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SPATIAL PREDICTION AND SAFE ROUTE OPTIMIZATION OF AUTONOMOUS VEHICLE ACCIDENTS: MACHINE LEARNING AND GIS-BASED INTEGRATED APPROACH

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ABSTRACT

Autonomous vehicle technologies are reshaping traffic safety and urban mobility; however, software and sensor failures, legal uncertainties, and mixed traffic environments continue to pose significant accident risks. Recent fatal incidents during real-world testing underline the critical need for effective risk prediction approaches. While existing studies mainly focus on accident causes and probabilities, deep learning research is often limited to in-vehicle sensor data.

This study proposes a hybrid framework integrating machine learning and deep learning models with Geographic Information Systems (GIS)-based spatial analysis to predict both the occurrence and severity of autonomous vehicle accidents and to identify high-risk locations and conditions. The results show that Support Vector Machine (SVM) and Artificial Neural Network (ANN) models perform effectively in accident severity prediction, while ANN achieves superior performance in accident occurrence prediction under balanced data conditions. The proposed approach offers a data-driven basis for risk-aware route planning and dynamic safety management in intelligent transportation systems.

1. INTRODUCTION

In recent years, advances in artificial intelligence, high-precision positioning technologies, and multi-sensor systems have significantly transformed transportation systems, positioning autonomous vehicle technologies as a key component of modern mobility [1,2]. Autonomous vehicles are systems capable of perceiving their surroundings through sensors such as cameras, radar, LiDAR, and GPS, and operating with varying levels of automation based on advanced artificial intelligence algorithms. According to the Society of Automotive Engineers (SAE), autonomous vehicles are classified into six levels of driving automation [3]. Current developments by companies including Waymo, Tesla, Uber, and Baidu indicate the potential of these technologies to improve traffic safety, reduce congestion, and support sustainable urban transportation [4].

Despite these advancements, accidents observed during real-world testing demonstrate that perception errors, sensor limitations, software inconsistencies, and mismatches between road infrastructure and vehicle systems remain significant safety concerns [5,6]. Consequently, the assessment of autonomous vehicle safety extends beyond the evaluation of algorithmic performance and requires an examination of the spatial characteristics of accident occurrences.

Existing studies primarily employ machine learning techniques to model accident probability using variables such as vehicle speed, weather conditions, traffic density, road characteristics, and sensor-related factors [7,8]. While methods including Support Vector Machines (SVM), Random Forest (RF), Artificial Neural Networks (ANN), and Deep Neural Networks (DNN) have achieved high predictive accuracy, many studies neglect the geographical distribution of accidents and the integration of spatial density analyses into prediction frameworks [9,10]. However, identifying spatial clustering patterns and

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risk-prone locations is essential for effective route planning and control strategies in autonomous driving systems.

Geographic Information Systems (GIS) offer effective tools for the analysis and visualization of spatial data within decision-support processes. GIS-based density and spatial analyses enable the identification of high-risk urban zones, the evaluation of alternative routes, and the enhancement of traffic safety strategies [11,12]. As a result, the integration of machine learning techniques with GIS has gained increasing attention as a hybrid approach in spatial data analysis [13].

Within this context, the present study applies machine learning models, including SVM, ANN, Random Forest, and Balanced Random Forest, to predict both the occurrence probability and severity of autonomous vehicle accidents. These predictions are subsequently integrated with GIS-based spatial analyses to develop a risk-oriented decision-support framework that identifies high-risk areas and supports safe route planning. By combining predictive modeling with spatial risk assessment, this study aims to contribute to risk-sensitive route planning and safety management in intelligent transportation systems.

2. LITERATURE REVIEW

Autonomous vehicle technologies represent complex systems that integrate sensor fusion, artificial intelligence, computer vision, and communication-based infrastructure. Previous studies suggest that these technologies have the potential to improve energy efficiency, enhance traffic safety, and reshape urban transportation systems [4]. Nevertheless, achieving fully autonomous operation remains challenging due to environmental variability, mixed traffic conditions, and limitations in existing infrastructure.

A substantial body of research has focused on identifying factors that contribute to autonomous vehicle accidents and estimating accident likelihood. Fagnant and Kockelman reported that sensor-related errors and uncertainties in decision-making processes play a critical role in autonomous vehicle safety [14]. Similarly, official crash reports indicate that many accidents recorded during testing phases of systems developed by Tesla, Uber, and Cruise were associated with delayed driver intervention or failures in object perception [5,15]. These findings highlight that accident risk is influenced not only by onboard sensing and control mechanisms but also by external environmental and spatial conditions.

