

Smart Weather-Aware and Safety-Optimized Route Planning Using Machine Learning and Spatial Risk Analytics

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Abstract

The environmental characteristics and weather conditions of cities directly influence the safety of city streets. Conventional navigation systems are optimized for the quickest possible travel times and shortest distances, without consideration for safety or the risks associated with travel through these areas. In this research, we propose an urban road safety framework that utilizes real-time environmental data and accident-prone locations to provide a comprehensive safety rating for a traveler's route based on the severity of potential accidents. We utilized a random forest model to develop a structured database of both road and environmental characteristics, which has a mean absolute error of 0.96, a root mean squared error of 1.13, and an R^2 score of 0.828, all measured against a 1-10 severity scale. For determining whether the risk of being involved in a serious accident is categorized as low, medium, or high, our model produced a classification accuracy rate of 78.67%. The risk prediction is then combined with environmental penalties for adverse conditions and penalty values for accident-prone areas to create a safety index at the route level. Our experimental testing was performed on various routes throughout Delhi and demonstrated that the proposed framework produces safety-conscious routes while maintaining little variance in travel time compared to time-optimal routes. These results demonstrate that utilizing predictive risk models with environmental intelligence can improve decision-making in urban navigation to reduce the risk of accidents.

Categories: Geographic Information Systems, Predictive Analytics, Machine Learning (ML)

Keywords: route safety, weather-aware navigation, machine learning, accident hotspots, risk-aware routing

Introduction

Urban route planning - finding the best path within a city - is one of the most important applications of modern navigation systems. Most navigation systems have focused on finding the shortest possible travel time or distance without considering the risks associated with travel (e.g., road safety). Many studies have demonstrated that environmental hazards (weather, low visibility, poor air quality) and historically accident-prone road segments can greatly influence roadway crash rates in urban areas. There are few, if any, routing systems that consider these risks when determining which route to take. In this paper, we propose a Safety-Aware Urban Route Planning System, which combines machine learning-based risk assessment with environmental and geospatial safety assessments to develop a composite safety measure for each route option. While many traditional navigation systems aim to optimize travel time or distance, the proposed system includes safety as an optimization goal. Safety-Aware Urban Route Planning System uses real-time data to determine environmental conditions, identifies areas with a history of accidents, and predicts the severity of collisions on all candidate routes. We used random forest (RF) models to predict collision risk for each route and used geospatial analysis to identify historically accident-prone zones. We then applied a spatial penalty function to calculate a composite safety score for each route. The overall safety scores enable users to compare alternative routes and

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make informed decisions regarding travel time versus travel safety. Our proposed framework was tested using Delhi's urban road network, and our experimental results show that routing travelers using safety as a primary consideration can reduce their exposure to hazardous areas while minimizing increases in travel time. These results provide strong evidence that combining predictive analytical methods, environmental intelligence, and geospatial risk mapping can lead to more effective decision-support systems for improving urban mobility safety.

The use of machine learning to predict the severity of traffic accidents has been widely documented using structured crash data. For example, Khanum et al. [1] demonstrated the ability to apply an RF model to predict crash severity using Indian expressway data provided by the Ministry of Road Transport and Highways and the National Highways Authority of India. Specifically, they showed that the RF model can effectively represent the complex interactions among road, vehicle, and environmental factors involved in predicting crash severity; however, the models did not perform well across a wide range of conditions. In another study, Ahmed et al. [2] evaluated the predictive capabilities of multiple classification algorithms (decision trees, RF, K-nearest neighbors, naive Bayes, and AdaBoost) and concluded that ensemble methods were generally superior to individual models. However, Yan and Shen [3] focused only on post-incident injury classification; they did not examine real-time routing applications. Yan and Shen [3] suggested that using RF with Bayesian optimization for performance and feature importance analysis improved both accuracy and interpretability. Similarly, Kumar and Kasa [4] stated that ensemble models such as RF and XGBoost showed good predictive performance. Despite these improvements, severity prediction is mostly handled independently, without being combined with preventive, route-level safety assessment.

Bad weather affects road safety, but most routing systems do not account for it. Qin and Luo [5] proposed a weather-aware routing method for aviation using restricted zones and A* search; however, it was not designed for road traffic. In road safety research, weather data is mainly used as an input for crash prediction rather than as a routing constraint. In most road studies, weather is used only to predict crashes, not to choose safer routes. Therefore, there is a gap between weather risk prediction and navigation guidance.

Crash-location studies are used to identify high-risk road areas. Many crashes occur at specific hotspots, such as intersections. Elvik [6] emphasized evidence-based safety planning using historical crash records but focused on policy-level interventions rather than individual navigation assistance. Recent studies of crash prediction models focus on both temporal and spatial risk estimation. Cai et al. [7] suggested an integrated spatiotemporal deep learning framework for short-term crash prediction using time-series regression and convolutional neural networks. Their framework outperformed traditional statistical and neural network models and demonstrated significant improvements in identifying dynamic traffic patterns for proactive safety management. Likewise, Sobhana et al. [8] introduced a hybrid machine learning approach using statistical models and classification techniques to predict accident severity and identify crash-prone hotspots. They demonstrated that hybrid modeling increases the robustness of predictions and supports decision-making for safe operations. Bhatti et al. [9] developed a mobile-based crash detection and alert system focusing on post-accident response rather than prevention. Advanced Internet of Vehicles-based approaches, such as the deep learning framework developed by Wei [10], predict accidents in real time, but they require expensive devices and robust network infrastructure, making them difficult to integrate into standard navigation apps.

