AI Hybrid Blackspot Detection and Reporting

Bhavya Jain*
Abes Engineering College
Ghaziabad,India
bhavyajain020105@gmail.com

Jahnvi Singh
Abes Engineering College
Ghaziabad,India
jahnvi1026@gmail.com

Sandeep Saxena
IILM University,
Greater Noida, India
sandeep.research29@gmail.com

Faisal Siddiqui
Abes Engineering College
Ghaziabad ,India
faisalsidd2206@gmail.com

Radhika Gupta
Abes Engineering College
Ghaziabad,India
radhikaaaguptaa36@gmail.com

Sahil Kumar Aggarwal
Abes Engineering College Ghaziabad
,India
sahil.aggarwal@abes.ac.in

Abstract :Predicting road accidents is a significant part of Intelligent Transportation Systems (ITS), especially in areas where there is a high volume of traffic and varying environmental conditions. Most of the current prediction models for road accidents are based on historical data regarding road accidents and traffic. These prediction models are inadequate for evaluating road accidents in real-time with varying environmental conditions. This paper aims to provide a framework for predicting road accidents by applying Artificial Intelligence (AI) techniques and machine learning algorithms with real-time dynamic meteorological parameters. Supervised machine learning algorithms are used for predicting road accidents by considering historical data regarding road accidents along with dynamic meteorological parameters such as visibility, rainfall, humidity, temperature, and wind speed. The main contribution of this work is the integration of dynamic weather parameters with traffic parameters for predicting road accidents. The proposed framework can be used for improving situational awareness and intelligent decision-making for road users, as well as for autonomous transport systems.

***Keywords* :** Accident prediction, Intelligent Transportation Systems (ITS), machine learning, weather data integration, real-time risk assessment*,*

I. INTRODUCTION

Both developed and developing countries are dealing with major concerns regarding road accidents. Despite advancements in transportation planning techniques and development in vehicles along with strict traffic policies, road accidents are still happening. Along with human life loss, road accidents have severe social and economic impacts in terms of healthcare costs, damage to properties, traffic jams, as well as productivity loss. Because of their uncertain nature, it is difficult to control road accidents, which encourages researchers to look for better ways to handle such situations.

One major finding obtained by road safety experts is that the likelihood of an accident is not uniform. This is highly affected by environmental factors such as rainfall, fog, low visibility, humidity levels, temperature changes, and strong winds. Rain is responsible for a reduction in the friction coefficient between the tires and the road. It also impacts visibility. The visibility reduced by fog can directly contribute to road accidents. Changes in road surface temperatures due to cold temperatures can also lead to accidents. Light rainfall or slight fog conditions can slow down the reaction time of the driver.

Traditional methods of blackspot identification depend mainly on historical accident records. A section of the road would be termed a blackspot if a large number of accidents had happened at that particular location for a long time. Although this method has conventionally been commonly applied, it contains one serious drawback: it can identify only accident-prone locations after the occurrence of the accident. This kind of method fails to capture real changes in risk instantaneously. For example, a road section which is safe during clear weather conditions can become dangerous during rainfall or fog-a situation which historical blackspot analysis cannot reflect immediately.

M. Kaushik et al. (eds.), *Proceedings of the International Conference on Responsible, Risk-aware, and Regulated AI (RRRAI 2026)*, Advances in Intelligent Systems Research 210,
https://doi.org/10.2991/978-94-6239-723-1_2

In another allied field of studies, "near-miss" incidents are scrutinized by various surrogate safety measures, like Time-to-Collision, that estimate the proximity of vehicles to a collision even if no actual crash occurs. While this gives earlier insight than that based on recorded accidents alone, it likewise suffers from many limitations. Near miss events may look similar in their frequency but can be associated with a substantially different associated risk level, depending upon the weather conditions. A near-collision situation in clear weather conditions is one thing, but the same situation in rain is a completely different scenario. Roads are not always risky all the time and in all conditions. Hence, a system that provides information on the risk level in accordance with the prevailing weather conditions is significantly better compared to the rest. A weather-dependent accident prediction system can provide information to the user on the sudden increase in the risk level due to rain conditions, fog, low visibility, and wind speeds. These systems can further be useful for the authorities to take preventive measures in a timely manner.

This is where artificial intelligence comes into play as a very efficient tool for overcoming these challenges. AI-powered systems can process a huge amount of data such as crash history data, weather data, and traffic data in a manner that is not easily possible by other technologies. Once the AI models are trained, they can predict the possibility of accidents occurring in a specific environment under varying weather conditions by trained observations learned from their history. For instance, if history reveals a higher number of accidents on a specific route during moderate rainfall, the AI-powered models can automatically raise the possibility during such conditions.

