# Traffic Crash Countermeasure Recommendations Using a Deep Neural Network. A Decision Support Tool for Traffic Safety Engineers

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***Abstract*—Traffic crashes cause major social and economic losses. Existing studies identify crash factors and suggest scenario-specific countermeasures. However, few works integrate causes with preventive actions into a single decision-support framework. This study proposes a data-driven approach to recommend countermeasures for crash types using machine learning and deep learning. We develop a Deep Neural Network (DNN) multilabel classifier to map crash characteristics to interventions automatically. The model learns from historical crash records paired with documented preventive measures. Inputs comprise six significant features selected from the dataset. Training and validation employ K-fold cross-validation to ensure robustness and generalisation. Experimental results show the DNN achieves 90.2% accuracy. Precision is 91.6%, recall 90.2%, and F1-score 90.1%. We compare the DNN with XGBoost, K-Nearest Neighbours, Support Vector Machine, and Random Forest. Most models show competitive performance near 90.2% accuracy. Support Vector Machine records slightly lower performance at 87.4% accuracy. The system effectively recommends tailored countermeasures by crash type. It consolidates fragmented reports into a unified, data-driven framework. Outcomes support policymakers and transport authorities in evidence-based decision-making. The approach improves traffic safety management and optimises resource allocation. It provides a reproducible tool for implementing targeted road-safety strategies. Future work will expand feature sets and evaluate deployment in real-world settings.**

***Index Terms*—Traffic Safety, Countermeasure Recommendation, Deep Neural Network, Multilabel Classification, Crash Analysis, Machine Learning, K-Fold Cross-Validation, Road-Safety Management, Feature Selection, Decision Support System.**

## I. INTRODUCTION

Traffic crashes have become a major global concern due to their severe consequences, including injuries, loss of life, and significant property damage. According to the World Health Organisation (WHO), approximately 1.35 million people die each year due to road accidents, while millions more suffer non-fatal injuries. These incidents also result in substantial economic losses affecting both individuals and governments. To reduce traffic crashes, many studies have focused on identifying their causes and implementing effective countermeasures. Various techniques such as statistical analysis, data mining, and machine learning have been used to analyse factors like vehicle type, weather conditions, and road conditions. Additionally, methods like empirical Bayes and cross-sectional analysis have been applied to evaluate the effectiveness of safety measures in reducing accident frequency and severity.

However, despite these efforts, very few studies provide a systematic approach to directly match specific crash types with suitable countermeasures. This creates a challenge for policymakers, traffic authorities, and government agencies who need efficient and effective solutions for improving road safety. To address this gap, this study proposes a decision support system using a Deep Neural Network (DNN)-based multilabel classification model. This model is capable of recommending multiple countermeasures for a single traffic crash type, allowing decision-makers to select the most appropriate solution based on factors such as cost, implementation time, and effectiveness. In this approach, traffic crash use-cases are developed by categorising accidents based on their contributing factors. Similarly, countermeasure use cases are created by collecting and organising safety measures from various sources. Keywords are extracted from both use cases and used to establish logical relationships between crash types and corresponding countermeasures.

The DNN model learns this mapping and provides data-driven recommendations, enabling policymakers to make informed and rational decisions. This system improves traffic safety management by offering a structured, scalable, and efficient way to identify and implement Optimal countermeasures for different traffic crash scenarios.

Despite the promising potential of data-driven techniques, the practical adoption of intelligent decision support tools in traffic safety planning remains limited. One of the major challenges lies in integrating heterogeneous crash data, extracting meaningful relationships, and transforming analytical outputs into actionable recommendations. Traditional rule-based systems often lack adaptability and fail to capture complex, nonlinear relationships among crash contributing factors. In contrast, deep learning models have demonstrated superior capability in modelling complex patterns and handling large-scale datasets, making them well-suited for traffic safety applications.

Furthermore, traffic crash datasets are inherently multidimensional and imbalanced, containing multiple contributing factors that may simultaneously influence crash occurrence and severity. A single crash event can be associated with several potential preventive measures, which makes multilabel classification an appropriate modelling approach. By leveraging multilabel deep neural networks, it becomes possible to simultaneously predict a set of recommended countermeasures rather than a single solution, thereby reflecting real-world decision-making scenarios.