Existing studies show that accident prediction, weather analysis, and smart-city systems are studied separately. Most systems focus on post-accident analysis rather than preventing accidents through safer routes. Navigation apps still choose routes based only on time or distance, not safety. No single system combines weather data, machine learning-based risk scores, and accident-affected areas. No system has provided clear and meaningful safety routes. Moreover, current navigation solutions primarily optimize travel time or distance without explicitly quantifying safety risk. There is a lack of unified frameworks that integrate real-time environmental data, machine learning-based risk estimation, and historical crash-prone zones to compute an interpretable route safety score.

To address this gap, the present work proposes a unified, safety-based route planning framework that uses live environmental data and machine learning-based crash risk prediction. It includes accident zones and crowdsourced hazard data, which help users choose safer routes, not just the fastest ones.

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Materials And Methods

This section discusses the methodology for calculating a route's safety score, as well as the collection of data from various sources used to calculate the safety scores of both the safest and fastest routes. The entire process is performed sequentially in stages that include entering the origin and destination, gathering real-time environmental information, calculating route risk, and finally computing the safety score.

System architecture

Safety-optimized route planning is supported by a multi-layered architecture. The architecture consists of separate layers: Frontend Layer, Backend Layer, Machine Learning Service Layer, and External Data Layers. The separation of these layers supports both the aggregation of large amounts of data and the reliability of the route safety score. In the Frontend Layer, users interact with the user interface to provide the source location and destination location. These two pieces of data allow the creation and display of candidate routes on the map by integrating with the Geoapify Routing API [11] and Leaflet [12]. In the Backend Layer, all the data collected from various sources (weather services, air quality indexes, machine learning predictions, user-submitted hazards, and officially designated accident-prone areas) are processed. Real-time weather data, Air Quality Index values, crowdsourced hazard reports, and historical accident zone information are all provided through external data sources. All layers in the architecture are separate; therefore, future changes to any layer will not affect other layers. In the Frontend Layer, users are able to see real-time weather information, risk scores for fast routes and safe routes, route visualization on the map, and user-submitted hazards, and they can submit hazard reports such as accidents, potholes, traffic congestion, waterlogging, etc. All hazard reports submitted by users are saved to the database and utilized in the calculation of the Route Safety Score. In the Backend Layer, all real-time weather data, air quality data, machine learning-based risk predictions via API calls, user-submitted hazards, and accident-prone zones are aggregated. By processing all these types of data together, the Backend Layer calculates the Route Safety Score. A Random Forest model is used in the machine learning component to estimate route risk based on environmental and contextual factors. Communication between the ML service and the Backend Layer utilizes APIs. Figure 1 shows the overall system architecture of the safety-aware route planning framework.

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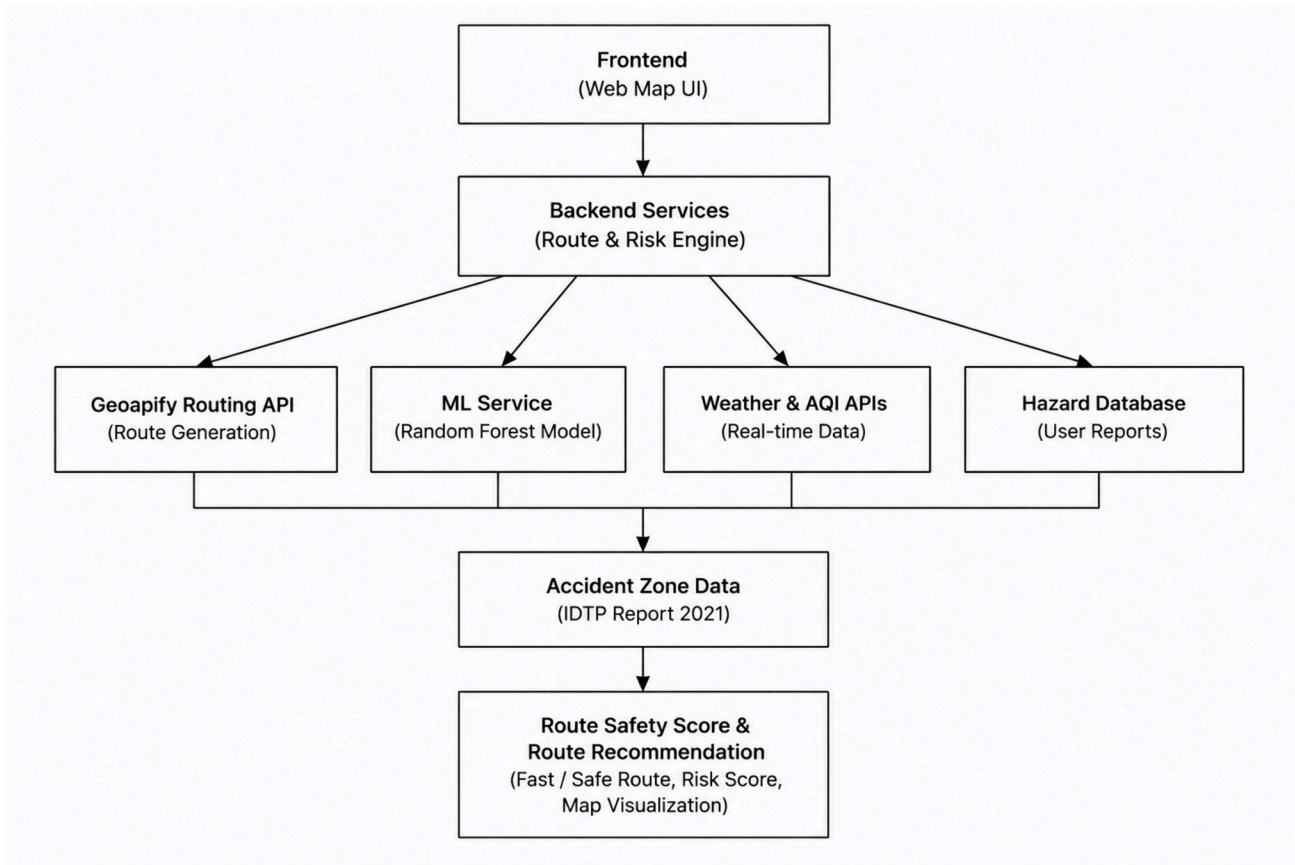


