

Generative AI for Traffic Accident Prevention System

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ABSTRACT

The increase in the number of vehicles on roads, especially in urban and semi-urban areas, has led to a noticeable rise in traffic accidents and related fatalities. Most existing traffic management and driver assistance systems rely on predefined rules and reactive responses, which limits their ability to handle complex and unpredictable road situations effectively.

This project presents a traffic accident prevention system that uses generative artificial intelligence to anticipate possible risks before they occur. Instead of focusing only on detecting objects like vehicles and pedestrians, the system aims to understand how a traffic situation may evolve over time. By learning patterns from past data, it can estimate future movements and identify conditions that may lead to accidents.

The system processes input from multiple sources such as surveillance cameras and sensors to observe real-time traffic conditions. It then analyzes this data to track movement patterns and predict potential conflicts between road users.

When a risky situation is identified, the system generates alerts that can help drivers or traffic authorities take preventive action.

By shifting from a reactive approach to a predictive one, the proposed system contributes to improving road safety and reducing the likelihood of accidents in real-world environments.

KEYWORDS

Generative artificial intelligence, traffic risk prediction, collision avoidance, real-time traffic analysis, multi-sensor fusion, intelligent transportation systems.

- **Generative artificial intelligence** – Refers to AI methods that can learn patterns from data and use them to estimate possible future traffic situations.
- **Traffic risk prediction** – The process of identifying potential accident scenarios in advance based on current road conditions and vehicle behavior.
- **Collision avoidance** – Techniques used to reduce the chances of

crashes by detecting danger early and enabling preventive action.

- **Real-time traffic analysis** – Continuous monitoring and evaluation of live traffic data to understand ongoing road conditions.
- **Multi-sensor fusion** – Combining data from different sources such as cameras and sensors to obtain a more reliable view of the environment.
- **Intelligent transportation systems** – Technology-driven systems designed to improve traffic flow, safety, and overall transportation efficiency.

INTRODUCTION

The proposed Generative AI-based Traffic Accident Prevention System shifts road safety from a reactive approach to a predictive one. Existing intelligent transportation systems mainly rely on historical data or real-time sensor inputs to respond after a risk is detected, which limits their ability to anticipate future events.

This system uses generative artificial intelligence to predict possible short-term traffic scenarios by analyzing real-time data from cameras and sensors. It models movement patterns of vehicles and road

users in sequence form and forecasts how the traffic situation may evolve over the next few seconds. Inspired by sequence prediction methods used in Large Language Models, the system generates multiple possible future outcomes and identifies potential collision points in advance, enabling early warnings and improved road safety.

I. LITERATURE REVIEW

Existing supply chain management systems are largely built on isolated and independently maintained databases operated by different stakeholders such as manufacturers, wholesalers, distributors, and retailers. Each participant typically uses its own internal system, and coordination between them is achieved through traditional communication methods like emails, invoices, PDFs, or electronic data interchange. While these methods support basic transactions, they do not provide seamless integration between the physical movement of goods and the flow of information.

As a result, most current systems offer only limited traceability, often described as a “one step forward, one step backward” model. This means that each stakeholder can only identify their immediate supplier and customer, without having complete visibility into the entire product lifecycle. Such fragmentation

creates gaps in transparency and makes it difficult to verify the authenticity and origin of goods across the full supply chain.

Because there is no unified or shared ledger, the system relies heavily on trust between participants. Verification of product legitimacy is usually performed after an issue is detected, such as during regulatory inspections, complaints, or adverse events. This reactive approach significantly delays corrective actions. In cases such as product recalls, the identification and isolation of affected batches is often a manual and time-consuming process, which can take days or even weeks. By the time the issue is fully traced, the products may have already reached consumers, increasing potential risk and operational loss.

