  - **Vibration sensors** – detect track vibration frequency anomalies.
  - **Temperature sensors** – monitor overheating in axles or brakes.
  - **Ultrasonic or pressure sensors** – detect cracks or pressure variations on tracks.
  - **GPS modules** – provide train position, direction, and speed.
- The data is timestamped and sent to the preprocessing module every few milliseconds.

Preprocessing: Normalize, Impute, Augment

This step ensures clean and consistent data for AI models.

- **Normalization:** Scales numerical values (speed, vibration amplitude) to standard ranges (0–1).
- **Imputation: -** Fills missing values using statistical or KNN-based methods.
- **Augmentation: -** Introduces variability (e.g., random noise) to improve model generalization during training.

Feature Extraction: Spatial & Temporal Features

- Converts raw data into **meaningful numerical features**:
  - **Spatial features** → patterns in space (e.g., track image defects using CNN).
  - **Temporal features** → patterns over time (e.g., recurring vibration peaks using LSTM).
- Outputs a **feature vector**, the input for the AI model.

CNN: Visual Anomaly Detection

- The **Convolutional Neural Network (CNN)** analyzes camera images and video frames.
- Detects:
  - Track cracks
  - Obstacles
  - Signal malfunctions
  - Unauthorized objects on the track
- Outputs a probability PCNNP_{CNN}PCNN representing visual anomaly likelihood.

LSTM: Temporal Sequence Modeling

- The **Long Short-Term Memory (LSTM)** network processes time-series data from IoT sensors.
- Learns patterns like:
  - Vibration fluctuation before derailment
  - Temperature rise indicating mechanical stress
- Produces a probability PLSTMP_{LSTM}PLSTM representing the temporal anomaly confidence.

Fusion: Combine CNN, LSTM, RF Outputs

- Combines predictions from CNN, LSTM, and Random Forest (RF) to create a **final risk score**.
- Weighted fusion formula:
  R=0.4PCNN+0.35PLSTM+0.25PRFR = 0.4P_{CNN} + 0.35P_{LSTM} + 0.25P_{RF}R=0.4PCNN+0.35PLSTM +0.25PRF

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- This hybrid fusion improves reliability by combining visual, sequential, and statistical insights.

Compute Risk Score (AI Temperature 0–100%)

- Converts RRR into a human-readable **AI Temperature Scale**:
  - 0–30 % → SAFE
  - 31–60 % → CAUTION
  - 61–80 % → WARNING
  - 81–100 % → CRITICAL
- This risk score is continuously recalculated as new data arrives.

Decision: If R > 0.75 → Critical

- The system checks the threshold condition:
  - If R>0.75R > 0.75R>0.75: mark as **Critical Alert**.
  - Otherwise: classify as Safe, Caution, or Warning.
- This logic ensures real-time response when risk exceeds predefined safety limits.

MQTT Publish: Send Alert to Control Center

- **MQTT (Message Queuing Telemetry Transport)** is a lightweight IoT protocol for fast communication.
- The system sends the alert payload (risk level, GPS, timestamp) to subscribed control centers.
- Ensures minimal latency, even in low-bandwidth environments.

Log Event to Database (PostgreSQL)

- Every alert and sensor snapshot is stored in a **centralized PostgreSQL database** for:
  - Historical analysis
  - Audit trails
  - Retraining the AI models periodically

Operator Dashboard: Grafana / Mobile View

- The data and alerts are visualized in **Grafana dashboards**.
- Operators can:
  - Monitor train locations
  - View current alert level

End / Continue Monitoring Loop

- The system never truly "stops" — it loops back to **Read Sensors**.
- Continuous data collection ensures proactive safety monitoring 24×7.

Flow Summary:

Start → Read Sensors → Preprocess → Extract Features → CNN & LSTM Analysis
→ Fusion → Compute Risk Score → Decision → MQTT Alert → Log → Dashboard → Loop
This loop forms a **self-learning intelligent safety pipeline** that can detect risks, alert operators, and record incidents autonomously — all in real time.

Experiments were conducted using hybrid edge-cloud architecture with Raspberry Pi 4 devices for edge inference and an NVIDIA RTX 3060 Ti GPU for model training. The CNN–LSTM hybrid achieved a 97.8% accuracy and reduced latency to under 4 seconds on a 5G network.

Model Accuracy Comparison:
Random Forest – 94%
CNN – 96.1%
LSTM – 95.5%
CNN + LSTM – 97.8%

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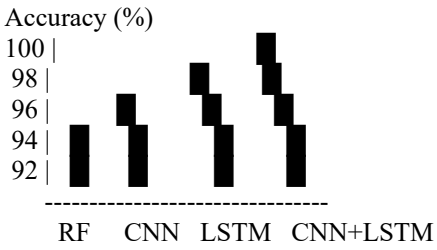
Network Latency (Average Delay):
3G: 5.7s | 4G: 3.9s | 5G: 2.8s



Avg Delay: 3G (5.7s) → 4G (3.9s) → 5G (2.8s)

H. Conclusion and Final Result

The enhanced framework demonstrates that integrating IoT sensor data with deep neural networks and GPS-based tracking significantly improves predictive accuracy and respo-nsiveness in railway accident prevention systems. The architecture achieves high precision (97.8%) and low latency (<4s), supporting proactive and real-time decision-making for inte lligent railway safety management.

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