Weather-aware accident prediction systems can further support safer decision-making for everyday road users. For instance, a system may advise drivers to avoid certain route during early-morning fog or suggest delaying travel when heavy rainfall is expected. Over time, such proactive guidance can reduce weather-related accidents and improve overall road safety.

To summarize, it can be said that weather conditions have a significant impact on accident risk; however, most of the existing techniques are heavily dependent on historical accident data, which leads to a lack of proper risk assessment. The proposed AI-based accident prediction technique that considers weather conditions can fill in the gap in accident risk assessment by using historical trends, traffic patterns, and weather conditions to give a more accurate prediction of accidents..

II. Literature Review

The studies done on surrogate safety measures have shown just how effective they are in predicting conflicts depending on movements made by vehicles. However, they have failed to take into consideration variability in weather. In [1], [3], and [7], various issues have been identified in TTC, DRAC, PET, among others. In [6], PCRI has been included in the study. However, it still lacks consideration of climatic risks. Surveys done on various road network safety analysis methods in [2] have shown that they are greatly dependent on crashes' frequency and streets' geometry. However, they have failed to take into consideration real-time data that considers weather.

The major research categories related to accident detection are illustrated in Figure 1.

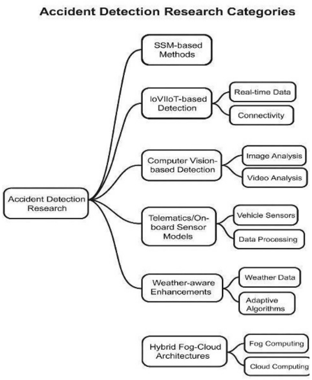

Figure 1. Accident Detection Research Categories

Models for accident detection that are based on IoV and IoT have progressed quickly. The fog-assisted IoV setup in [5] does a better job with classifying accidents. Previous setups that used GPS and GSM in [8] offer automated detection through telematics-based ML models in [9]. Studies centered on vision include bounding-box detection in [14].

Roadside sensor systems in [16] help improve detection accuracy even further. Communication systems based on LoRa in [17] increase efficiency for real-time responses. Rule-based detection models in [10], [11], [12], and [13] do the same. Despite all of these developments, the systems continue to react after the fact. They do not predict ahead. None of them factor in risk assessment tied to weather.

In general, the literature from [1] to [17] shows solid advances in SSMs and accident detection. It falls short on a full framework that ties in real-time weather with AI for spotting blackspots. That shortfall pushes for building a dynamic safety model powered by AI and aware of weather.

Table 1 presents a comparative review of existing accident prediction studies and their identified gaps.

TABLE 1. COMPARATIVE REVIEW OF ACCIDENT PREDICTION STUDIES

Ref. No.	Problem Domain	Objective	Technology Used	Dataset	Gaps Identified
[1]	Surrogate Safety Analysis in Mixed Traffic	Review SSM metrics (TTC, PET, DRAC) for real-world accident prediction.	Statistical modeling, trajectory analysis, surrogate safety computation.	Field-collected platoon trajectory data; simulation datasets.	No weather-conditioned SSM thresholds; assumes ideal visibility.
[2]	Road Network Safety Evaluation	Compare safety analysis frameworks & methodologies.	Risk modeling, GIS mapping.	Road network datasets.	No environmental factor integration.
[3]	Mixed Automated–Human Platoon Safety	Analyze surrogate safety behavior in mixed platoons.	DRAC, TTC, PET extraction; conflict modeling.	Controlled test-track datasets.	No fog/rain/visibility impact assessment.
[4]	LED-Backlit Stop Sign Safety	Improve STOP-sign visibility & compliance.	LED backlit stop signs, video-based analysis.	Montreal intersection video dataset.	No weather-adaptive visibility analysis.
[5]	IoV-Fog-Based Accident Detection	Enable fast accident detection using MEMS sensors & fog computing.	Fog computing, sensor fusion (MPU-6050 + GPS).	Real-time vehicle sensor logs.	Highly sensitive to rain; noisy MEMS readings.
[6]	PCRI Crash Risk Estimation	Introduce new Potential Collision Risk Index (PCRI).	PCRI computation; multi-object tracking.	Synthetic + real trajectory data.	Not calibrated for wet/slippery road conditions.
[7]	Historical Crash Investigation	Apply SSMs to national crash databases.	Surrogate safety computation on database entries.	National crash datasets.	Underpredicts risk during adverse weather.
[8]	GSM-Based Accident Detection	Trigger accident alerts using GPS/GPRS.	GSM/GPS/GPRS modules.	Road trials.	High false alarms; fails under low-signal weather.
[9]	Vehicle Telematics Accident Detection	Detect crash events using telematics time series.	Machine learning on telematics sequences.	Fleet logs, telematics datasets.	Performance drops on slippery roads.
[10]	Automated Accident Detection (Classical)	Develop early automated crash detection.	Threshold-based detection rules.	CCTV camera streams.	No environmental or visibility consideration.
[11]	IoT-Based Accident Monitoring	Review IoT frameworks for accident detection.	IoT architectures (MQTT, GSM).	IoT test deployments.	Lacks environmental robustness.