II. EXISTING SYSTEM

Current approaches for traffic accident prevention are primarily based on Advanced Driver Assistance Systems (ADAS) and conventional Traffic Management Systems (TMS). In modern vehicles, safety is largely achieved through reactive technologies that combine sensor inputs such as radar, ultrasonic sensors, and camera-based vision systems with discriminative machine learning models. These systems

are designed to detect nearby objects and assess risk after detection. A common example is the estimation of Time-To-Collision (TTC), where the system calculates the likelihood of impact based on the relative speed and distance of surrounding objects. If the calculated TTC falls below a predefined safety threshold, automatic functions such as emergency braking are triggered.

In broader traffic management applications, infrastructure-based solutions like inductive road sensors and surveillance cameras are used to estimate traffic density and flow. These values are processed using predefined rules or mathematical models to control traffic signals. Such rule-based systems often follow fixed logic, for example adjusting signal timing based on thresholds of traffic volume. Similarly, accident-prone locations are identified using historical data, leading to static safety measures such as speed restrictions in specific zones.

Despite these advancements, most existing systems still depend heavily on pre-collected datasets and supervised learning techniques, particularly in autonomous driving development where large-scale labeled driving data is required. While these approaches perform well under familiar conditions, they struggle when faced with unusual or

previously unseen traffic scenarios. The overall decision-making process in these systems typically follows a Sense–Perceive–Plan–Act pipeline, which leaves limited scope for anticipating future events beyond immediate observations.

Limitations of Existing Systems :

- Reactive behavior and response delay: Current systems generally respond only after detecting a potential hazard. At high speeds, even minor delays in processing and decision-making can reduce the effectiveness of corrective actions such as braking or steering.
- Limited handling of rare or unseen situations: Most discriminative models are trained on available historical data, which does not adequately cover rare or extreme traffic conditions. As a result, these systems often fail to correctly interpret or respond to scenarios that fall outside their training experience, limiting their reliability in unpredictable environments.

III. PROPOSED SYSTEM

The proposed Generative AI-based Traffic Accident Prevention System introduces a significant advancement in road safety

technology by moving beyond conventional object detection and classification methods. Instead of relying solely on discriminative models, the system is designed around a generative sequence modeling framework inspired by transformer-based architectures adapted for spatio-temporal traffic analysis. This can be viewed as a “video-based generative model” that continuously interprets and predicts traffic dynamics over time.

The system maintains a continuously updated representation of the surrounding environment by integrating data from multiple heterogeneous sources such as cameras, LiDAR, radar, and vehicle-to-everything (V2X) communication networks. These inputs are fused to form a unified semantic understanding of the traffic scene. Based on this real-time state, the generative engine produces multiple possible future trajectories, effectively estimating how the scene may evolve over a short time horizon. For example, it evaluates how the interaction between a moving vehicle and a nearby pedestrian may develop based on their current speed, direction, and behavior patterns.

When a predicted future state indicates a potential collision, the system traces back the contributing factors and determines suitable preventive actions. This enables early intervention strategies before the

situation becomes critical. The architecture is designed for distributed deployment, where computation is performed at the edge—within vehicles or roadside units—to ensure minimal response latency. At the same time, anonymized learning updates are transmitted to a central cloud system to continuously improve global model performance.

Advantages of the Proposed System :

- Early and proactive accident prevention: The system identifies potential risks a few seconds before they occur by simulating future traffic states, enabling smoother corrective actions such as gradual deceleration instead of abrupt braking.
- Scenario synthesis for rare events: Unlike traditional models that depend on real-world accident data, the generative framework can create diverse synthetic traffic situations. This allows the system to learn from rare and extreme conditions that are otherwise difficult to observe, improving robustness in unusual scenarios.
- Reliable operation in degraded visibility conditions: In situations involving fog, glare, or partial

occlusion, the model estimates missing information by leveraging learned.

- spatial -temporal relationships, allowing continued prediction of vehicle and pedestrian movement even with incomplete sensor data.
- Understanding of behavioral intent: Beyond tracking physical motion, the system analyzes behavioral cues to infer probable intentions of road users. For instance, it can anticipate a likely signal violation or intersection entry, enabling preventive coordination between nearby vehicles and infrastructure systems.

