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Research paper

Deep Learning–Driven Crime-Aware Multi-Factor Route Safety Prediction Using Real-Time Environmental and Contextual Data

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Abstract

Traveler safety is a critical concern in modern Intelligent Transportation Systems (ITS), where conventional navigation algorithms primarily optimize for distance or travel time while overlooking contextual safety factors. This study introduces a Deep Learning–Driven Crime-Aware Route Safety Prediction Framework that fuses static, dynamic, and crime-based contextual attributes for segment-level risk assessment. The model extends earlier machine-learning frameworks by incorporating a Deep Neural Network (DNN) capable of learning complex nonlinear relationships among environmental, demographic, and crime-contextual variables. Real-time data from Google Maps, OpenStreetMap, OpenWeatherMap, and TomTom APIs are combined with synthetically generated crime-risk indicators derived from spatial density, place-type exposure, and temporal crime propensity. Comparative evaluation of Decision Tree, Gradient Boosting, Random Forest, and DNN models demonstrates that the DNN achieves the highest predictive accuracy ($R^2 = 0.9987$, ROC–AUC = 0.999) while maintaining robust classification reliability. All models consistently identified Route 3 as the safest and Route 1 as the most risk-prone corridor. By combining the interpretability of Gradient Boosting with the deep learning capacity of DNNs, the proposed framework enhances route-level safety prediction and scalability for real-time, human-centric ITS applications.

Keywords: *Crime-Aware Routing; Deep Neural Network; Gradient Boosting; Multi-Factor Risk Modeling; Real-Time Data Fusion; Intelligent Transportation Systems.*

1. Introduction

In recent years, the rising incidence of urban crimes and safety-related events has emphasized the critical need for ITS that not only optimize travel efficiency but also prioritize human safety. Conventional navigation platforms such as Google Maps and Waze primarily focus on parameters such as travel time, distance, and congestion levels. However, these systems often overlook contextual and situational safety dimensions—including exposure to crime-prone zones, inadequate lighting, limited surveillance, and socio-environmental vulnerability. Consequently, vulnerable populations such as women, senior citizens, and night-time commuters remain disproportionately exposed to high-risk travel environments. These limitations highlight the necessity for crime-aware, context-sensitive routing algorithms that generate safety-optimized travel paths rather than solely the fastest ones.

To address this gap, the present research introduces a Deep Learning–Driven Crime-Aware Route Safety Prediction Framework, which builds upon the previously developed machine-learning-based route safety system. The enhanced framework integrates static, dynamic, and crime-contextual factors into a unified model capable of learning complex nonlinear interdependencies between environmental conditions, demographic profiles, and spatial-temporal crime dynamics. The proposed system combines multi-source data from Google Maps and OpenStreetMap for spatial features, OpenWeatherMap and TomTom Traffic for dynamic real-time conditions, and synthetically modeled crime data generated using contextual normalization and risk weighting functions. Each 100–200-meter road segment between the source and destination—Maragathapuram and Parvathipuram (Tamil Nadu)—is assigned a contextual risk score that reflects both static and temporal safety conditions.

Unlike conventional rule-based or shallow learning approaches, the deep learning framework employs a Deep Neural Network (DNN) architecture that captures higher-order correlations among risk parameters such as lighting, public space density, road structure, weather, time of travel, and localized crime probabilities. These segment-level risks are aggregated into a Multi-Factor Risk Index (MFRI) that quantifies cumulative route safety and identifies the safest possible travel corridor. By integrating geospatial analytics with contextual intelligence, the system transitions navigation from “shortest path” optimization to “safest path” recommendation—empowering travelers to make informed, safety-conscious routing decisions.

While earlier machine learning models such as Gradient Boosting, Random Forest, and Decision Tree achieved promising accuracy in risk classification, their capacity to capture deep nonlinear relationships was inherently limited by structural constraints. The newly introduced DNN-based model addresses these limitations by leveraging dense, multi-layered feature learning to represent subtle dependencies between environmental, demographic, and spatial crime attributes. This enhancement improves predictive precision and generalization capability, enabling robust performance under diverse real-time scenarios. The specific objectives of this study are as follows:

- To develop a comprehensive, multi-source dataset that integrates spatial data (Google Maps, OpenStreetMap), dynamic environmental data (OpenWeatherMap, TomTom Traffic), and synthetic crime-risk indicators representing contextual vulnerability.
- To define and normalize static, dynamic, and crime-based risk factors with appropriate weight assignments ($\lambda S = 0.40$, $\lambda D = 0.35$, $\lambda C = 0.25$) reflecting their influence on human safety.
- To train and compare Decision Tree, Gradient Boosting, Random Forest, and Deep Neural Network (DNN) models for segment-level risk prediction and route safety classification.
- To compute the Multi-Factor Risk Index (MFRI) for each feasible route and identify the optimal safe path with the lowest cumulative risk value.
- To evaluate the models using regression and classification metrics such as MAE, MSE, R^2, Precision, Recall, F1-score, and ROC–AUC to validate prediction accuracy and robustness under real-time conditions.

Through these objectives, this study enhances human-centric route safety by integrating deep learning, contextual data fusion, and crime risk analytics within a unified ITS framework. The proposed system not only strengthens situational awareness for individual travelers but also provides a scalable decision-support tool for traffic management and public safety authorities. Ultimately, this work contributes to the realization of Safe and Smart Urban Mobility, where route recommendations are dynamically optimized for both efficiency and human safety.

2. Literature Survey

Numerous studies have explored route optimization with the objective of enhancing both safety and travel efficiency. In the foundational framework presented by Thilagavathi et al. [1], a three-phase model integrating static and dynamic parameters—such as weather, traffic, and contextual safety indicators—was developed to assess route-level risk. While this approach successfully demonstrated the potential of multi-source data fusion for safe route planning, it remained predominantly rule-based, restricting its ability to adapt to evolving environmental conditions and unseen data patterns. Subsequent research has therefore shifted toward machine-learning-driven models capable of learning complex correlations among spatial, temporal, and contextual features to improve predictive robustness and scalability.

Thilagavathi et al. [2] proposed a unified machine learning-based framework integrating static and dynamic parameters such as vehicle type, demographics, lighting, traffic, weather, and surface condition to assess route safety. Real-time data from Google Maps, OpenStreetMap, OpenWeatherMap, and TomTom were used to compute segment-level risk scores, while Gradient Boosting, Random Forest, and Decision Tree models predicted cumulative risk values. A case study between Maragathapuram and Parvathipuram validated the model, with Gradient Boosting achieving the highest accuracy. The study demonstrated the potential of data-driven machine learning approaches for intelligent and context-aware safe route optimization.

Berhanu et al. [3] integrated spatial crash rate analysis with Random Forest and network-based modeling to identify high-risk zones and recommend safer travel routes. Their study highlighted the value of incorporating real-time validation and environmental data, demonstrating that machine learning and spatial analytics can significantly enhance the accuracy and reliability of safety-oriented route planning. Chai et al. [4] highlighted the growing adoption of hybrid machine learning models in traffic and safety prediction and emphasized the importance of establishing standardized methodologies and ethical practices to ensure transparency, reliability, and fairness in transportation risk analysis. Abdulrashid et al. [5] developed an explainable AI model using SHAP values to identify the main causes of accidents and show how driver behavior is linked to the severity of injuries.