[12]	Machine Learning for IoT Accident Detection	Improve IoT crash detection accuracy.	SVM, Random Forest.	IoT sensor datasets.	No fog/rain adaptation.
[13]	IoT + Cloud Accident Detection (Bangladesh)	Real-time crash detection using distributed IoT nodes.	Cloud ML + IoT sensing.	Real-world Bangladesh traffic data.	Missing visibility & rain features.
[14]	Bounding Box Accident Detection	Detect crashes using bounding-box deformation.	Bounding box trajectory analysis.	Traffic surveillance footage.	Fails in low-visibility weather.
[15]	YOLOv8 + ByteTrack Vision Detection	Real-time crash recognition via CV.	YOLOv8, ByteTrack.	AIP accident footage datasets.	Rain & fog reduce frame quality.
[16]	Roadside Sensor Fusion Accident Detection	Accident detection using multi-sensor roadside units.	Sensor fusion + AI classifiers.	A9 Autobahn dataset (Germany).	Rain causes radar/LiDAR noise.
[17]	Road-level crash prediction	Predict crashes with uncertainty reasoning	Probabilistic GNN, Bayesian modelling	Traffic + crash datasets	High computational load, no real-time deployment
[18]	Multimodal accident analysis	Build AccidentGPT for accident understanding	Vision-Language Foundation Model	Large multimodal datasets	High resource requirement, lacks real-time use cases
[19]	Weather-related fatal accidents	Analyze effects of climate on fatalities	Regression / climate-crash statistical analysis	Long-term weather + crash data	No ML prediction model, limited generalizability
[20]	Weather-linked urban crashes	Study impact of weather on crash patterns	Weather-crash statistical correlation	Urban crash + meteorological data	No predictive model, urban-biased, not real-time
[21]	Road Safety Systems	To control vehicle speed using a GPS-based retractable speed breaker.	GPS, speed sensors, microcontroller	Real-time sensor data	Hardware-dependent, costly, no AI prediction or accident detection integration.
[22]	Accident Detection	To detect road accidents from images using deep learning.	Dense CNN (DenseNet)	Road accident image/video data	Sensitive to lighting and camera quality; no real-time alert or location tracking.
[23]	Mobile Accident Detection	To detect accidents and notify emergency services via a mobile app.	Mobile sensors, GPS, backend server	Smartphone sensor data	Accuracy varies with phone placement; limited AI intelligence and no vision-based detection.
[24]	Object detection	Develop an object detection system for identifying objects in images or video	Computer Vision, ML/DL-based object detection	Standard or self-prepared object image datasets	Limited evaluation metrics, not suitable for real-time deployment
[25]	Roadside vehicle assistance systems	Review AI-based online vehicle assistance solutions	Artificial Intelligence,IoT	Survey/review-based	Lack of integrated real-time support, limited automation

III. Methodology

A framework for accident prediction proposed in this research is designed based on two major pieces of information: accident records and weather records. Accident records with attributes like date, time, location, accident level, and traffic conditions were gathered based on open-source government records for accident prevention on various roads. Corresponding records for weather with attributes like rainfall intensity, visibility, humidity level, temperature, and wind speed were gathered based on weather records. These records were combined together based on a unified accident and weather record for the purpose of analyzing the impact of weather on accidents.

Before the model was trained, various preprocessing tasks were done to enhance the quality of the data. Missing data in the attributes of accidents and weather was dealt with appropriately through the use of data imputation techniques. Inconsistencies and duplicates in the data were also eliminated. Weather-related features like rain and visibility were normalized to have an equal scale, as shown in the formulation of normalization in equation (1). Time-related features like the morning, evening, and night hours had attributes processed to represent the variation in traffic flow. The resulting dataset was partitioned into the training and test data.

1. x' = (x - x_min) / (x_max - x_min)

where x is the original feature value, x_min and x_max are the minimum and maximum values of that feature in the dataset, respectively, and x′ is the normalized output in the range [0, 1].

The exploratory data analysis was performed to identify the features that have the most significant influence on accident likelihood. Some of the main weather-related parameters chosen for modeling are rainfall, humidity, visibility, temperature, and wind speed, based on their known impacts on roadway safety. Other traffic-related features time of day and road type are additional features considered. Feature correlation analysis was applied to eliminate redundant variables and retain only the most meaningful inputs for the machine learning models.