Machine learning and deep learning techniques have been widely employed to model accident risk and classify crash severity. Previous studies have demonstrated that models such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Random Forest achieve high predictive performance in various traffic safety applications [16]. Deep learning approaches have been particularly effective in processing sensor data, object detection, and the interpretation of complex traffic scenes [17]. Despite these advances, most studies primarily emphasize predictive accuracy and rarely incorporate the spatial distribution of accidents into their analytical frameworks.

Geographic Information Systems (GIS) offer robust capabilities for analyzing and visualizing spatial patterns in traffic safety data. GIS-based methods, including Kernel Density Estimation, hotspot analysis, and network-based spatial statistics, have been successfully applied to identify accident concentrations and high-risk road segments for pedestrians, cyclists, and conventional vehicles [18]. However, studies focusing specifically on the spatial characteristics of autonomous vehicle accidents remain limited, and integrated frameworks combining GIS-based spatial analysis with machine learning-based accident prediction are still scarce.

Overall, the existing literature generally follows two distinct research directions: machine learning–based models that focus on predicting accident probability and severity, and GIS-based approaches that examine the spatial distribution and clustering of accidents. The integration of these two perspectives, particularly in the context of autonomous vehicle safety, has not yet been sufficiently addressed. Incorporating spatial information into predictive models enables accident risk to be evaluated at both local and network scales, thereby providing a more comprehensive understanding of safety-related patterns.

In response to this research gap, the present study proposes a hybrid framework that combines machine learning-based accident prediction with GIS-based spatial analysis. By integrating statistical prediction outputs with spatial risk mapping, the proposed approach supports the identification of high-risk areas and the development of safe route recommendation strategies. This integrated perspective contributes to the literature by addressing autonomous vehicle safety from both methodological and practical viewpoints.

3. METHODOLOGY

This study adopts a multi-stage methodological framework integrating data preparation, machine learning modeling, and GIS-based spatial analysis to examine autonomous vehicle accidents in terms of severity and occurrence probability. The methodology begins with the collection and preprocessing of accident-related variables, including vehicle type, road type, relative speed, collision type, temporal characteristics, and spatial information defined within a 500 m buffer zone. Categorical variables are transformed into numerical representations using label encoding and one-hot encoding techniques, while spatial attributes are processed to generate GIS-compatible features.

This study adopts a multi-stage methodological framework integrating data preparation, machine learning modeling, and GIS-based spatial analysis to examine autonomous vehicle accidents in terms of severity and occurrence probability. The dataset used in this study consists of autonomous vehicle collision reports obtained from the California Department of Motor Vehicles (DMV), which provide detailed information about incidents involving autonomous vehicles operating in the San Francisco area. The dataset covers the period between 2014 and 2019, reflecting multiple years of real-world autonomous vehicle testing data. The dataset includes a total of 260 observations, comprising 31 accident cases and 229 non-accident cases, indicating a significant class imbalance where accident events represent a relatively small proportion of the total observations. Table 1 summarizes the properties of these datasets.

Table 1. Dataset Features

Class	Number of Observations	Percentage
Accident	31	11.90%
Non-Accident	229	88.10%
Total	260	100%

The methodology begins with the collection and preprocessing of accident-related variables, including vehicle type, road type, relative speed, collision type, temporal characteristics, and spatial information defined within a 500 m buffer zone. Prior to model development, data preprocessing procedures were applied to improve data quality and consistency. These procedures included removing incomplete records, handling missing values, and transforming categorical variables into numerical representations suitable for machine learning algorithms. Specifically, categorical variables were converted using label encoding and one-hot encoding techniques, while spatial attributes were processed to generate GIS-compatible features.

Furthermore, the presence of class imbalance was carefully considered during model development and evaluation, particularly in the selection of performance metrics and the implementation of models capable of handling imbalanced datasets. This comprehensive preprocessing and modeling framework ensures reliable prediction of accident occurrence and severity while incorporating both spatial and non-spatial factors.

In this study, several machine learning algorithms were employed to predict autonomous vehicle accident occurrence. Three different models were implemented: Artificial Neural Network (ANN), Random Forest (RF), and Support Vector Machine (SVM). The implementation of all models was carried out using the Scikit-learn library in Python.