FIGURE 1: Overall System Architecture of the Safety-Aware Route Planning Framework

API, Application Programming Interface; AQI, Air Quality Index; IDTP, Intelligent Data Transmission Protocol; ML, Machine Learning; UI, User Interface

Integrated route safety modeling and risk assessment

When a traveler’s destination and starting point are entered, the routing API [11] generates route data, including several coordinate points, the overall distance of the route, and the approximate time required for travel. To minimize computation time, only the midpoint coordinate(s) of the route will be selected as representative points to collect current environmental conditions. For each route generated, environmental data, including visibility, AQI, wind speed, and temperature, will be obtained from the OpenWeather API [13]. Environmental data are used to compute direct environmental risk penalties and are also provided as inputs to the machine learning model so that there is a consistent, unbiased analysis of environmental risk. The RF algorithm has been selected to develop a machine learning-based risk forecasting model because it can analyze different types of data, recognize complex nonlinear relationships among variables, and make robust, reliable forecasts. Real-world accident risk is also incorporated into route evaluation via user-submitted hazardous location reports. Hazardous locations are defined as those areas where users have identified hazards associated with the route. When a route passes through a reported hazardous location, an additional penalty will be assessed against the route. Accident-prone locations are similarly modeled as geographic regions, and routes that pass through these areas will receive additional risk penalties. A fast route score is generated as a baseline measure for comparison with the safety-aware route. The fast route score includes environmental factors but excludes the use of machine learning models for predicting accidents or injuries, as well as user hazard reports and official accident-prone

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zone reports. The fast route score is generated by calculating penalties based on air quality, visibility, wind, and rainfall, with a maximum possible score of 100. The fast route score serves as a reference to show how much safer routes can be planned when all the safety factors are considered. The baseline fast route risk score is computed using Equation (1):

$$R_{fast} = \min(100, P_{aqi} + P_{visibility} + P_{rain} + P_{wind}) \quad (1)$$

To calculate the safety score for a route, data from multiple components are used, including user-reported hazard penalties, accident-prone zone penalties, wind penalties, air quality penalties, visibility penalties, and the safety prediction score from the machine learning model. The safety score ranges from 0 to 100 and is categorized into low, medium, and high risk levels. This improves interpretability, and the route with the lowest score is considered the safest. The composite safety score is defined using Equation (2):

$$R_{final} = \min(100, w_{ml} \cdot R_{ml} + P_{aqi} + P_{visibility} + P_{rain} + P_{wind} + P_{hazard} + P_{zone}) \quad (2)$$

The terms R_{final} , R_{ml} , w_{ml} , P_{aqi} , $P_{visibility}$, P_{rain} , P_{wind} , P_{hazard} , and P_{zone} represent the components of the final route risk score. The RF model predicts accident severity on a 1-10 scale. This prediction is converted to a 0-100 machine learning risk value by multiplying the predicted severity by 10. The resulting machine learning risk is assigned a weighting factor of $w_{ml} = 0.6$ in the composite route risk calculation. The remaining components are implemented as additive penalties. AQI contributes 0, 10, 20, 25, or 30 points according to increasing AQI thresholds. Visibility contributes 20 points for fog and 10 points for haze. Rainfall contributes 10 points when rainfall exceeds 2 mm and 20 points when it exceeds 10 mm, while wind contributes 10 points when wind speed exceeds 10 m/s. User-reported hazards located within 300 m of a route and submitted within the preceding 24 hours contribute a penalty equal to five times their reported severity. Each unique official accident-prone zone intersected by a route contributes 15 points. The final score is capped at 100 to maintain a consistent 0-100 risk scale, with lower values representing lower estimated route risk.