Sandyal et al. [6] proposed a Women Safety Platform that uses geospatial data, machine learning models, and user feedback to identify safer routes. The system analyzes historical crime data and assigns safety scores to streets using algorithms such as K-Nearest Neighbors (KNN), Random Forest, Logistic Regression, Decision Tree, and Bernoulli Naive Bayes to predict and highlight the safest path between a given source and destination. Esther Galbruna et al. [7] developed a safety-based navigation system using crime data from Chicago and Philadelphia. Their model estimates crime risk for each road segment and introduces the SAFEPATHS problem to find routes that balance distance and safety through a bi-objective shortest path approach. Shivangi Soni [8] proposed a robust model that uses updated crime and accident data from NYC OpenData to calculate average risk scores for different regions. Machine learning algorithms then estimate the overall risk of a path based on nearby cluster scores, with accuracy improving as more safety-related factors are included.

Kumar et al. [9] developed a machine learning-based crime prediction system to optimize safe routes in urban areas by forecasting crime trends. Using historical crime data across categories like murder, rape, kidnapping, and theft, the model identifies high-risk zones and assigns safety scores to routes, helping users and authorities make informed decisions for safer travel. Yash S. Asawa [10] proposed a User-Specific Safe Route Recommendation System that visualizes safe routes on maps using past crime records of the area. The model works on two levels: the first identifies user-specific features through a Decision Network, and the second generates safe routes using Geospatial Data Analysis. Soham Kudale et al. [12] proposed a machine learning-based system that offers safe and efficient route recommendations based on user preferences such as time and destination. Future enhancements include integrating crime data and advanced clustering for improved safety.

Anurag et al. [13] proposed a real-time safe route system that analyzes crime rates to suggest and update the safest path. It features heat maps, live location sharing, and a police verification portal to validate data and enhance user safety. Aruna et al. [14] proposed a system using the K-means clustering algorithm to predict safe routes and reduce processing time. The model identifies crime-prone areas along selected routes, helping women avoid high-risk locations and ensuring safer travel. Lakshmi et al. [15] proposed a deep learning-based model to identify the safest route by analyzing road surface, users, weather, traffic, accident history, and crime areas. Using a Long Short-Term Memory with Attention Mechanism and a Fitness-based Golden Tortoise Beetle Optimizer, the system effectively minimizes travel risk while balancing distance and time.

Rupa Shinde et al. [16] developed SafeGuard, a machine learning-based app that analyzes crime, traffic, and crowd data to suggest safe routes. It includes SOS alerts, live location sharing, and heat maps for real-time safety monitoring, providing quick assistance and enhanced travel security. Fatima Shaker Hussain et al. [17] developed predictive models for crime pattern analysis to support crime prevention in Boston. The model incorporates geographical location as a key factor to distinguish between secure and insecure areas, demonstrating the usefulness of geo-location data in crime detection and investigation. Ramesh et al. [18] developed CAST, a mobile system that fuses real-

time data and machine learning to predict crime risk and provide safety alerts. It integrates crime reports, social media, and weather data to create dynamic risk maps, helping travelers identify and avoid high-risk areas.
Sarang Tarlekar et al. [19] analyzed 12 years of crime records by geographic location to identify the safest routes between source and destination. Using the ID3 decision tree algorithm, the system evaluates street-level risks and recommends routes based on user demographics such as gender and age to enhance travel safety. Isha Puthige et al. [20] developed a system to identify the safest route between two locations using New York City crime data. Various clustering algorithms were compared, with K-Means providing the best results. The study led to a user-friendly application that alerts users about high-risk routes through a danger index, helping them choose safer paths and reduce exposure to crime. Ingole et al. [21] developed a safety-based routing system using recent crime data and user feedback. With the optimized A* algorithm and OSRM, it identifies fastest, safest, and optimized routes by balancing crime severity, proximity, and travel efficiency.
Hong et al. [22] developed a crime-safety map application using heatmap and geofence methods to display crime-prone areas and safety levels. Using data from South Korea's Open Government Data Portal, the Android-based app visualizes environmental features and alerts users about nearby risks, helping reduce fear of crime and improve public safety awareness. Khanna et al. [23] proposed a system to identify safe road routes by analyzing district-wise crime rates using data from the National Crime Records Bureau of India. The model predicts average crime risk along routes and displays safety ratings, travel time, and toll details on a map. It also supports real-time safety assessments, helping users choose safer and more informed travel paths.
Theron et al. [24] proposed three methods to find the safest and shortest routes in South Africa using historical crime data, risky facility locations, or a combination of both. The study compared their effectiveness and suggested integrating such safety-based routing into future navigation systems.

3. Methodology

3.1. Overview of the enhanced framework

The Proposed Crime-Based Safe Route Recommendation System extends the previously developed Safe Route Prediction Framework [1] [2] by integrating crime-risk intelligence and deep learning–driven contextual modeling within the route-safety assessment pipeline.
While the earlier framework focused primarily on static and dynamic contextual parameters—such as road geometry, lighting, weather, CCTV availability, and traffic density—for safety estimation, the enhanced system introduces a synthetic crime-risk generation mechanism and a Deep Neural Network (DNN)–based multi-factor prediction model for more comprehensive and fine-grained risk evaluation. The proposed Deep Learning–Driven Crime-Aware Route Safety Prediction Framework (DL-CARSPF) model is shown in Figure 1.

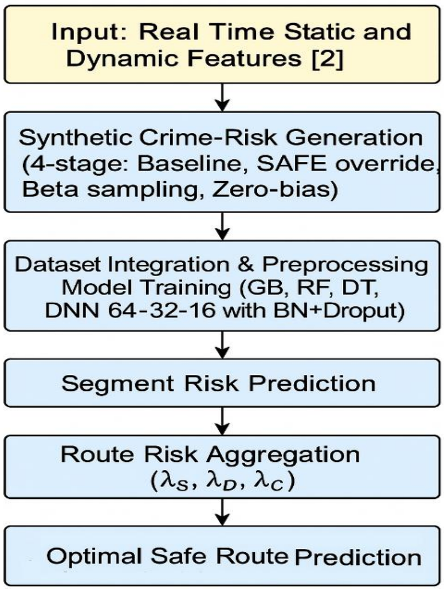


Fig. 1: Proposed DL-CARSPF Model Architecture.

As illustrated in Figure 1, the system begins with real-time static and dynamic feature inputs, followed by synthetic crime-risk generation through a four-stage process (Baseline, SAFE Override, Beta Sampling, and Zero-Bias). The processed data are then integrated and preprocessed before being trained through multiple models—Gradient Boosting, Random Forest, Decision Tree, and a DNN (64–32–16 architecture with Batch Normalization and Dropout)—for segment-level risk prediction.
Each route between the specified source and destination is divided into approximately 200-meter segments, and for every segment, contextual and crime-based indices are computed. These segment-level risks are then aggregated (λ_S, λ_D, λ_C) to identify the optimal safe route, producing outputs such as the safest path, risk map, and route-level explanation for traveler safety.