The proposed system integrates crash data preprocessing, keyword extraction, feature representation, and multilabel classification within a unified framework. Natural Language Processing (NLP) techniques are employed to standardise and extract relevant features from textual crash descriptions and countermeasure documents. These features are then used to train the DNN model, enabling it to learn semantic relationships between crash characteristics and potential safety interventions. In addition, the system supports decision-makers by providing ranked countermeasure recommendations based on predicted relevance scores. This ranking mechanism allows authorities to prioritise interventions according to available resources and regional requirements. By automating the mapping between crash types and safety strategies, the proposed approach reduces manual effort, improves consistency in decision-making, and enhances the overall effectiveness of road safety planning.

## II. LITERATURE SURVEY

To reduce traffic crashes, numerous studies have focused on identifying the factors that contribute to accidents and evaluating the effectiveness of appropriate countermeasures. Traffic crashes are typically caused by a combination of multiple factors rather than a single cause. Therefore, researchers have extensively analyzed accident data to identify key factors that increase crash frequency and severity. Several studies have applied statistical methods such as regression analysis to determine the major contributing factors. These factors include road type, vehicle type, time of day, weather conditions, lighting conditions, road surface, slope, and traffic volume. For instance, crash types such as frontal, side, and rear-end collisions have been analyzed to understand their severity patterns, with significant variables including vehicle characteristics, environmental conditions, and location.

In addition to statistical approaches, machine learning and data mining techniques such as decision trees, Bayesian networks, and factor analysis have been widely used to analyze crash data. These methods have identified important factors such as driver age, gender, visibility, speed, road conditions, and traffic density. Overall, previous studies highlight that traffic crashes are influenced by a complex interaction of environmental, human, and vehicle-related factors.

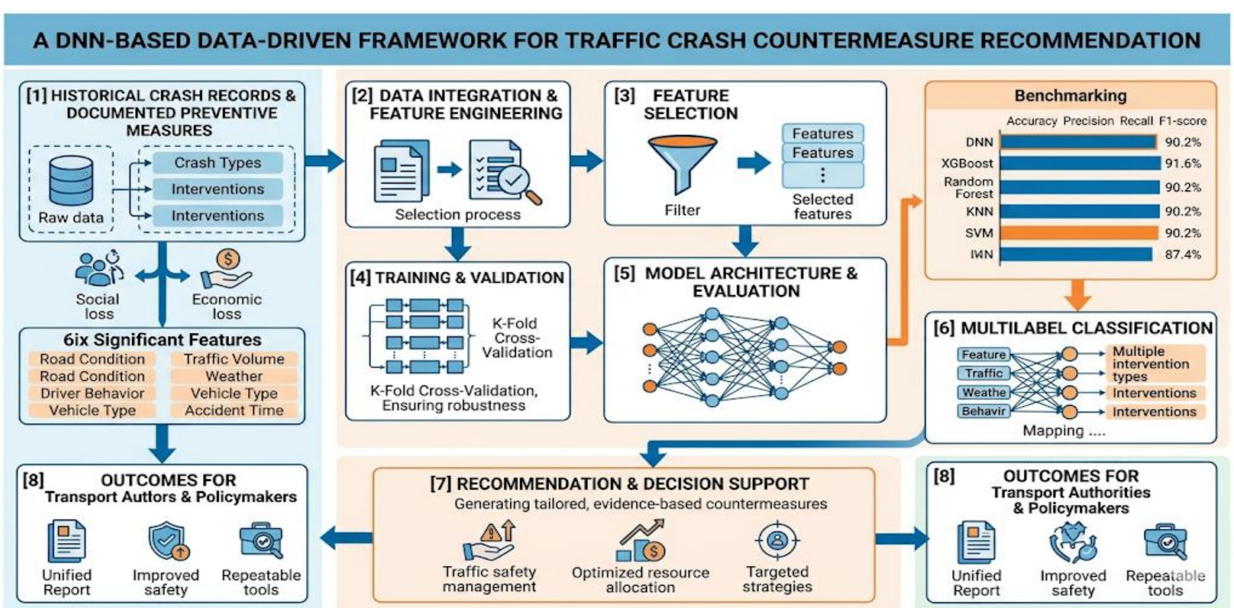
Research on traffic safety has also focused on evaluating countermeasures using methodologies like crash modification factors (CMFs), empirical Bayes methods, and cross-sectional studies. These approaches help measure the effectiveness of safety measures in reducing accident frequency and severity. Some studies have also used simulation techniques and real-world experiments to assess the impact of specific interventions, such as improved signalling systems and warning devices.