Results And Discussion

Experimental setup

The proposed system was implemented using Node.js v22.21.1 and Python 3.12.10. The frontend was developed using React 19.2.0, React-Leaflet 5.0.0, Leaflet 1.9.4, Axios 1.13.2, and Vite 7.2.4. The backend was developed using Express 5.2.1, Mongoose 9.0.2, Axios 1.13.2, CORS 2.8.5, and dotenv 17.2.3, with MongoDB Atlas used as the cloud database for storing user-reported hazards. The machine learning service was implemented using Flask 3.0.0, Flask-CORS 4.0.0, scikit-learn 1.3.2, XGBoost 2.0.3, Pandas 2.1.4, NumPy 1.26.4, SciPy 1.11.4, and Joblib 1.3.2 and was deployed using Gunicorn 21.2.0. Routes were generated through the Geoapify Routing API, while real-time weather and AQI data were obtained from the OpenWeatherMap API. Historical accident-prone locations were obtained from the Delhi Traffic Police Report (2021). Experiment 1 evaluated six representative origin-destination (OD) pairs across the Delhi-National Capital Region under comparable environmental conditions, while Experiments 2 and 3 used representative subsets for detailed validation and ablation analysis.

Experimental evaluation and results

The proposed system was built with React.js for the frontend and Node.js and Express.js for the backend server. It used an RF-based Flask prediction service for hazard forecasting. Route generation was performed through the Geoapify Routing API. Weather and AQI data were provided by the OpenWeatherMap API. Historical accident-prone locations (Delhi Traffic Police Report, 2021) were provided as input to the application, along with user-reported incidents stored in MongoDB. A total of 1,500 synthetically generated records were used for the development and evaluation of the machine learning-based risk estimation component. Detailed information regarding dataset preparation, training, and testing is provided in the following subsection. For Experiment 1, six representative OD pairs were tested under similar environmental conditions. Experiments 2 and 3 were conducted using representative subsets of these routes to evaluate accident hotspot validation and component-wise ablation, respectively.

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The dataset consisted of 1,500 synthetically generated records used to train and evaluate the risk estimation module. The dataset contained environmental and road-related attributes, including weather condition, road type, road surface condition, traffic density, location, date, and time. For the machine learning experiments, weather condition, road type, and surface condition were used as model input features, while accident severity was used as the target variable. Accident severity was represented as an ordinal target variable with 10 possible values, ranging from 1 (low severity) to 10 (high severity). Prior to training the model, categorical features in the dataset were converted into numerical values through a process known as label encoding. The dataset was checked for missing values before model training, and no missing values were identified in the final dataset. The dataset was randomly split into two groups: one group comprised 1,200 records for model training, and the other comprised 300 records for evaluating the performance of the trained model. Due to the mixed feature types and the potential complexity of the relationships among the variables, an RF regressor was selected because it can model nonlinear relationships and handle heterogeneous structured features. The model was configured with 100 estimators, no limit on maximum depth, and a fixed random seed of 42 to ensure reproducibility. The trained model achieved a mean absolute error (MAE) of 0.9607, a root mean squared error (RMSE) of 1.1376, and an R^2 of 0.828 on the test dataset. These performance metrics indicated that the model explained approximately 82.8% of the variance in accident severity based on the selected environmental and road attributes, demonstrating strong predictive performance within a structured modeling framework. In addition to producing predicted accident severity values, the model produced categorized risk class labels for routes (Low: 1-3; medium: 4-7; high: 8-10). In the generated dataset, 361 records (24.1%) were categorized as low risk, 679 records (45.3%) as medium risk, and 460 records (30.7%) as high risk. Based on these categories, the model achieved an overall accuracy of 78.67% and a macro-F1-score of 0.79. An analysis of the confusion matrix showed that the model effectively detected high-risk scenarios, with good precision and recall values for all three classes. These results demonstrated that the machine learning component provided reliable and interpretable risk estimates, supporting its integration into the composite route safety scoring framework. To further evaluate the stability of the proposed model, five-fold cross-validation was performed using the same RF configuration. The model achieved an average MAE of 0.9629 ± 0.0100 , an RMSE of 1.1367 ± 0.0116 , and an R^2 of 0.8192 ± 0.0126 across the five folds, indicating consistent predictive performance and low variability across different data splits.

Comparison with alternative machine learning models

To justify the selection of RF, its performance was compared with those of three commonly used tree-based ensemble models: XGBoost, CatBoost, and LightGBM (Table 7). All models were evaluated using the same 1,500-record dataset, the same three model input features, an identical 80:20 train-test split, and a fixed random seed of 42 (Table 2). RF achieved the lowest MAE (0.9607), while XGBoost and LightGBM achieved marginally lower RMSE values (1.1375 compared with 1.1376 for RF). The R^2 values were effectively identical across RF, XGBoost, and LightGBM (0.8280), while CatBoost achieved 0.8279. These results indicate that all four models provided highly comparable predictive performance on the evaluated dataset. RF was therefore retained as the primary model because it achieved the lowest MAE while providing comparable overall predictive performance to the alternative ensemble methods.