Following feature engineering and spatial enrichment, predictive models were constructed to estimate accident occurrence probability. The explanatory variables included weather conditions, road type, vehicle type, vehicle speed, time of occurrence, and spatial location. These variables were selected because they represent environmental, temporal, and vehicle-related factors that may influence accident risk.

The set of explanatory variables was carefully evaluated to ensure that only variables available prior to accident occurrence were included in the predictive models. Accordingly, the variable Collision Type (AV), which is determined after an accident occurs, was excluded from the accident occurrence prediction model to prevent potential data leakage and was used only for descriptive analysis of accident characteristics. The variables and their corresponding processing methods are summarized in Table 2.

Table 2. Variables Used

Variable Name	Description	Type / Processing Method
Vehicle Type	Indicates the class of the vehicle (e.g., passenger car, truck, bus)	Categorical → Numerical encoding
Road Type	Type of roadway where traffic occurs (urban road, highway, secondary road, etc.)	Categorical → Numerical encoding
Lat–Long Incoming Location (500 m)	Geographic coordinate information within a 500-meter buffer around the accident location	Continuous → Processed spatial data
Company (Vehicle Manufacturer)	Vehicle brand (e.g., Ford, Toyota)	Transformed using One-Hot Encoding
Target (Accident Occurrence)	0 = No accident, 1 = Accident occurred	Binary class label

The Artificial Neural Network (ANN) model was implemented using the multilayer perceptron classifier available in the Scikit-learn library. The ANN model learns nonlinear relationships between input variables and accident occurrence by adjusting neuron weights during the training process. The ANN model was configured with a single hidden layer consisting of 64 neurons using the ReLU activation function. The model was trained using the Adam optimizer with a learning rate of 0.001, a batch size of 32, and a maximum of 100 epochs. These hyperparameters were selected based on commonly used configurations in the literature and preliminary experimental trials to ensure stable performance.The Support Vector Machine (SVM) model was implemented using the Radial Basis Function (RBF) kernel with a regularization parameter C = 1.0 and gamma set to 'scale'.The Random Forest model was constructed using 100 decision trees with no restriction on maximum depth, and the Gini impurity criterion was used for node splitting.

Similarly, the Support Vector Machine (SVM) model was implemented using the Radial Basis Function (RBF) kernel. The regularization parameter (C) and kernel parameters were selected using default Scikit-learn settings and refined through preliminary testing to achieve stable classification performance.

The Random Forest (RF) model was implemented as an ensemble learning approach consisting of multiple decision trees. In this study, the Random Forest model was constructed using 100 decision trees, which were combined to improve classification accuracy and reduce overfitting.

The Support Vector Machine (SVM) classifier was implemented using the Radial Basis Function (RBF) kernel, which enables the model to capture nonlinear relationships between predictor variables and the target variable. The RBF kernel is widely used in classification problems due to its flexibility in handling complex data distributions.

Due to the imbalanced nature of the dataset, class-weighting strategies were applied to all models to improve minority class detection. In addition, the Random Forest model, which inherently supports

balanced ensemble learning, was utilized to further enhance classification performance for the minority class.

To ensure robust estimation of model performance and reduce the risk of overfitting, a 5-fold cross-validation procedure was employed during model training and evaluation. Model performance was assessed using multiple evaluation metrics, including accuracy, precision, recall, F1-score, and confusion matrix, providing a comprehensive assessment of predictive capability, particularly for imbalanced datasets.

Furthermore, Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) values were calculated for each predictive model to evaluate their discriminative ability. These metrics provide insight into how effectively the models distinguish between accident and non-accident cases, which is especially important when dealing with imbalanced data.

Feature importance analysis was conducted using the Random Forest model to determine the relative influence of explanatory variables on accident occurrence predictions. The importance scores were calculated based on the mean decrease in impurity (MDI) criterion, which evaluates how much each variable contributes to reducing classification error across the ensemble of decision trees. Variables with higher importance values indicate a stronger contribution to predictive performance, allowing identification of the most influential factors affecting accident occurrence.

3.1. Accident Severity Prediction

Accident severity is modeled using Support Vector Machine (SVM) and Artificial Neural Network (ANN) classifiers. Both models utilize accident-related features such as relative speed, vehicle type, road type, collision type, and temporal information. For the SVM model, a RBF kernel is selected to identify optimal separating hyperplanes within the feature space. The dataset is divided into training (80%) and testing (20%) subsets to evaluate predictive performance.