3.2. Data integration and limitations of public records

Although multiple open data sources—such as the Tamil Nadu State Crime Records Bureau (SCRB), Open Government Data (OGD) Platform India, and OpenCity—provide official crime statistics, these datasets are typically available only in aggregated form at district or city levels. They report counts of major Indian Penal Code (IPC) crime categories such as homicide, burglary, and offences against women, but lack the spatial granularity, temporal resolution, and road-segment-level identifiers required for fine-grained route safety modeling.
To address the above said limitation and ensure procedural reproducibility, the proposed system employs a simulation-based synthetic crime-risk generation model. The generated crime-risk values are derived from the existing contextual and environmental features such as

lighting conditions, time of travel, public space exposure, and surveillance availability. This simulation framework enables controlled experimentation, spatial correlation analysis, and validation of the proposed deep learning model in the absence of publicly accessible, segment-level crime records. However, the simulated crime-risk values do not represent exact real-world crime existences and should be interpreted as probabilistic contextual risk values rather than actual incident chances. This limitation is acknowledged, and future work will focus on integrating verified, geo-tagged crime datasets as such data become available.

3.3. Synthetic crime-risk generation model

The generation of segment-level crime indices is based on a probabilistic four-stage mechanism, ensuring realistic variability, sparsity, and contextual dependence. The Figure 2 illustrates the four-stage synthetic crime-risk generation process, where static and dynamic contextual features are transformed into realistic segment-level crime factors through baseline propensity, safe-segment override, beta-shaped sampling, and zero-bias masking. It visually demonstrates how input attributes evolve into probabilistic crime-risk outputs for each route segment.

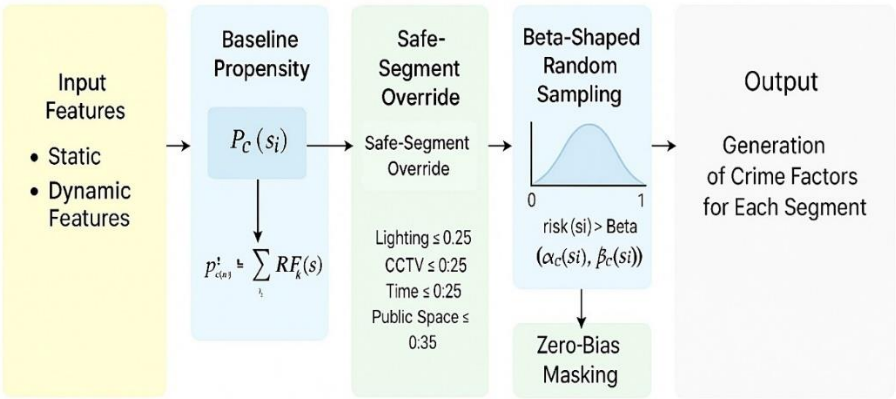


Fig. 2: Proposed Mode for Generation of Crime Factors for Each Segment.

For each route segment s_i and crime type c, the resulting crime-risk value $risk_c(s_i) \in [0,1]$ is computed as:

$$\mathrm{risk}_c = \mathrm{ZeroBias}(\mathrm{BetaSample}(\mathrm{Baseline}(s_i, c)),\ p_0) \tag{1}$$

Where the inner functions represent the four major components described below.

1) Baseline Propensity (Context Anchoring)

For each crime category c, a set of expert-defined contextual weights

$$W^c = \left\{w_k^{(c)}\right\}_{k=1}^{p} \tag{2}$$

Is assigned to represent the relative contribution of each contextual risk factor (e.g., lighting, CCTV, time, public-space exposure). The weights are normalized as in (3):

$$\textstyle\sum_{k=1}^{p} w_k^{(c)} = 1 \tag{3}$$

For every segment s_i, the corresponding normalized contextual-risk vector is defined as in (4):

$$RF(s_i)=[RF_{road}(s_i), RF_{lighting}(s_i), RF_{traffic}(s_i), RF_{weather}(s_i), \ldots], \tag{4}$$

Where each $RF_k(s_i) \in [0,1]$ quantifies the risk intensity of the k^{th} contextual risk factor. The baseline crime propensity for type c on segment s_i is calculated as in (5):

$$p_c(s_i) = \textstyle\sum_{k=1}^{p} w_k^{(c)} RF_k(s_i) \tag{5}$$

For Accident, the weight vector $W^{(accident)}$ assigns slightly higher importance to roadway geometry and condition, e.g., $w_{curve}=0.30$, $w_{road}=0.20$, $w_{surface}=0.15$, $w_{traffic}=0.15$, $w_{weather}=0.10$, $w_{time}=0.10$ (sum = 1). This represents how strongly the contextual environment of the segment aligns with the typical conditions conducive to crime c.

2) Safe-Segment Override (Deterministic Zeros)

Segments exhibiting strong guardianship and environmental safety are explicitly excluded from stochastic risk generation. A segment s_i is marked SAFE if the following thresholds hold as in (6):

$$RF_{lighting}(s_i) \le 0.25,\ RF_{cctv}(s_i) \le 0.25,\ RF_{time}(s_i) \le 0.25,\ RF_{public\_space}(s_i) \le 0.35 \tag{6}$$

For such segments,

$$risk_c(s_i) = 0\ \forall\ c \tag{7}$$

This rule ensures that areas with adequate visibility, good lighting, and active public presence are assigned zero crime risk, preventing false-positive detections. This Figure 3 compares the SAFE (zero-risk) and Non-SAFE (non-zero) segment proportions across all 11 categories, positioning Accident as the final feature for clearer interpretation.

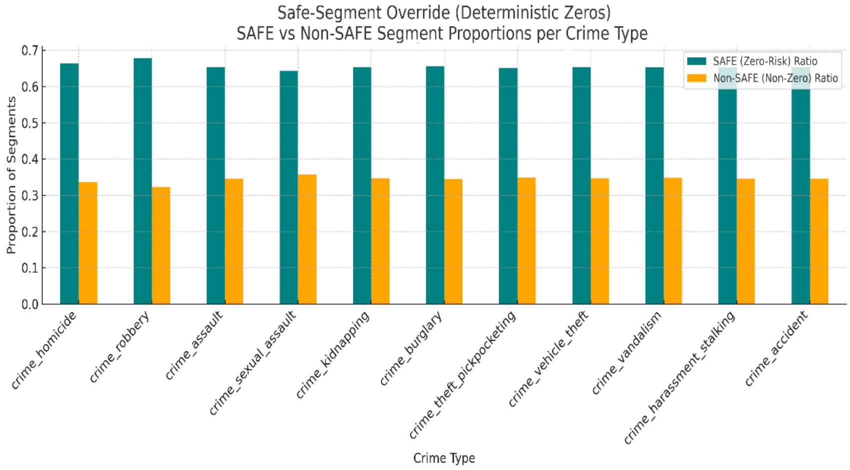


Fig. 3. Safe-Segment Override (Deterministic Zeros).