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Model	MAE	RMSE	R ²
Random Forest	0.9607	1.1376	0.8280
XGBoost	0.9611	1.1375	0.8280
CatBoost	0.9614	1.1378	0.8279
LightGBM	0.9611	1.1375	0.8280

TABLE 1: Performance Comparison of Machine Learning Models

CatBoost, Categorical Boosting; LightGBM, Light Gradient Boosting Machine; MAE, Mean Absolute Error; RMSE, Root Mean Square Error; XGBoost, Extreme Gradient Boosting

Item	Value
Dataset type	Synthetic dataset
Number of records	1,500
Data generation	Python-based synthetic data-generation procedure
Model input features	Weather condition, road type, surface condition
Target variable	Accident severity (1–10)
Missing values	None
Preprocessing	Categorical feature preprocessing
Encoding method	Label encoding
Train-test split	80:20 (1,200/300)
Random seed	42

TABLE 2: Dataset Description and Preprocessing Summary

As the machine learning development dataset was synthetically generated and did not contain personally identifiable information, no individual-level privacy concerns were involved. The publicly available Delhi Traffic Police report used to identify accident-prone zones was acknowledged as the source of the hotspot data.

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Experiment 1: Fast versus safe route comparison

The comparison of Baseline Fast Routing and Safety-Aware Routing (SAR) was conducted on an equal basis with respect to environmental conditions. The machine learning risk component remained the same for the same contextual inputs; however, penalties related to accident-prone zones, hazard reports, and environmental factors caused the composite safety scores to vary. The ML Risk column represents the risk score predicted by the RF model, while AQI denotes the Air Quality Index obtained from the OpenWeatherMap API. Table 3 shows that for each of the six test routes, the SAR mode resulted in a higher composite risk score than the Baseline Fast Routing mode, which reflects a more comprehensive assessment of overall roadway safety. Importantly, the average travel time variation between the fast route and the safe route was less than 2% for all routes tested, and several of the routes were found to have identical duration values. Therefore, these results demonstrate that enhanced safety differentiation can be achieved without significant compromise in travel efficiency. Figure 2 presents the comparison of composite risk scores for fast and safety-aware routes.

Route	Mode	Distance (km)	Duration (min)	Risk Score	ML Risk	AQI	Weather
R1	Fast	13.19	17.98	20.0	–	167	Mist
R1	Safe	13.19	17.98	61.8	19.7	167	Mist
R2	Fast	17.14	19.31	20.0	–	170	Mist
R2	Safe	17.14	19.31	31.8	19.7	170	Mist
R3	Fast	20.31	20.32	20.0	–	160	Mist
R3	Safe	20.31	20.32	31.8	19.7	160	Mist
R4	Fast	30.88	37.82	20.0	–	167	Mist
R4	Safe	30.88	37.82	31.8	19.7	167	Mist
R5	Fast	8.87	7.63	0.0	–	53	Clear
R5	Safe	8.87	7.63	11.8	19.7	53	Clear
R6	Fast	652.31	412.63	10.0	–	134	Clear
R6	Safe	652.31	412.63	21.8	19.7	134	Clear

TABLE 3: Fast Route vs Safety-Aware Route Risk

AQI, Air Quality Index; ML, Machine Learning

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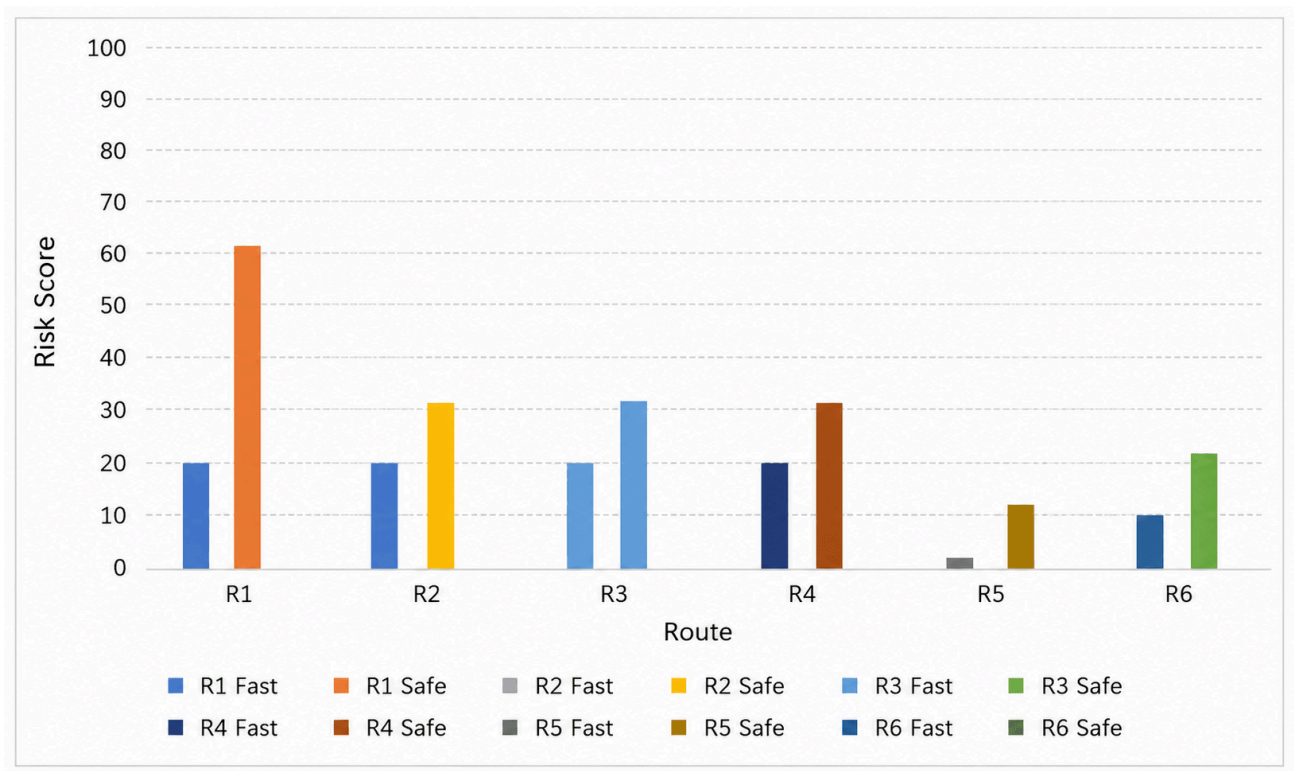