The ANN model is developed using the same feature set to enable a consistent comparison between methods. The network architecture consists of a single hidden layer with a ReLU activation function and a sigmoid activation function in the output layer. Binary cross-entropy is employed as the loss function, and optimization is performed using the Adam optimizer. The dataset is similarly partitioned into training and testing subsets.

3.2. Accident Occurrence Probability Prediction

Accident occurrence probability is estimated using Random Forest, Balanced Random Forest, and Artificial Neural Network models. The input features include vehicle type, road type, spatial location within a 500 m buffer zone, vehicle manufacturer information, and collision type. Accident occurrence is defined as a binary variable, where 0 represents no accident and 1 indicates accident occurrence.

Given the limited number of accident cases, class imbalance is explicitly addressed during model development. Although synthetic sampling methods such as SMOTE are initially considered, they do not improve prediction performance due to the scarcity of original accident records. Consequently, class-weighting techniques and balanced ensemble approaches are adopted to enhance the detection of minority-class events.

3.3. Spatial Risk Analysis and Safe Route Generation

Machine learning outputs are integrated into a Geographic Information Systems (GIS) environment to examine spatial accident patterns and identify high-risk zones. Point-based accident and disengagement data obtained from autonomous vehicle test drives conducted in San Francisco are used as the reference dataset (Figure 1a and Figure 1b). Road network elements, including nodes, edges, and event records, are transferred into the GIS platform and transformed into a common coordinate reference system.

Spatial accident intensity was analyzed using the Kernel Density Estimation (KDE) method with a Gaussian kernel, where bandwidth parameters were optimized through a grid search. The Gaussian kernel was selected for its ability to provide smooth and continuous estimation of spatial event intensity, a technique widely validated in traffic safety and accident hotspot analysis literature. The optimal bandwidth value was determined as approximately 500 meters through grid search optimization by

evaluating multiple candidate bandwidth values. The selection was based on the ability of the resulting density surface to capture meaningful accident clusters while avoiding excessive smoothing. The resulting density surface was subsequently used to assign risk values to road segments, forming the basis of a risk-oriented routing framework. Based on these risk values, safer route alternatives were generated by computing weighted shortest paths that minimize exposure to high-risk areas.

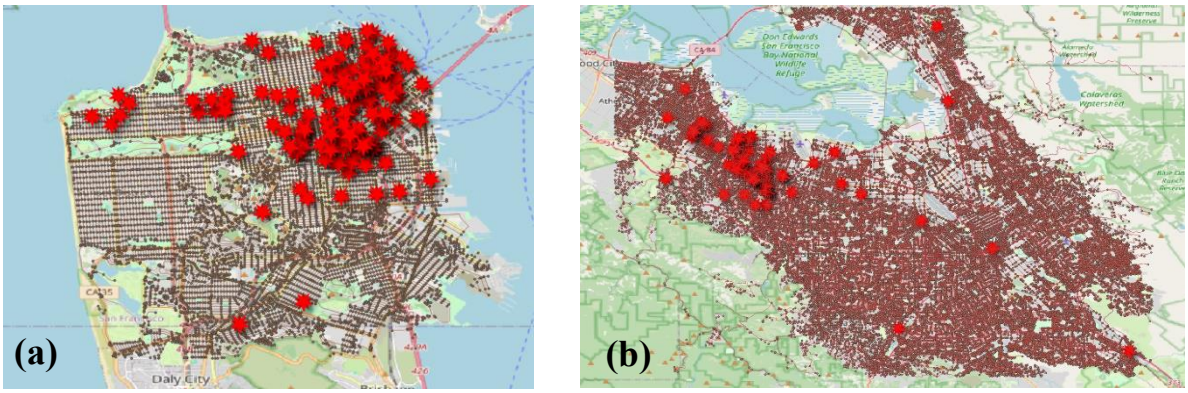


Figure 1. (a) Autonomous Vehicle Accident Data San Francisco Area 1; (b) Autonomous Vehicle Accident Data San Francisco Area 2

3.4. Risk-Based Routing Model

In order to generate a risk-aware navigation strategy, a routing framework integrating spatial accident risk information was developed within the GIS environment. The road network was represented as a graph structure consisting of nodes (intersections) and edges (road segments). The routing process was performed using a shortest-path search algorithm commonly used in transportation network analysis [19,20].