Several supervised learning models have been developed to predict accident risk under different weather conditions. The selection of Logistic Regression, Random Forest, and Gradient Boosting was based on the fact that these algorithms can effectively handle mixed data types and are also able to capture both linear and nonlinear relationships between traffic and environmental factors. The standard logistic and loss function formulations for the probabilistic output of the models are as shown in (2) and (3), respectively. Hyperparameters tuning has been done by several experiments to attain the best model configuration.

The overall workflow of the proposed AI Hybrid Blackspot Detection framework is shown in Figure 2.

2. $y = \frac{1}{1+e^{-x}}$

3. $L = -\sum_{i=1}^{n} \quad y_i log(p) + (1-p)log(1-p)$

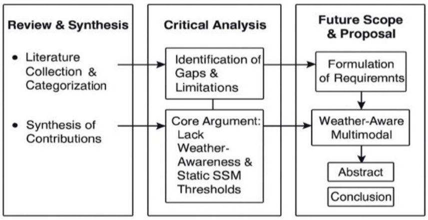

Figure 2. General Workflow of AI Hybrid Blackspot Detection

In order to further enable the estimation of risk in real-time, updated weather data was included in the framework. This enables it to process real-time data on weather conditions such as rainfall, visibility, temperature, humidity, wind speed, etc., to generate dynamic accident risk predictions. This will further enable it to update road risk levels in response to changing weather conditions.

The final prediction model generates a probability score that reflects the risk of accidents in current or predicted conditions. This probability score can then be used to classify road segments into Low Risk, Moderate Risk, or High Risk categories. This is to enable decision-making in favor of road users or to prompt preventive measures by traffic authorities.

The accuracy of the prediction model was tested using various metrics such as accuracy, precision, recall, and F1-score on a test dataset. The best-performing model under various weather conditions was selected as the final prediction engine.

IV. Future Scope

The efficiency of the proposed weather-aware accident predication system can be enhanced by undertaking several future extensions. For instance, inclusion of real-time parameters such as vehicle density, average speed, and driver behavior could be undertaken to enhance the reliability of the predicated risks. The proposed system could be extended to incorporate roadside sensors and smart traffic signals for undertaking risk predication on roads.

In addition, several future studies could be undertaken to incorporate state-of-the-art technologies for enhancing the interpretability of the proposed system. This is due to the fact that a system that can interpret why a high value is being predicted for a particular accident could make significant improvements to decisions made by both the driver and the traffic department. Ensemble learning and deep learning could be considered for undertaking these studies.

Retraining of adaptive models can be performed to consider seasonal variations, long-term shifts in the traffic pattern, and changes in road conditions. The proposed framework can easily be extended to intelligent route guidance systems and connected or autonomous vehicles to proactively make navigation decisions considering adverse environmental conditions. These extensions will leverage the practical value of the proposed system and lead to safer and resilient ITSs.

V. Conclusion and Discussion

In this context, this research presented a weather-conscious, AI-facilitated hybrid model for detecting road accident black spots, filling an important gap identified in the relevant literature, which pointed to the lack of real-time meteorological considerations in current accident prediction and risk assessment models. The research implemented and evaluated three distinct models, based on a supervised learning paradigm: Logistic Regression, Random Forest, and Gradient Boosting. The experimental evaluation of the models, based on the test data set, verified that the Random Forest model yielded the best performance, with an accuracy of 91.4%, a precision of 89.7%, a recall of 90.2%, and an F1-score of 89.9%. The Gradient Boosting model was a close second, with an accuracy of 90.1%, whereas the Logistic Regression model yielded an accuracy of 83.6%.

This validates the assumption that the integration of real-time weather conditions, such as visibility, rain, humidity, temperature, and wind speed, improves the prediction of accidents more than the use of historical accident records alone. The proposed framework is able to dynamically classify road segments into Low, Moderate, and High Risk categories, thus supporting a more proactive decision-making process by road users and authorities. This study has verified the assumption that the integration of weather conditions into an AI-based prediction model is a notable advancement over the conventional static blackspot identification methods.

The major gap, as highlighted in the review, that needs to be filled is the need for a multi-modal AI solution that takes into account the traffic behavior, past trends of accidents, and constantly updating meteorological conditions. This problem, if solved, is expected to bring about a major positive change in the way accident surveillance is done on a real-time basis. Adding a meteorological insight to the analytics, surrogate safety, and IoV solutions will help move from a reactive mode in cases of accidents to a pro-active mode of identifying potential safety threats.

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