FIGURE 2: Comparison of Composite Risk Scores for Fast and Safety-Aware Routes

Experiment 2: Accident hotspot validation

In this experiment, we compared predicted route risk with real-world accident hotspot data. The accident-prone zones were taken from the official report and were used for evaluation, not for training. For each route, we calculated the overlap with accident zones and counted the penalties when intersections occurred. Table 4 shows the accident hotspot intersection and penalty analysis for five different routes. Finally, the results show that routes intersecting official accident-prone zones received additional penalties in the safety-aware configuration. For the evaluated routes, R1, R4, and R5 intersected one or more accident-prone zones, resulting in additional penalties of 30, 30, and 15 points, respectively. These results demonstrate that the framework explicitly incorporates historically identified accident-prone locations into route-level risk estimation. This shows that our system is aligned with real-world accident patterns. Figure 3 presents the accident hotspot intersection analysis for the evaluated routes.

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Route	Fast Zone Penalty	Safe Zone Penalty	Zone Count
R1	0	30	2
R2	0	0	0
R3	0	0	0
R4	0	30	2
R5	0	15	1

TABLE 4: Accident Hotspot Intersection and Penalty Analysis

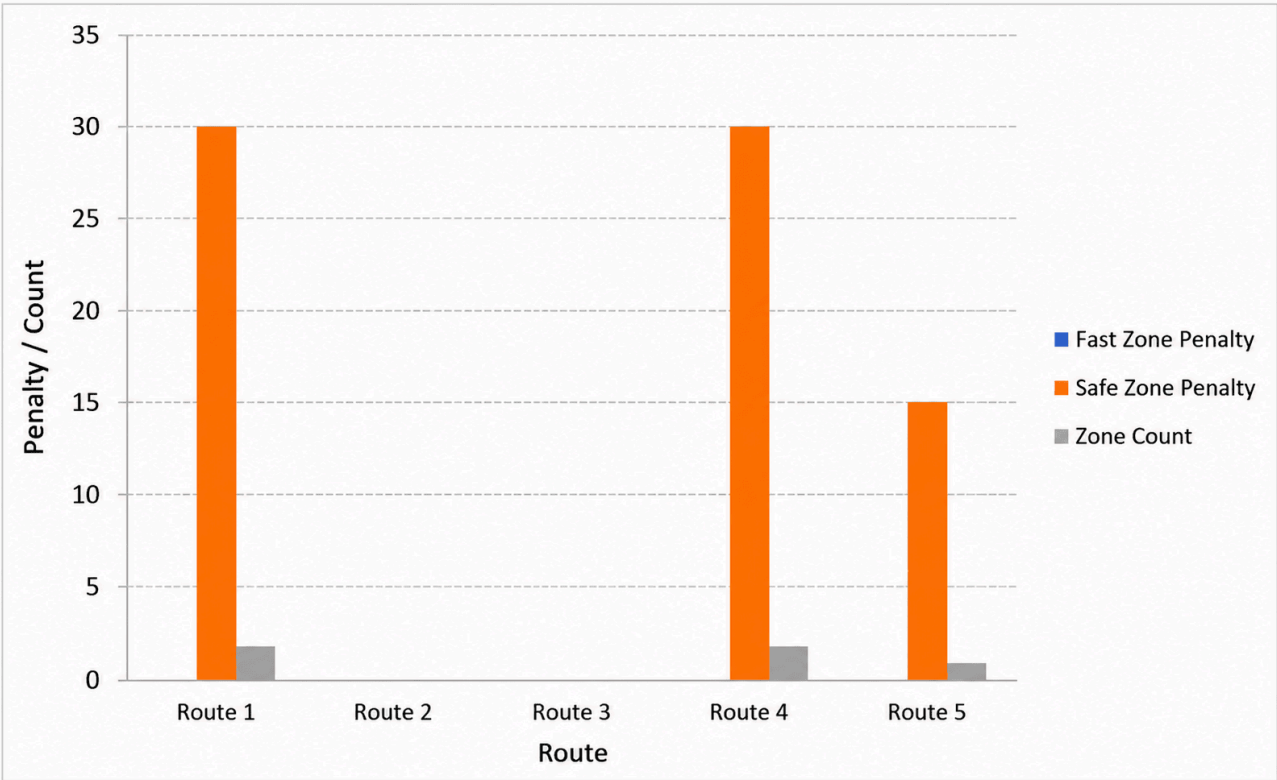


FIGURE 3: Accident Hotspot Intersection Analysis for Evaluated Routes

Experiment 3: Ablation study

This experiment was carried out to check the impact of each component, where every component was disabled once and the result was calculated (Table 5). In the results, we observed that without the machine learning component, the risk score became significantly lower while environmental factors remained moderate. Figure 4 denotes the ablation study

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showing the impact of individual risk components. Therefore, we conclude that every component was important for safety risk prediction.