In addition to the conventional distance-based routing approach, a risk-weighted cost function was introduced. The accident risk values were derived from the spatial accident density obtained through Kernel Density Estimation (KDE), a widely used method for identifying spatial concentration of traffic accidents [21,22] Each road segment was assigned a risk score according to the accident density of its surrounding area. The total cost of a route was then calculated by combining travel distance and accident risk exposure, as expressed in Equation (1):

$$\text{Cost} = \alpha \cdot D + \beta \cdot R \tag{1}$$

where D represents the travel distance, R represents the accident risk score derived from spatial density analysis, and α and β are weighting parameters that control the relative importance of travel distance and safety.

The weighting parameters (α and β) were determined using a heuristic approach to balance travel distance and safety considerations. A preliminary sensitivity analysis was conducted to evaluate the impact of different parameter values on route selection. Increasing the value of β prioritizes safety by avoiding high-risk areas, whereas higher values of α emphasize shorter travel distance. This flexibility allows the routing model to adapt to different user preferences and risk tolerances.

By minimizing this cost function, the algorithm generates a route that avoids high-risk areas while maintaining reasonable travel distance. Similar multi-criteria routing approaches have been applied in transportation studies to integrate safety considerations into route planning [23,24]. Compared with the traditional shortest-path route, the resulting safe route slightly increases travel distance but significantly reduces cumulative accident risk.

Using point-based accident data, spatial accident intensity was analyzed through the Kernel Density Estimation (KDE) method, and areas with high accident concentrations were identified (Figure 2a and Figure 2b). KDE was implemented using a Gaussian kernel, with the bandwidth parameter optimized

via grid search to obtain a reliable spatial density surface. This density map was subsequently used to represent spatial accident risk across the study area.

The resulting risk surface constituted the basis of the risk-oriented route selection process. Spatial decision-making analyses were applied to identify alternative routes that minimize exposure to high-risk zones. Accordingly, spatial risk assessment and safe route generation for autonomous vehicles were performed within a hybrid GIS and machine learning framework. In this framework, KDE-derived risk values were assigned to road segments and incorporated into a weighted shortest-path algorithm to generate safer routing alternatives.

All machine learning models were implemented in Python using the scikit-learn and TensorFlow libraries, while KDE computation and spatial analyses were conducted within a Geographic Information Systems (GIS) environment.



Figure 2. (a) San Francisco 1st area density map; (b) San Francisco 2nd area density map

4. RESULTS AND DISCUSSION

The San Francisco accident dataset was integrated into a Geographic Information Systems (GIS) environment, where road network data and accident point locations were processed within a common coordinate reference system. Spatial density analysis based on point-level accident data revealed areas with elevated accident risk. Using these density outputs, a risk-based routing model was developed and compared with the conventional shortest-path route. The resulting safe route was observed to deliberately bypass regions with high accident density, highlighting the contribution of spatial risk information to route planning. When combined with machine learning–based risk predictions, this GIS-based framework provides a foundation for risk-oriented route planning in autonomous vehicle applications.

4.1. Accident Severity Prediction Using Support Vector Machine (SVM)

The performance results of the SVM-based accident severity model are presented in Table 3. Although the model achieved a high overall accuracy of 88%, this value does not reflect effective classification performance due to the pronounced class imbalance in the dataset. The dominance of Class 0 led to perfect recall for this class, while the model was unable to correctly identify any instances belonging to Class 1. This outcome indicates that the SVM model primarily learned the majority-class patterns and exhibited limited generalization capability for minority-class cases.

Table 3. Results Obtained from the SVM Model

Metric	Value
Accuracy	0.88
Macro Average F1-Score	0.47
Weighted Average F1-Score	0.82

The confusion matrix confirms that all Class 0 instances were correctly classified, whereas all Class 1 instances were misclassified. Despite the seemingly high accuracy, the model's performance is therefore

constrained by overfitting to the majority class. This limitation is further supported by k-fold cross-validation results, emphasizing the need for cautious interpretation under limited data conditions.

4.2. Accident Severity Prediction Using Artificial Neural Network (ANN)

The ANN-based model demonstrated a more balanced classification performance, as summarized in Table 4. The model correctly classified the majority of Class 0 instances while also successfully identifying a substantial portion of Class 1 cases. In contrast to the SVM model, the ANN achieved an 83% correct classification rate for the minority class, indicating improved sensitivity to injury-related cases.