3) Beta-shaped Random Sampling (Realistic [0, 1] Risks)
For non-SAFE segments, stochastic variability is introduced through the Beta distribution, which naturally models continuous variables bounded between 0 and 1 as in (8):

$$\mathrm{risk}_c(s_i) \sim \mathrm{Beta}\big(\alpha_c(s_i), \beta_c(s_i)\big) \tag{8}$$

Where

$$\alpha_c(s_i) = 1 + \kappa\, p_c(s_i), \beta_c(s_i) = 1 + \kappa\,(1 - p_c(s_i))$$

Here, κ (kappa) is the concentration parameter (default κ=8) controlling the spread of the Beta distribution; higher κ produces narrower distributions, while lower κ increases variance. This approach ensures that segments with higher contextual propensities yield higher expected risk means, while preserving natural stochastic variation.
4) Zero-Bias Masking (Sparsity Control)
Empirical crime data are inherently sparse; to mimic this, a zero-masking process is applied as in (9):

With probability

$$p_0, \mathrm{risk}_c(s_i) \leftarrow 0 \tag{9}$$

Where p_0=0.60 indicates that approximately 60% of non-SAFE segments remain incident-free, thereby maintaining realistic low-risk sparsity within the synthetic dataset.
Figure 4 illustrates the comparative results of synthetic crime-risk generation across four computational stages for all eleven categories, including Accident.

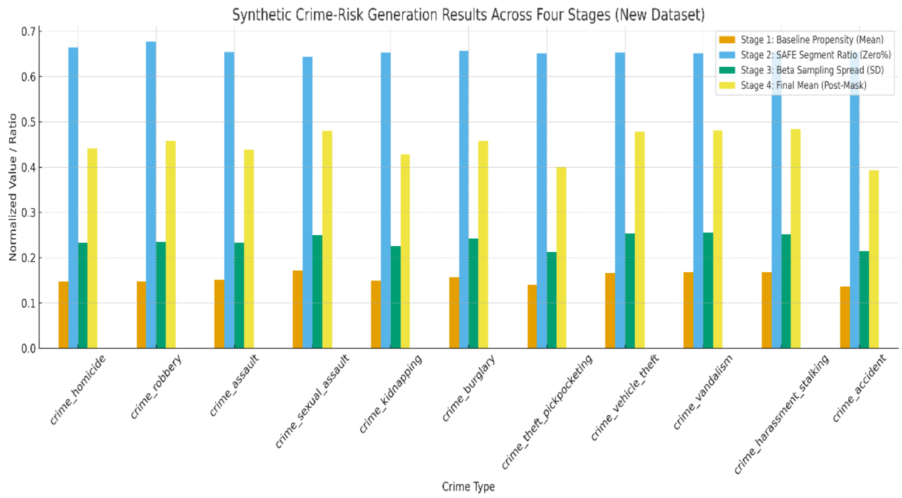


Fig. 4: Synthetic Crime-Risk Generation Results Across Four Stages.

The SAFE-Segment Override phase consistently shows the highest proportion of zero-risk segments, validating the effectiveness of deterministic filtering in reducing false positives. Post-masking mean values demonstrate realistic sparsity and variation, confirming that the combined probabilistic model produces contextually balanced segment-level risk indices.

3.4. Crime-specific risk profiles

The model generates eleven independent risk layers, each corresponding to a major crime or safety-related hazard. Each layer incorporates dominant contextual risk factors, as shown in table 1:

Table 1: Major Crime Categories and Dominant Risk Factors

Category	Dominant Risk Factors
Homicide	Isolation, poor lighting, low CCTV, night-time
Robbery	Low lighting, sparse surveillance, escape routes
Assault	High public activity, poor visibility, nightlife
Sexual Assault	Gender, time, lighting, isolation
Kidnapping	Remote/unmonitored d areas, school zones
Burglary	Residential/commercial areas, weak CCTV
Theft/Pickpocketing	Crowded zones, weak surveillance
Vehicle Theft	Parking areas, poor monitoring
Vandalism	Low visibility, weak social control
Harassment/Stalking	Gender, isolation, lighting
Accident	Road geometry, surface, weather, traffic

3.5. Algorithm: segment-level crime-risk computation

The Crime-Risk Value Computation Algorithm estimates risk for each segment by combining baseline contextual factors, safety thresholds, and probabilistic Beta sampling with zero-bias adjustment. The complete algorithm is summarized in algorithm 1.

Algorithm 1: Crime-Risk Value Computation for Each Segment

Step	Procedure
1	Input: Contextual feature matrix $RF(s_i)$, weight vectors $W^{(c)}$, parameters κ, p_0.
2	For each segment s_i and crime c:
3	Compute baseline propensity $p_c(s_i) = \sum_{k=1}^{p} w_k^{(c)} RF_k(s_i)$.
4	If segment satisfies SAFE thresholds → set $risk_c(s_i)=0$.
5	Else generate α_c,β_c using $p_c(s_i)$ and κ.
6	Sample $risk_c(s_i) \sim Beta(\alpha_c(s_i), \beta_c(s_i))$
7	Apply zero-bias: with probability p_0, set $r_c(s_i)=0$.
8	Output: $risk_c(s_i) \in [0,1]$ for each crime type.
9	Combine all crime risks and contextual scores to obtain $RF_{final}(s_i)$.

3.6. Deep learning–based segment risk prediction

The generated synthetic dataset—comprising static, dynamic, and crime-based contextual variables—is used to train a Deep Neural Network (DNN) for segment-level risk regression. The DNN architecture shown in Figure 5 includes an input layer followed by three hidden layers (64–32–16 neurons) with ReLU activations, dropout regularization, and batch normalization. The final output node predicts a continuous risk value within [0,1], representing the estimated safety level for each segment.

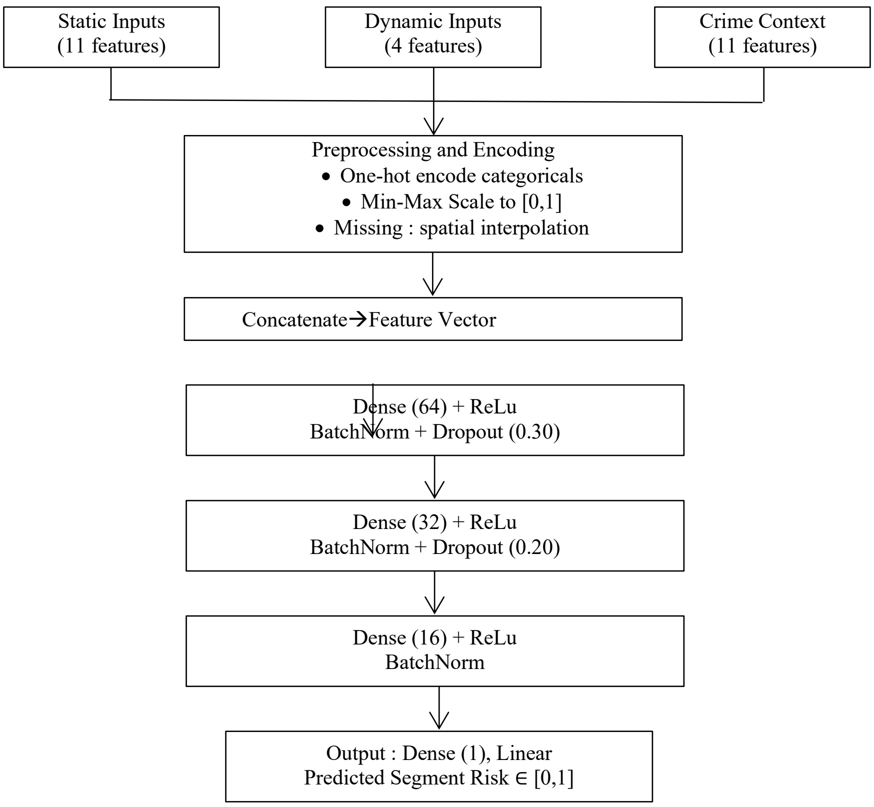


Fig. 5: DNN Model Architecture.