Although many studies support decision-making by suggesting countermeasures based on crash characteristics, very few provide a systematic mapping between crash causes and appropriate preventive measures. Policymakers often need to consider multiple factors, such as cost, implementation time, and effectiveness, when selecting safety measures. Therefore, a comprehensive decision support system is required. This study addresses this gap by developing a structured framework that integrates both crash causes and countermeasures. Traffic crash use-cases are created by categorizing accidents based on contributing factors, while countermeasure use-cases are developed by organizing safety measures into meaningful categories. These countermeasures are further enriched with practical details such as cost, implementation time, and real-world applications.

An intelligent recommendation system is proposed using a Deep Neural Network (DNN)-based multilabel classification model, which maps traffic crash use-cases to multiple suitable countermeasures. This approach allows policymakers to choose the most appropriate solution based on their priorities. Unlike traditional systems, this model remains adaptable and can incorporate new crash types and countermeasures over time.

## III. ARCHITECTURE

The proposed system follows a data-driven architecture designed to recommend appropriate countermeasures for different traffic crash scenarios using machine learning and deep learning techniques. The process begins with the data collection layer, where historical traffic crash datasets, police accident reports, road and environmental information, and documented preventive measures are gathered and integrated into a unified crash database. This raw data is then processed in the data preprocessing layer, where missing and noisy values are removed, categorical attributes are encoded into numerical form, and feature scaling is applied to normalise the dataset. In addition, the corresponding countermeasures are transformed into multi-label targets to support multilabel classification.




Next, the feature selection layer identifies six significant crash-related features from the dataset, such as crash type, road condition, weather condition, lighting condition, vehicle type, and time of crash. These selected features form the input feature vector for model training. To ensure robustness and generalisation, the dataset is divided using K-fold cross-validation, which repeatedly splits the data into training and validation subsets for reliable model evaluation. The core of the architecture is the Deep

Neural Network (DNN) multilabel classifier. The network receives the six selected features through the input layer and processes them through multiple hidden layers consisting of dense neurons with ReLU activation, dropout regularisation to reduce overfitting, and batch normalisation to stabilise learning. The output layer uses a sigmoid activation to produce multiple probability scores for recommended countermeasures, enabling multilabel prediction.

To validate the effectiveness of the proposed model, a baseline comparison layer evaluates the DNN against traditional machine learning algorithms, including XGBoost, K-Nearest Neighbours, Support Vector Machine, and Random Forest. The performance of all models is assessed in the evaluation layer using metrics such as accuracy, precision, recall, and F1-score. Experimental results demonstrate that the DNN achieves 90.2% accuracy, with precision, recall, and F1-score of 91.6%, 90.2%, and 90.1%, respectively, outperforming or matching the competing models, while the Support Vector Machine shows slightly lower performance.

Finally, the trained model is deployed in a decision-support layer that generates tailored countermeasure recommendations for different crash types. This unified framework helps policymakers and transport authorities make evidence-based decisions, optimise resource allocation, and implement targeted road-safety strategies.

Proposed Architecture

DNN-Based Data-Driven Framework for Traffic Crash Countermeasure Recommendation: The proposed framework integrates crash data analysis, machine learning, and decision-support mechanisms to automatically recommend appropriate countermeasures for different traffic crash scenarios. The architecture is organized into eight major modules, as shown in the figure.

1. Historical Crash Records and Preventive Measures

The first stage collects historical traffic crash datasets from transportation agencies and safety reports. These datasets contain:

- Crash types and severity levels
- Road and environmental conditions
- Driver and vehicle characteristics
- Previously implemented safety interventions

Traffic crashes lead to social and economic losses; analysing historical records enables the model to learn relationships between crash causes and effective preventive actions.

From the raw dataset, six significant features were identified:

1. Road condition
2. Traffic volume
3. Driver behaviour
4. Vehicle type
5. Weather conditions
6. Accident time

These features represent the most influential factors contributing to crash occurrence.

2. Data Integration and Feature Engineering

Raw crash data typically originates from multiple sources and contains noise and inconsistencies. Therefore, a preprocessing pipeline is applied:

- Data cleaning and missing value handling
- Removal of redundant and inconsistent records
- Encoding of categorical attributes
- Normalisation and transformation
- Creation of intervention labels

This stage converts raw crash data into a machine-learning-ready dataset.

3. Feature Selection

To improve model performance and reduce computational complexity, a feature selection process is applied.