Route	Configuration	Risk Score
A1	FULL	61.8
A1	NO_ML	50.0
A1	NO_AQI	41.8
A1	NO_WEATHER	61.8
A1	NO_HAZARD	31.8
A2	FULL	31.8
A2	NO_ML	20.0
A2	NO_AQI	11.8
A2	NO_WEATHER	31.8
A2	NO_HAZARD	15.0

TABLE 5: Ablation Study Results for Risk Score Components

AQI, Air Quality Index; ML, Machine Learning

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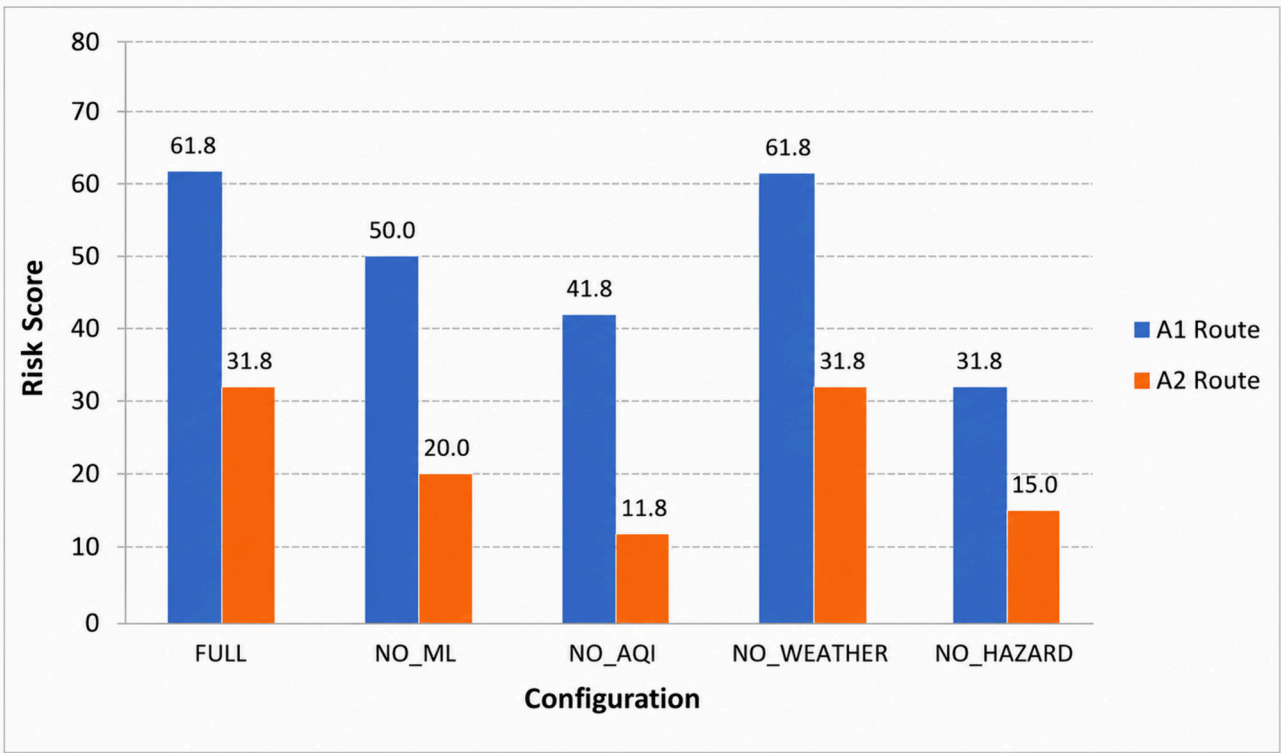


FIGURE 4: Ablation Study Showing the Impact of Individual Risk Component

AQI, Air Quality Index; ML, Machine Learning

Across all the above experiments, we observed that the proposed system not only considered safe routing but also prioritized safety. Weather data, machine learning predictions, and accident data were combined to provide clearly differentiated safety-aware routes and results that closely reflected real-world conditions.

Discussion

The proposed system was compared with that of Khanum et al. [1], who used an ensemble RF model to classify accident severity from historical crash data along Indian highways. While their research showed how effective ensemble models were at estimating accident severity, it also had the limitation of being an offline model. In contrast, the proposed system combines machine learning-based accident severity prediction as part of a real-time safety assessment of all potential routes. Instead of evaluating accident risk at individual crash sites, this system evaluates the entire set of potential routes by combining the predicted accident severity with current environmental conditions, air quality readings, user-reported hazards, and known accident hotspots along the route to create a single safety score for each route. As such, this system can support safety-aware navigation proactively, instead of reactively analyzing accidents after they have occurred. Table 6 summarizes the key differences between Khanum et al. [1] and the proposed system.