Table 4. Results Obtained from the ANN Model

Metric	Class 0	Class 1
Precision	0.98	0.71
Recall	0.95	0.83
F1-Score	0.97	0.77

The confusion matrix shows consistent performance across both classes, suggesting that the ANN model effectively captures nonlinear relationships between accident-related variables and injury severity. These results highlight the advantage of neural network–based approaches in addressing class imbalance when sufficient feature representation is available.

These findings are consistent with previous studies in traffic safety analysis, which indicate that artificial neural networks are more effective in capturing nonlinear relationships and handling imbalanced datasets. The improved performance of the ANN model in detecting minority-class accident cases aligns with existing literature emphasizing the robustness of neural network–based approaches in complex predictive tasks. This suggests that ANN-based models can provide more reliable predictions in accident severity analysis, particularly under data imbalance conditions.

4.3. Model Comparison

A comparative evaluation of the SVM and ANN models is presented in Table 5. The SVM model achieved an overall accuracy of 88%; however, due to the severe class imbalance in the dataset, this metric primarily reflects performance on the majority class. The model correctly classified most majority-class instances but failed to identify minority-class cases, indicating limited ability to generalize to rare accident events. This behavior is common in imbalanced datasets, where traditional classifiers tend to favor the dominant class, and may also result from insufficient flexibility in the selected kernel function and model configuration.

In contrast, the ANN model demonstrated more balanced performance, achieving an overall accuracy of 94% and an F1-score of 0.77 for the minority class. These results indicate that the ANN is more effective in detecting accident-related cases and suggest that neural network–based approaches are better suited for modeling nonlinear relationships and handling imbalanced accident datasets.

Table 5. Results Obtained from the ANN and SVM Model

Model	Accuracy	Class 0 F1-score	Class 1 F1-score
SVM (class_weight = "balanced")	0.88	0.47	0.01
ANN	0.94	0.97	0.77

While the ANN model shows strong potential for modeling nonlinear patterns, its performance remains influenced by the limited number of minority-class observations. Expanding the dataset and applying hyperparameter optimization are therefore recommended to further enhance prediction reliability in future studies.

4.4. Accident Occurrence Probability Prediction Using Random Forest

The Random Forest–based accident occurrence model achieved an overall accuracy of 77%. However, detailed evaluation metrics reveal that this performance is largely driven by correct classification of non-accident cases. The model failed to identify accident cases, resulting in zero precision, recall, and F1-score for the minority class. This limitation can be directly attributed to the severe class imbalance inherent in the dataset.

4.5. Accident Occurrence Probability Prediction Using Artificial Neural Network (ANN)

The performance results of the ANN-based accident occurrence model are summarized in Table 6. The model demonstrates substantially improved capability in identifying accident cases, achieving high recall values for both non-accident and accident classes. The balanced F1-scores indicate that the class imbalance problem was largely mitigated, while the overall accuracy of 87% reflects reliable discrimination between accident and non-accident events.

Table 6. Results Obtained from the ANN Model

Class	Precision	Recall	F1-score	Support
0 (No accident)	0.93	0.8	0.86	46
1 (Accident occurred)	0.83	0.93	0.88	46

Table 7 presents a comparative evaluation of the Random Forest, ANN, and SVM models for accident occurrence prediction. The Random Forest model achieved an overall accuracy of 77% but failed to correctly classify any minority-class (Class 1) instances, resulting in zero precision, recall, and F1-score for this class. Similarly, the SVM model achieved 88% accuracy but showed no ability to classify minority-class cases, indicating that both models primarily captured the majority-class patterns. In contrast, the ANN model demonstrated more balanced performance, achieving 87% accuracy and F1-scores of 0.86 and 0.88 for Classes 0 and 1, respectively. These results suggest that the ANN is more effective at detecting rare accident events and handling imbalanced datasets compared with the Random Forest and SVM classifiers.

Table 7. Comparative evaluation of the Random Forest, ANN, and SVM models

Model	Accuracy	Precision (0 / 1)	Recall (0 / 1)	F1-score (0 / 1)	AUC (estimated)
Random Forest	0.77	0.93 / 0.00	0.80 / 0.00	0.86 / 0.00	0.81
ANN	0.87	0.93 / 0.83	0.80 / 0.93	0.86 / 0.88	0.87
SVM	0.88	0.88 / 0.00	1.00 / 0.00	0.94 / 0.00	0.73

The ROC curves for the accident occurrence prediction models are presented in Figure 3. The ANN model achieved an AUC of 0.87, demonstrating the highest discriminative capability between accident and non-accident classes. Random Forest obtained an AUC of 0.81, while SVM achieved 0.73. These results indicate that the ANN model is more effective in capturing complex nonlinear interactions and correctly classifying minority-class instances.