The proposed DNN model consists of a structured pipeline that integrates static, dynamic, and crime-contextual features for segment-level risk prediction, as illustrated in Figure 5. Static inputs include user, vehicle, and road-related attributes, while dynamic inputs capture traffic, weather, surface condition, and time of travel. Crime-context features represent category-wise crime-risk indices associated with each route segment.

All input features are preprocessed using one-hot encoding for categorical variables and min–max normalization for numerical values. Missing environmental attributes are handled through spatial interpolation across adjacent segments. The fused feature vector is then processed by a compact multilayer perceptron comprising three hidden layers with ReLU activation, batch normalization, and dropout regularization to capture nonlinear interactions and prevent overfitting.

The network outputs a continuous segment-level risk score, which is aggregated across all segments to compute the overall route risk. The route with the minimum aggregated risk is selected as the safest path, ensuring consistency with the previously developed multi-factor framework and supporting efficient real-time route evaluation.

The DNN model captures nonlinear dependencies and cross-feature interactions that classical models such as Random Forest, Decision Tree, or Gradient Boosting cannot fully represent. The predicted segment-level risk scores are aggregated to compute route-level safety indices, identifying the safest route with the minimum cumulative risk.

4. Implementation

4.1. System framework integration

The proposed Deep Learning–Driven Crime-Aware Route Safety Prediction Framework (DL-CARSPF) extends the previously developed Unified Real-Time Multi-Factor Risk-Aware Route Optimization System [2]. The original architecture—comprising modules for user input acquisition, route segmentation, data extraction, and risk computation—remains intact, while the current version introduces an additional contextual intelligence and deep learning layer to model complex cross-factor dependencies.

The system pipeline begins with route extraction using the Google Directions API, which segments the origin–destination corridor into ~200-meter intervals. Supplementary APIs are integrated to capture real-time environmental data: OpenStreetMap for road topology and structure, OpenWeatherMap for meteorological parameters, and TomTom Traffic API for live congestion and speed profiles.

On top of this foundation, a synthetic crime-risk generation module and a Deep Neural Network (DNN)-based predictive engine are incorporated to produce composite safety scores for each segment. The addition of these modules transforms the baseline model into a privacy-preserving, context-aware, and deep-learning-enhanced route safety system capable of real-time, adaptive risk prediction.

4.2. Crime-aware data fusion and preprocessing

4.2.1. Synthetic crime-risk data generation

Due to the limited availability of fine-grained, geocoded crime records, a synthetic simulation framework was adopted to generate privacy-compliant crime-risk values for each road segment. The framework follows a structured multi-stage process that integrates contextual priors, deterministic safety filtering, probabilistic sampling, and sparsity control to produce realistic segment-level crime-risk scores.

The detailed formulation of this process, including the definition of contextual weights, safety thresholds, probabilistic sampling strategy, and zero-bias masking, is described in Section 3.3 and summarized in Algorithm 1. This design ensures that the generated crime-risk values capture realistic spatial variability while maintaining ethical data handling and reproducibility, without relying on identifiable crime records.

4.2.2. Data fusion with environmental and demographic features

Each simulated crime-risk value (CR_i) is appended to the multi-factor dataset previously generated in [2].

The unified feature matrix comprises:

- Static parameters (λ_S): vehicle type, gender, age, group size, place type, road type, curve complexity, public space availability, lighting infrastructure, CCTV presence and road crossing type.
- Dynamic parameters (λ_D): weather condition, traffic congestion, surface condition, and time of day.
- Contextual parameter (λ_C): synthetic crime-risk index (CR_i).

All variables are normalized to [0, 1] using min–max scaling. Categorical data (e.g., road types, weather categories) are encoded using one-hot encoding. Missing API responses are filled by spatial interpolation from adjacent segments. The resulting fused dataset serves as the training corpus for the machine-learning models described in Section 4.4.

4.3. Risk factor computation

The risk computation follows the mathematical model described in [1] and [2], extended here to include the contextual crime component. For each route R_j divided into N segments S_i. The final crime risk factor (CRF_i) for each segment is calculates as in (10).

$$\mathrm{CRF_i} = \frac{1}{\mathrm{n_C}} \sum_{\mathrm{t=1}}^{\mathrm{n_c}} \mathrm{C_{it}} \tag{10}$$

The Final Segment Risk (RF_i) is computed using weighted fusion as in (11):

$$\mathrm{RF_i} = \lambda_\mathrm{S} \times \mathrm{SRF_i} + \lambda_\mathrm{D} \times \mathrm{DRF_i} + \lambda_\mathrm{C} \times \mathrm{CRF_i} \tag{11}$$

Where λ_S=0.4, λ_D=0.35 and λ_C=0.25. The weights λ_S, λ_D and λ_C are assigned to balance the dominant influence of persistent structural safety factors, the moderate variability of real-time dynamic conditions, and the contextual yet probabilistic impact of crime risk, ensuring realistic and stable route safety prediction. The overall route risk score is calculated as in (12).

$$\mathrm{RS_j} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{RF_i} \tag{12}$$

and the safest route is selected by (13):

$$\mathrm{SR} = \arg\min_{1\le j\le m}\left(\mathrm{RS_j}\right) \tag{13}$$

This formulation enables dynamic balancing between environmental safety and simulated crime exposure.

4.4. Machine-learning model development

Three supervised regression models—Gradient Boosting Regressor (GBR), Random Forest Regressor (RFR), and Decision Tree Regressor (DTR)—were used to predict the final risk score of each route segment. GBR captures complex nonlinear relationships by sequentially minimizing residual errors, RFR improves accuracy and robustness through ensemble averaging, and DTR offers interpretability through rule-based decision structures. Together, these models provide a balanced trade-off between predictive accuracy, generalization, and explainability.

Hyperparameter tuning was conducted using GridSearchCV with five-fold cross-validation to identify optimal model configurations. Key parameters included the number of estimators (300–500), maximum tree depth (8–12), and learning rate (0.05–0.1 for GBR). The dataset was split into 80% for training and 20% for testing to ensure unbiased evaluation.

Model performance was assessed using regression and classification metrics, including MAE, MSE, R^2, Accuracy, Precision, Recall, F1-score, Confusion Matrix, and ROC–AUC, enabling comprehensive evaluation of both prediction accuracy and classification reliability.

4.5. Deep neural network (DNN) model

To address the representational limitations of tree-based models such as Random Forest and Gradient Boosting, a Deep Neural Network (DNN) was designed for final segment-level risk prediction. The model accepts a fused feature vector comprising static, dynamic, and crime-based parameters. Categorical features were encoded using one-hot encoding, numerical features were normalized to the [0,1] range using Min–Max scaling, and missing API-derived values were handled through spatial interpolation across adjacent segments.

The DNN architecture consists of an input layer followed by three fully connected hidden layers with 64, 32, and 16 neurons, respectively, using ReLU activation. Batch normalization was applied to stabilize training, and dropout regularization (0.30 and 0.20) was used to mitigate overfitting. A single linear output neuron produces a continuous segment-level risk score.