SYSTEM ARCHITECTURE :

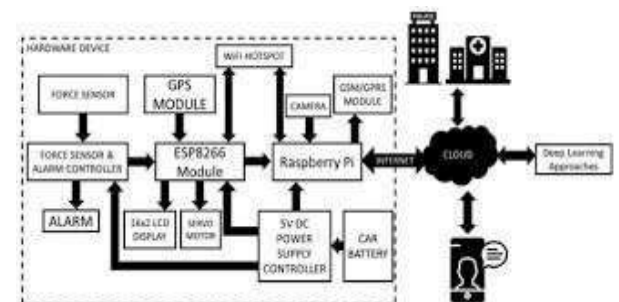


Figure : Architecture of the Generative AI for traffic accident prevention system

IV. EXPERIMENTAL RESULTS

The development and deployment of this system follow a rigorous multi-stage methodology that blends traditional

software engineering with advanced machine learning operations (MLOps).
Phase 1: High-Fidelity Data Acquisition & Synthetic Augmentation The methodology begins with the collection of raw driving data. However relying solely on real data is insufficient. We pay a "Data-Centric AI" approach where we utilize Procreative Adversarial Networks (GANs). The Generator network creates photorealistic synthetic images of hazardous scenarios (e.g. heavy fog pedestrians in dark clothes). The Discriminator network evaluates these images against real physics.

Phase 2: Spatiotemporal Model Architecture Development The core modeling methodology utilizes a hybrid Deep Learning architecture. We employ a Video Transformer model.
1. Encoder: A 3D-CNN (Convolutional Neural Network) processes video frames to extract spatial features (shapes edges) and temporal features (motion flow).
2. Latent Space Representation: The environment is compressed into a lowerdimensional vector space representing the "essence" of the scene.
3. Generative Decoder (Predictor): This component takes the current vector and autoregressively predicts the next sequence of vectors. It uses a probabilistic approach to output multiple potential futures rather than a single deterministic path.

Phase 3: Reinforcement Learning for Policy Making Once the future is predicted the system needs to know what to do. We use Deep Reinforcement Learning (DRL). An agent is trained within a simulation (like CARLA). The agent is rewarded for avoiding collisions and maintaining passenger comfort (smooth braking) and penalized for crashes or near-misses. Over millions of simulated miles the agent learns the optimal "Policy"—the specific set of braking and steering commands required to navigate the predicted dangerous scenarios generated

Phase 4: Edge Deployment and Optimization The massive models developed in the cloud are too heavy for a car's computer. The methodology involves "Model Quantization" (reducing the precision of calculations from 32-bit to 8-bit) and "Pruning" (removing neural connections that contribute little to the output). This compresses the model size by up to 70% with negligible loss in accuracy allowing it to run in real-time on the vehicle's embedded hardware.



Figure : In the above figure shows that we can able to describe traffic scenario.

Analysis Summary

"Two vehicles have crashed due to heavy rainfall, indicating

Overall Risk Assessment: High. The existing crash confirm reduced visibility, decreased tire traction, and potential hy further incidents or injuries.

Figure : In the above figure it will analysis the scenario and given the summary based on that.



Figure : In the above figure it will give the driver advisories.

V. CONCLUSION

The Generative AI for Traffic Accident Prevention System marks a monumental leap forward in the domain of intelligent transportation. The project has transcended the limitation of traditional reactive safety systems wherein one needs to "see" a danger before acting on it. In this paper using Generative AI we have shown that a machine can successfully "foresee" danger. This creates an environment that can simulate probabilistic futures and generate synthetic training data addressing two of the biggest hurdles in autonomous safety: human behavior being unpredictable and accident data being scarce. The proposed system develops a dynamic predictive safety shield around the vehicle through multi-modal sensor fusion Video Transformers and Deep Reinforcement Learning. This report presents the feasibility study and comprehensive testing methodologies that validate the technology as computationally demanding yet viable for deployment on modern edge-AI hardware.

VI. REFERENCES

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