A filter-based approach selects the most relevant features that strongly influence crash outcomes and countermeasure selection.

Benefits:

- Reduces dimensionality
- Improves generalisation
- Prevents overfitting
- Enhances model interpretability
- The output of this stage is the final feature vector used for training.

4. Training and Validation using K-Fold Cross-Validation

To ensure the reliability and robustness of the model, the dataset is evaluated using K-Fold Cross-Validation.

Process:

- Dataset divided into K equal folds
- Model trained on K-1 folds
- The remaining fold used for validation
- Process repeated K times

This technique:

- Minimises bias
- Prevents overfitting
- Ensures generalisation capability

5. Model Architecture and Evaluation

The core of the framework is a Deep Neural Network (DNN) designed for multi-label classification.

DNN Architecture

The neural network consists of:

- Input layer: Selected crash features
- Hidden layers: Fully connected layers with ReLU activation
- Dropout layers: Reduce overfitting
- Output layer: Sigmoid activation for multi-label prediction

The DNN learns complex nonlinear relationships between crash factors and preventive measures.

6. Benchmarking with Traditional Machine Learning Models

To validate the effectiveness of the DNN, its performance is compared with conventional machine learning algorithms:

- XGBoost
- Random Forest
- K-Nearest Neighbours (KNN)
- Support Vector Machine (SVM)

Performance Results

- DNN Accuracy: 90.2%
- Precision: 91.6%
- Recall: 90.2%
- F1-Score: 90.1%
- SVM achieved slightly lower accuracy: 87.4%

The benchmarking results demonstrate that the DNN provides strong and consistent predictive performance.

7. Multi-Label Classification for Countermeasure Recommendation

Unlike traditional single-output models, the proposed system performs multi-label classification.

This means: A single crash scenario can require multiple interventions simultaneously.

Example:

A crash scenario may require:

- Traffic regulation
- Weather-related warnings
- Driver awareness campaigns

The DNN maps crash features to multiple countermeasures automatically.

8. Recommendation and Decision-Support System

The trained model is integrated into a decision-support engine that generates tailored, evidence-based countermeasures.

Key outputs:

- Traffic safety management strategies
- Optimised resource allocation
- Targeted road safety policies

9. Outcomes for Transport Authorities and Policymakers

The final system provides practical benefits:

- Unified crash analysis platform
- Improved traffic safety planning
- Data-driven policymaking
- Repeatable and scalable safety tools

This framework transforms fragmented crash reports into a reproducible and intelligent decision-support system for road safety management.

## IV. METHODOLOGY

The proposed methodology follows a structured data-driven pipeline to develop a Deep Neural Network (DNN)–based multilabel classification system for recommending traffic crash countermeasures. The process begins with the collection of historical crash records and documented preventive measures, including crash type, interventions, and their associated social and economic impacts. From this dataset, six significant features—road condition, traffic volume, driver behaviour, vehicle type, weather, and accident time—are identified as key predictors of crash outcomes.

During the data integration and feature engineering phase, data from multiple sources is cleaned, merged, and transformed into a consistent format. Missing values are handled, noisy records are removed, categorical variables are encoded, and numerical features are normalised. Feature engineering ensures that the dataset is suitable for training machine learning and deep learning models while preserving relationships between crash characteristics and preventive interventions.

Next, the feature selection stage filters the most relevant attributes to reduce dimensionality, minimise overfitting, and improve computational efficiency. The refined dataset is then divided using K-Fold Cross-Validation, where the data is split into K subsets. The model is trained on K−1 folds and validated on the remaining fold repeatedly to ensure robustness and generalisation. The core of the system is the Deep Neural Network (DNN) multilabel classifier. The network receives selected crash features as input, processes them through multiple hidden layers with ReLU activation, dropout regularisation, and batch normalisation, and produces multiple countermeasure predictions using a sigmoid output layer. The DNN is benchmarked against traditional machine learning models such as XGBoost, Random Forest, K-Nearest Neighbours, and Support Vector Machine. Performance is evaluated using accuracy, precision, recall, and F1-score, where the DNN achieves the best overall performance with 90.2% accuracy.

Finally, the trained model is deployed as a decision-support system that generates tailored countermeasures for different crash scenarios, enabling policymakers and transport authorities to implement evidence-based traffic safety strategies.