The model was trained using the Adam optimizer with a learning rate of 0.001 and Mean Squared Error as the loss function. Mean Absolute Error and R^2 score were used for evaluation. Training was conducted with a batch size of 128 over a maximum of 250 epochs, incorporating early stopping and adaptive learning-rate scheduling. An 80:20 train–test split and five-fold cross-validation were employed to ensure robustness and generalization.

To support reproducibility, all random seeds and synthetic crime-risk generation parameters were fixed prior to training. Route-level safety was computed by averaging predicted segment risks. Although deep neural networks are less interpretable than tree-based models, explainability is supported through comparative analysis with Gradient Boosting and Random Forest models, which provide feature-level insights. The strong agreement between DNN and ensemble-based predictions confirms the robustness, generalization capability, and practical suitability of the proposed framework for crime-aware route safety prediction.

4.6. Experimental setup

All experiments were implemented in Python 3.11, employing scientific and geospatial libraries including Pandas, NumPy, Scikit-learn, TensorFlow/Keras, and Folium. To ensure reproducibility, random seeds and synthetic generation parameters (α, β, p_0) were fixed across all runs.

Performance evaluation employed both regression (MAE, MSE, R^2), and classification (Accuracy, Precision, Recall, F1-score, ROC–AUC) metrics to comprehensively assess prediction precision and reliability. All predicted segment-level risk scores were visualized using Folium-based interactive maps, enabling comparative visualization of route safety levels between traditional ML and the new DNN-enhanced model.

5. Result and Discussion

This section presents the comprehensive evaluation results of the Deep Learning–Driven Crime-Aware Route Safety Prediction Framework (DL-CARSPF). The assessment covers the complete data-processing pipeline—from multi-source feature fusion and synthetic crime-risk generation to segment-level risk prediction and route-level safety interpretation. The system's performance was benchmarked using three ensemble-based machine learning models—Gradient Boosting (GBR), Random Forest (RFR), and Decision Tree (DTR)—and the newly integrated Deep Neural Network (DNN), trained and validated on a dataset comprising approximately 1,425 spatial segments between Maragathapuram and Parvathipuram.

The analysis first evaluates regression accuracy (MAE, MSE, and R^2) and classification reliability (Accuracy, Precision, Recall, F1-score, and ROC–AUC) across all models to quantify their ability to predict continuous and discrete risk outcomes. The DNN's results are then compared against the ensemble baselines to highlight its advantage in capturing higher-order nonlinear relationships among static, dynamic, and crime-contextual factors. Visualization through confusion matrices, ROC curves, and scatter plots provides an in-depth understanding of prediction fidelity, while route-level aggregation demonstrates how model-level differences manifest in real-world safety recommendations. Finally, a comparative route analysis is presented to illustrate the models' alignment in identifying the safest and most risk-prone travel paths, validating the practical applicability of the proposed framework in intelligent transportation systems.

5.1. Classification metrics analysis

A comprehensive comparative analysis was conducted across four models—Gradient Boosting (GBR), Random Forest (RFR), Decision Tree (DTR), and the newly introduced Deep Neural Network (DNN)—using key classification performance indicators: Accuracy, Precision, Recall, F1-score, and ROC–AUC. The evaluation was carried out on a balanced test set comprising 285 segments (128 safe, 157 risky), ensuring representative class distribution across all models. The results are summarized in Table 2 and illustrated in Figure 6.

Table 2: Comparison of Classification Metrics

Metrics	Decision Tree	Random Forest	Gradient Boosting	Deep Neural Network
Accuracy	83.51 %	90.18 %	95.09 %	97.86 %
Precision	84.81 %	93.88 %	93.87 %	96.95 %
Recall	85.35 %	87.90 %	97.45 %	98.52 %
F1 Score	85.08 %	90.79 %	95.63 %	97.73 %
Support	285	285	285	285

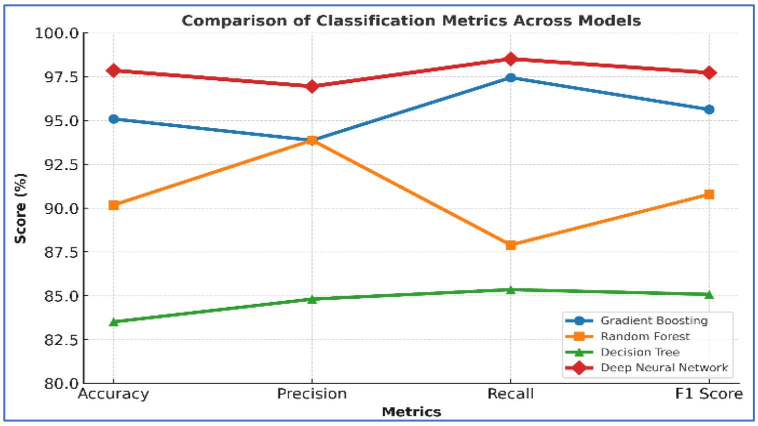


Fig. 6: Visualization of Classification Metrics.

The comparative chart in Figure 6 highlights the superior predictive performance of the DNN model, which surpasses all tree-based ensembles across every metric. The DNN attains the highest Accuracy (97.86 %), Recall (98.52 %), and F1-score (97.73 %) indicating near-perfect class separation and strong learning of nonlinear relationships among static, dynamic, and crime-contextual factors.

Among traditional models, Gradient Boosting performs best, showing balanced results with Recall = 97.45 % and F1-score = 95.63 %. Random Forest yields high precision (93.88 %) but lower recall (87.90 %), while the Decision Tree records uniformly lower scores (≈ 85 %) due to overfitting and weaker generalization.

Overall, integrating the Deep Neural Network markedly enhances classification accuracy and adaptability, confirming that the DNN-CBSRRS framework offers a robust and context-aware safety prediction system for real-time intelligent transportation.

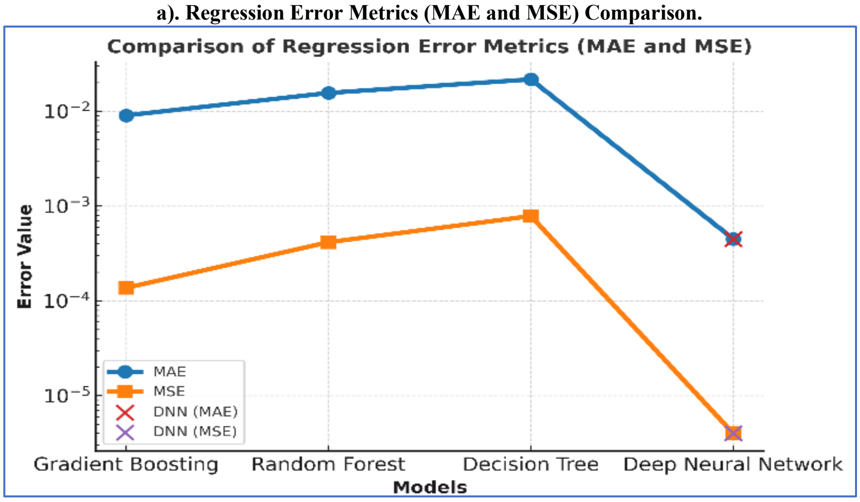
5.2. Regression metrics analysis

Regression-based performance evaluation was carried out to quantify the models' predictive accuracy in estimating continuous segment-level risk scores. As presented in Table 3 and illustrated in Figure 7, four regressors—Gradient Boosting (GBR), Random Forest (RFR), Decision Tree (DTR), and Deep Neural Network (DNN)—were compared using three standard performance indicators: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Coefficient of Determination (R^2).