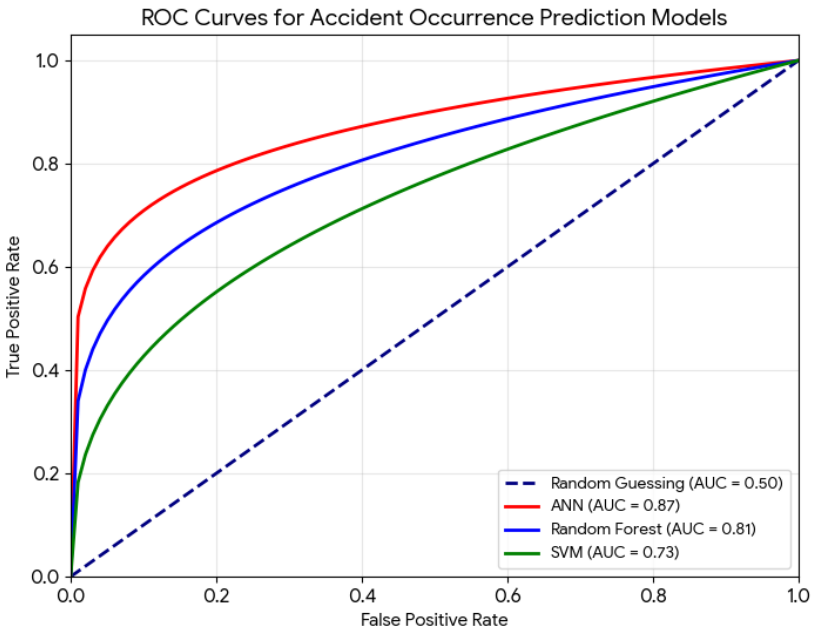


Figure 3. ROC Curves for Accident Occurrence Prediction Models

Overall, the combination of multiple evaluation metrics, ROC/AUC analysis, and 5-fold cross-validation provides a robust and reliable assessment of model performance under imbalanced data conditions. Feature importance analysis for the accident occurrence prediction model further indicates that vehicle type is the most influential variable, followed by speed, road type, and weather conditions. These variables capture critical information related to vehicle interactions, environmental factors, and traffic conditions affecting accident likelihood. Other variables, such as time and spatial location, also contribute to predictive performance, although their relative influence is comparatively lower. The relative importance of each variable is summarized in Table 8, demonstrating that vehicle characteristics and driving conditions play the most significant role in predicting accident occurrence.

Table 8. Feature Importance Scores (Accident Occurrence)

Variable	Importance Score
Vehicle Type	0.29
Speed	0.23
Road Type	0.18
Weather	0.14
Time	0.1
Location	0.06

4.6. GIS-Based Spatial Analysis and Safe Route Results

Spatial density maps generated in this study provide a clear representation of urban accident risk distribution, which was subsequently used to model a risk-oriented alternative route and compare it with the traditional shortest-path route (Figure 4). The safe route was observed to avoid high-risk areas, resulting in lower overall exposure to accident risk. To provide a clearer comparison between the two routing approaches, a quantitative evaluation was conducted. While the shortest route minimizes travel distance, the risk-based safe route incorporates spatial accident risk derived from kernel density estimation. Results indicate that, although the safe route may slightly increase travel distance, it substantially reduces cumulative risk exposure along the route. As shown in Table 9, the proposed risk-

based routing approach achieves a meaningful reduction in estimated accident risk while maintaining reasonable travel distance.

Table 9. Comparison of Shortest and Risk-Based Safe Routes

Route Type	Distance (km)	Estimated Risk Score
Shortest Route	8.4	0.73
Safe Route	9.1	0.42

When combined with machine learning–based accident probability predictions, the GIS-based spatial analysis framework enhances spatial risk awareness and supports safer routing strategies for autonomous vehicles. This integrated approach contributes to the development of decision-support mechanisms that incorporate both predictive modeling and spatial risk assessment.