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Feature/Aspect	Khanum et al. [1]	Proposed System
ML Algorithm	Random Forest	Random Forest
Data Type	Historical accident data	Live weather + AQI + accident zones
Prediction Level	Accident severity	Route-level safety risk
Real-time Routing	No	Yes
Weather Integration	No	Yes
Accident Hotspot Usage	No	Yes, road accident report [14]
Safe Route Recommendation	No	Yes
Application Type	Post-accident analysis	Preventive navigation support

TABLE 6: Key Differences Between the Existing Study and the Proposed System

Note: The existing study refers to the approach described by Khanum et al. [1].
AQI, Air Quality Index; ML, Machine Learning

The experimental findings demonstrate that the incorporation of safety factors into the decision-making process concerning which route was most desirable affects how routes are evaluated but does not significantly diminish travel efficiency. In all instances, the SAR option produced higher composite risk scores than did the Baseline Fast Routing option; therefore, the SAR option provided a better representation of the risks associated with each risk component (i.e., accident-related and environmental) than did the Baseline Fast routing option. Additionally, the accident hotspot validation illustrated that routes identified as high risk were often located within historically recognized areas where accidents had occurred, thus validating the relationship between the risk predictions and the actual safety patterns in these regions, although the accident hotspot validation dataset was not used in the development of the predictive models. In addition, the ablation study demonstrated that removing individual components, including the machine learning, AQI, weather, and user-reported hazard components, resulted in changes to the predicted route risk. This supports the contribution of the integrated risk components to the overall route-level risk estimation. In summary, the proposed SAR system enhances traditional navigation systems by explicitly addressing the need to provide safe routing alternatives to users while maintaining a focus on optimizing travel efficiency. By combining predictive analytics with environmental and geospatial intelligence, the SAR system can provide a practical means of evaluating and selecting safe routes through cities. The proposed SAR framework will be studied in greater detail in future studies to better understand its predictive accuracy, scalability, and reliability.

The route-level evaluation was conducted using a limited set of representative origin-destination pairs within the Delhi-NCR region because the available historical accident-prone-zone information was geographically limited. In addition, the machine learning development dataset consisted of 1,500 synthetically generated records based on the available road and environmental attributes. Therefore, the reported results should be interpreted as a Delhi-NCR-focused case study rather than as evidence of broad geographical generalizability. Validation using larger real-world datasets and geographically diverse cities would be required to further establish the generalizability and robustness of the proposed framework.

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Future research will also investigate the use of continuous environmental data sampling throughout entire route segments rather than at representative midpoint locations so that SAR can make more precise distinctions between risks in different areas of a city or region. Future research will investigate the inclusion of additional high-resolution geospatial road-level data to provide more accurate localization of hotspots and accident-prone zones. Further research will investigate the inclusion of temporal characteristics (i.e., time of day and dynamic changes in traffic density) to provide SAR with increased sensitivity to context-related risk factors. From a systems point of view, potential future developments may involve developing scalable backend infrastructure, integrating real-time data streaming into SAR, and extending SAR to mobile platforms to allow for more widespread adoption in the field.

Data and code availability

The full weather-based route planner implementation (backend, frontend, machine learning models, experimental results, and processed data) is publicly available through the GitHub repository [15]. The supplementary materials, including the dataset and supporting files, are publicly available on Google Drive [16]. The historical accident-prone zone dataset used in this study was manually created from the publicly available Delhi Traffic Police Accident Prone Locations Report (2021) [14].

Conclusions

This research describes a new safety-aware approach to urban route finding based on the integration of real-time environmental information, machine learning-based hazard assessment, accident-prone zone identification, and user-reported hazards into a single safety score. In contrast to most current navigation systems that emphasize the shortest time and distance to a destination, this method includes safety as a distinct routing objective. The RF model yielded an MAE of 0.96, an RMSE of 1.13, and an R^2 value of 0.828 on a 1-10 severity scale, with a classification accuracy of 78.67% for low, medium, and high risk categories. A comparative evaluation of safety-driven routing showed a lower rate of exposure to known accident-prone zones, with less than 2% variance in travel time relative to the fastest possible routes used as a baseline. The results of this research demonstrate the potential for improved decision-making through the inclusion of predictive analytics, environmental intelligence, and geospatial risk modeling in the development of safer urban routes. Additionally, the safety-aware framework developed in this research can be implemented in a practical and scalable way to integrate safety-driven routing capabilities into contemporary navigation systems.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Suraj Kumar

Acquisition, analysis, or interpretation of data: Suraj Kumar, Anam Aaliya, Devendra Kumar

Drafting of the manuscript: Suraj Kumar, Anam Aaliya

Critical review of the manuscript for important intellectual content: Anam Aaliya, Devendra Kumar

Supervision: Devendra Kumar

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue.

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Data Availability Statements

The data (and/or code) supporting this study are openly available in GitHub at <https://github.com/thesurajcode/weather-route-planner-ml>, reference Not applicable.

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