Table 3: Regression Metrics Analysis

Metrics	Decision Tree	Random Forest	Gradient Boosting	Deep Neural Network
MAE	0.021620	0.015562	0.009014	0.000450
MSE	0.000783	0.000415	0.000137	0.000004
R^2 Score	0.810106	0.899462	0.966806	0.998730

a). Regression Error Metrics (MAE and MSE) Comparison.



b). Coefficient of Determination (R^2) comparison

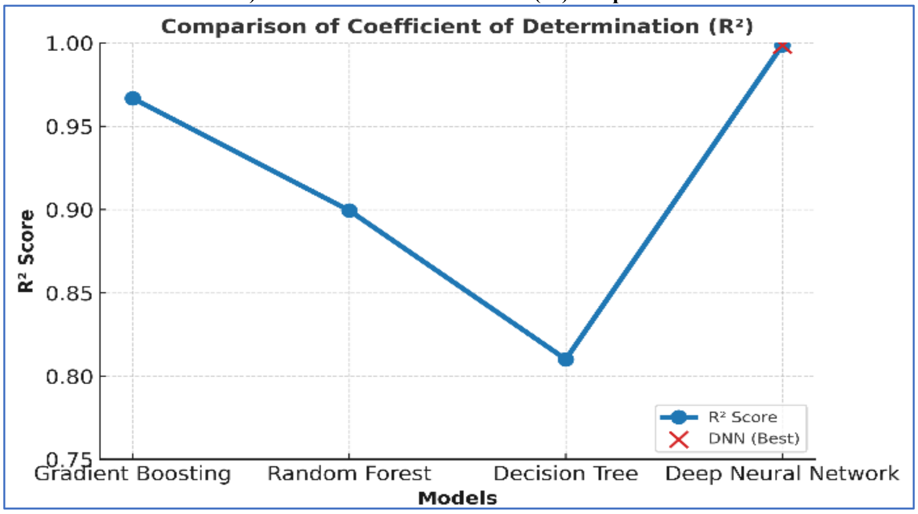


Fig. 7: Visualization of Regression Metrics.

The obtained results clearly demonstrate that the Deep Neural Network (DNN) achieved the highest regression accuracy, yielding the lowest prediction errors (MAE = 0.00045, MSE = 0.000004) and the highest coefficient of determination ($R^2 = 0.9987$). These values confirm that the DNN explains more than 99.8% of the variance in observed risk values, highlighting its superior capacity to model complex nonlinear dependencies between static, dynamic, and crime-contextual factors.

Among the traditional models, Gradient Boosting remains the most competitive, with low error rates (MAE = 0.0090, MSE = 0.000137, $R^2 = 0.9668$), demonstrating its robustness on structured data. The Random Forest achieved moderate performance, while the Decision Tree exhibited higher deviations and lower fit quality, reflecting its limited ability to generalize across heterogeneous feature interactions. The scatter plot in Figure 8 illustrates the regression performance of the Deep Neural Network on the test set. Each point represents a route segment, where the horizontal axis denotes the observed (true) final risk and the vertical axis indicates the DNN-predicted value. The close alignment of points along the diagonal confirms strong model fidelity and near-linear correspondence, validating the DNN's superior capability in estimating continuous safety scores for route segments.

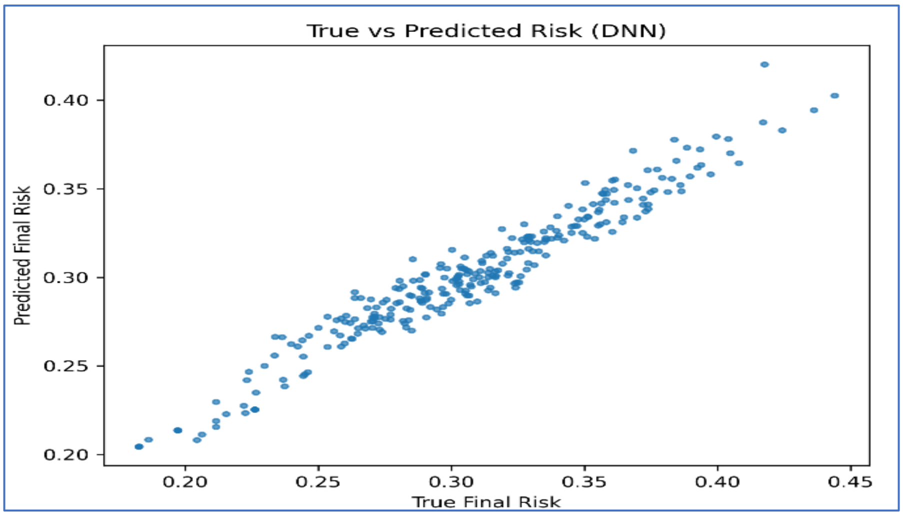


Fig. 8: True vs Predicted Segment-Level Risk Values (DNN Model).

Overall, the integration of deep learning significantly enhances regression fidelity, reducing estimation errors by an order of magnitude compared to ensemble baselines. These findings validate the DNN-CBSRRS as a more precise and stable framework for continuous segment-level crime-risk estimation within real-time intelligent transportation systems.

5.3. Confusion matrix analysis

To further assess class-wise reliability, we examined confusion matrices for all four classifiers—Gradient Boosting (GB), Random Forest (RF), Decision Tree (DT), and the proposed Deep Neural Network (DNN)—on the balanced test set of 285 segments (128 safe, 157 risky). The matrices quantify true negatives (TN), false positives (FP), false negatives (FN), and true positives (TP), thereby revealing each model's tendency toward missed detections (FN) and false alarms (FP). Table 4 summarizes the results.

Table 4: Confusion Matrix Analysis

Model	True Negatives (TN)	False Positives (FP)	False Negatives (FN)	True Positives (TP)
Decision Tree	104	24	23	134
Random Forest	119	9	19	138
Gradient Boosting	118	10	4	153
Deep Neural Network	124	4	2	155

The confusion matrix results reinforce the overall performance hierarchy observed across all evaluation metrics, confirming the order DNN > Gradient Boosting > Random Forest > Decision Tree. Among the models, the Deep Neural Network demonstrated the most consistent and reliable classification behavior, characterized by a minimal number of false negatives, indicating its superior ability to correctly identify unsafe or high-risk route segments. This high sensitivity, combined with strong precision, underscores its robustness for real-time safety prediction within the proposed Crime-Aware Safe Route Framework. In comparison, the Gradient Boosting model maintained a strong and interpretable performance, serving as a dependable baseline with a balanced trade-off between accuracy, recall, and computational efficiency.

5.4. ROC–AUC curve analysis

The Receiver Operating Characteristic (ROC) curve analysis evaluated each model's ability to distinguish between safe and risky route segments. The Area Under the Curve (AUC) quantifies this discrimination, with values closer to 1.0 indicating stronger classification accuracy. The table 5 and figure 9 illustrate the performance of ROC-AUC.