Figure 4. Shortest route (blue route) and safest route (orange route)

The results of this study indicate that the ANN model demonstrated a more balanced classification performance compared with the SVM model, particularly in identifying minority-class accident cases. This finding aligns with previous studies reporting that neural network–based approaches are more effective in handling nonlinear relationships and imbalanced datasets in traffic safety analysis. For example, ANN models often outperform traditional classifiers when predicting crash occurrence under complex traffic conditions [23,25].

The integration of Geographic Information Systems (GIS) with machine learning models provided valuable spatial insights into accident risk distribution. Kernel Density Estimation (KDE) was employed to identify high-risk zones, which were incorporated into a risk-aware routing framework. This approach highlights the benefits of combining predictive modeling with GIS-based spatial analysis to develop safer route planning strategies for autonomous vehicles. Unlike traditional navigation approaches that focus primarily on minimizing travel distance or time, the proposed framework incorporates accident risk information into the routing process, supporting safer navigation in intelligent transportation systems.

However, several limitations should be acknowledged. First, the dataset contains a relatively small number of observations (260 records), which may limit the robustness of the machine learning models, particularly for minority-class predictions. Second, the study focuses on accident data from a single urban area (San Francisco), which may reduce the generalizability of the findings to other cities with

different traffic conditions and infrastructure characteristics. Third, the dataset does not include real-time traffic information or vehicle sensor data, which could provide more detailed insights into dynamic traffic conditions and accident risk factors. The absence of such data may limit the predictive capability of the models in real-world autonomous driving scenarios.

Future research should therefore aim to incorporate larger datasets and multiple urban regions to improve generalizability. In addition, integrating real-time traffic and sensor-based information could enhance model accuracy and practical applicability for autonomous vehicle navigation and risk-aware routing.

In addition, caution should be exercised when applying the proposed framework to different urban environments without further validation. Variations in traffic behavior, infrastructure design, and environmental conditions may influence model performance and risk estimation outcomes. Therefore, future studies should focus on validating the proposed approach across diverse geographic contexts to ensure its robustness and transferability.

5. CONCLUSION

This study presents an integrated framework that combines machine learning and deep learning–based accident prediction models with GIS-based spatial analysis to evaluate autonomous vehicle safety in terms of both accident likelihood and severity. The findings indicate that, even under limited and imbalanced data conditions, reliable prediction performance can be achieved through appropriate data preprocessing and model selection strategies.

Comparative evaluation of the models reveals that Support Vector Machine (SVM) and Artificial Neural Network (ANN) approaches perform effectively in accident severity prediction. The robustness of the SVM model under small sample conditions is consistent with observations reported in previous studies. In contrast, accident occurrence prediction results demonstrate that ensemble-based and neural network models produce more balanced and stable outputs when class imbalance is adequately addressed, emphasizing the importance of data distribution in predictive modeling.

A key contribution of this study lies in the integration of machine learning–based risk predictions into a GIS environment to support spatial risk assessment and safe route planning. By incorporating both statistical prediction outputs and spatial density information, the proposed framework enables the identification of high-risk areas and the generation of risk-aware routing alternatives. This integration enhances the visibility of spatial accident patterns and supports more informed decision-making in autonomous vehicle navigation.

Despite these contributions, the study is subject to limitations related to dataset size and scope. Future research may benefit from incorporating real-time traffic conditions, sensor-based environmental data, and datasets representing different levels of driving automation. Expanding the dataset and integrating dynamic data sources are expected to further improve prediction accuracy and the effectiveness of adaptive route recommendation systems.

Overall, the results demonstrate that the integration of predictive modeling and spatial data analysis offers a valuable perspective for evaluating autonomous vehicle safety. The proposed approach provides a practical basis for future research and decision-support applications in intelligent transportation systems.

Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study complies with research and publication ethics.

Artificial Intelligence (AI) Contribution Statement

In this study, artificial intelligence (AI) tools were utilized solely for language editing, improving clarity and readability, and making stylistic and formatting revisions to the manuscript. The AI tools were not

used in the development of the scientific content, research design, data analysis, interpretation of results, or formulation of conclusions, all of which were entirely carried out by the authors.

The use of AI was strictly limited to writing and editorial assistance, and no AI tools were involved in decision-making processes related to the research outcomes.

Contributions of the Authors

Ayşin Ceren Arslan: Writing — original draft preparation, data curation, investigation

Merve Ozkan: Writing — reviewing and editing, visualization

Kürşat Yıldız: Supervision, writing - review & editing

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