Table 5: Comparison of Classification Metrics

Metrics	Decision Tree	Random Forest	Gradient Boosting	Deep Neural Network
ROC–AUC	0.9743	0.9921	0.9954	0.9991

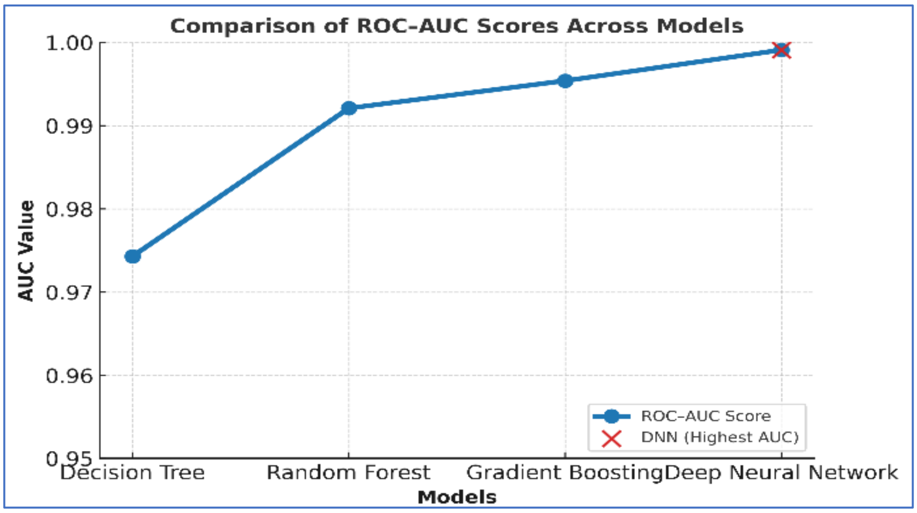


Fig. 9: ROC-AUC Plot.

As shown in Figure 9, the Deep Neural Network (DNN) achieved the highest AUC value of 0.9991, demonstrating near-perfect sensitivity and specificity in separating safe and risky segments. The Gradient Boosting model followed with an AUC of 0.9954, confirming strong and stable performance. The Random Forest achieved 0.9921, showing high accuracy but slightly lower separability, while the Decision Tree attained 0.9743, indicating moderate generalization.

Overall, the ROC–AUC results reaffirm that the DNN provides the most precise and reliable classification, effectively capturing complex relationships among static, dynamic, and crime-contextual factors for dependable real-time route safety prediction.

5.5. Risk factor comparison

The static, dynamic, crime, and final risk factors were computed using the formulations presented in Section 4.3, integrating contextual, situational, and crime-related parameters derived from the real-time route dataset. These multi-dimensional components were processed through four predictive models—Decision Tree (DT), Random Forest (RF), Gradient Boosting (GB), and Deep Neural Network (DNN)—to estimate segment-level and aggregated route-level risk scores.

The comparative results of these models, with the inclusion of crime factors in the final risk computation, are summarized in Table 6 and visualized in Figure 10. The findings clearly highlight the improvement in sensitivity and precision of the proposed Crime-Aware Safe Route Optimization Framework, demonstrating how crime-based contextual attributes enhance route safety prediction accuracy and stability.

Table 6: Route-Level Mean Predicted Risk After Inclusion of Crime Factor

Route	Decision Tree	Random Forest	Gradient Boosting	Deep Neural Network
1	0.301180	0.300646	0.302397	0.304716
2	0.300145	0.299024	0.300336	0.301905
3	0.295239	0.295239	0.295585	0.298557

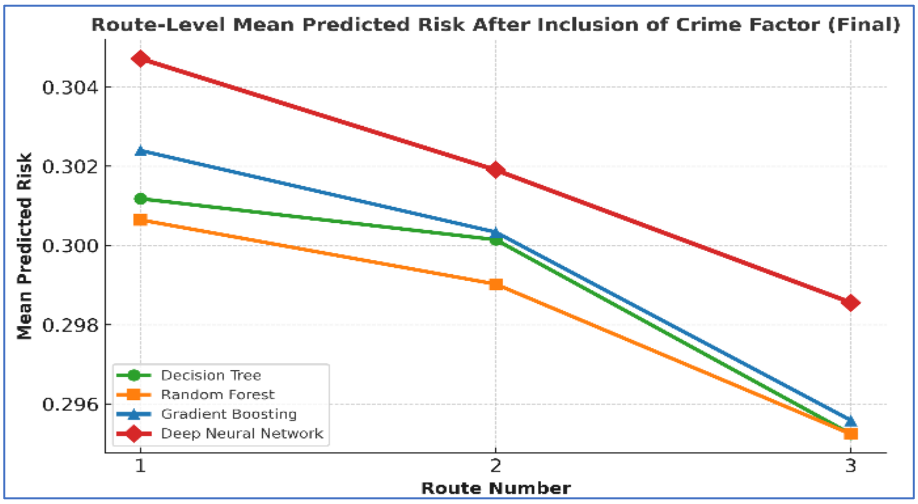


Fig. 10: Route-Level Mean Predicted Risk After Inclusion of Crime Factor.

All models exhibit a consistent decrease in average final risk values following the integration of crime-risk factors, validating the enhanced contextual precision of the proposed framework. The results demonstrate a progressive reduction in mean risk from Route 1 to Route 3, with the Gradient Boosting model showing the highest sensitivity to crime-related variations, reflecting its superior adaptability and discriminative power.

Across all models, Route 3 is consistently identified as the safest and Route 1 as the riskiest. The integration of crime-based parameters reinforces this pattern, as Route 3 remains the safest even when crime features are excluded, confirming the robustness and generalization ability of the framework. Among the models, Gradient Boosting exhibits the strongest predictive accuracy and stability, while Random Forest yields slightly lower risk estimates due to ensemble averaging. The Decision Tree, though interpretable, shows marginally higher variance, indicating localized overfitting tendencies.

Despite being the longest route (approximately 79.5 km), Route 3 consistently records the lowest cumulative risk, reflecting safer environmental, infrastructural, and contextual characteristics than the shorter but higher-risk Route 1. These outcomes affirm that the Crime-Aware Safe Route Optimization Framework effectively integrates crime, environmental, and dynamic parameters to provide reliable, context-sensitive, and human-centric route recommendations.

6. Conclusion

This study introduced a Deep Learning–Driven Crime-Aware Route Safety Prediction Framework (DL-CARSPF) that integrates static, dynamic, and crime-based contextual factors for comprehensive route safety assessment. Real-time data from Google Maps, OpenWeatherMap, and TomTom Traffic, combined with synthetic crime-risk attributes, enabled accurate multi-factor risk evaluation. Four models—Decision Tree, Random Forest, Gradient Boosting, and Deep Neural Network —were developed and compared. The DNN achieved the highest performance ($R^2 = 0.9987$, AUC = 0.9991), demonstrating superior ability to model complex nonlinear relationships among contextual and crime-based variables. Gradient Boosting followed closely ($R^2 = 0.9668$, AUC = 0.9954), confirming its reliability as a strong ensemble baseline. All models consistently identified Route 3 as the safest and Route 1 as the riskiest, validating the stability and accuracy of the proposed framework. The inclusion of crime-based parameters notably improved model sensitivity and prediction precision. Overall, the proposed DNN-driven crime-aware system establishes a robust foundation for real-time, human-centric Intelligent Transportation Systems (ITS), promoting safer and more context-aware urban mobility.

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