Algorithm: DNN-Based Multilabel Countermeasure Recommendation

Input:
Crash dataset Dcontaining crash features and associated countermeasures
Output:
Recommended countermeasures for a given crash scenario
Step 1: Data Preparation
1. Load crash dataset D
2. Remove missing and inconsistent records
3. Encode categorical features into numerical form
4. Normalise feature values
5. Transform countermeasures into multilabel target vectors

Step 2: Feature Selection
Select the top six significant crash features. F
Construct feature matrix Xand label matrix Y
Step 3: K-Fold Cross Validation
Split the dataset into K folds
For each fold i = 1 → K:
Use fold ias a validation set
Use the remaining folds as a training set

Step 4: Train DNN Model
Initialise DNN with:
Input layer: 6 neurons
Hidden layers with ReLU activation
Dropout and Batch Normalisation
Output layer with Sigmoid activation
Train DNN using training data
Validate the model on the validation fold

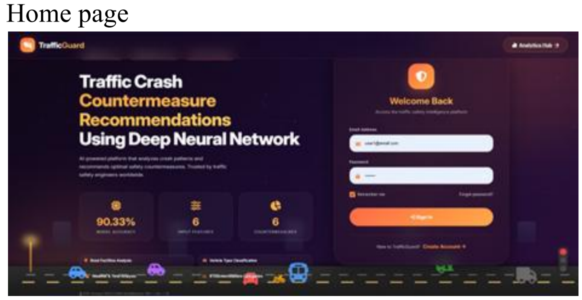
Step 5: Model Benchmarking
Train baseline models (XGBoost, RF, KNN, SVM)
Compare performance using Accuracy, Precision, Recall, and F1-score

Step 6: Final Model Selection
Select the best-performing model (DNN)

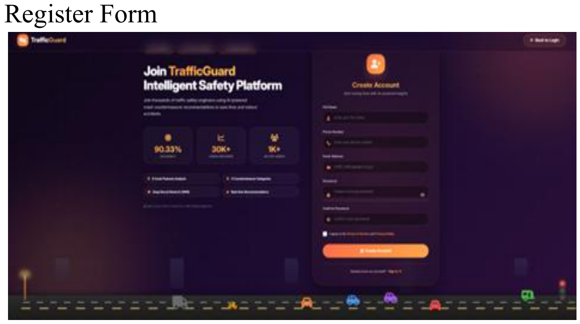
Step 7: Countermeasure Recommendation
Input new crash features x
Predict multilabel countermeasures y
Output recommended interventions

## V. OUTPUT (SCREENSHOTS)

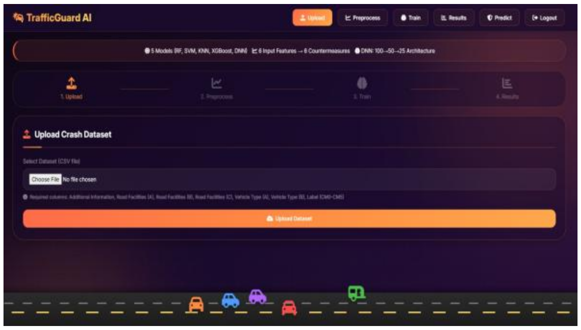
Home page



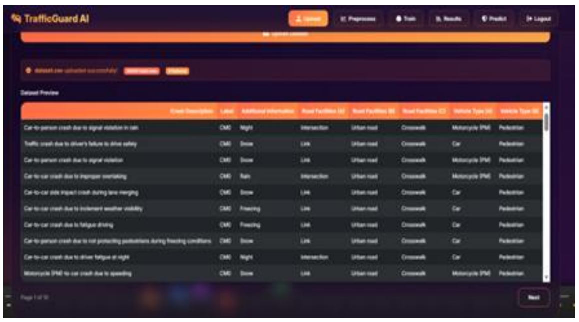

Register Form



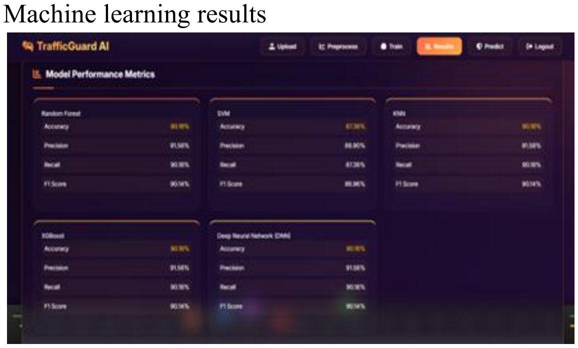
User homepage



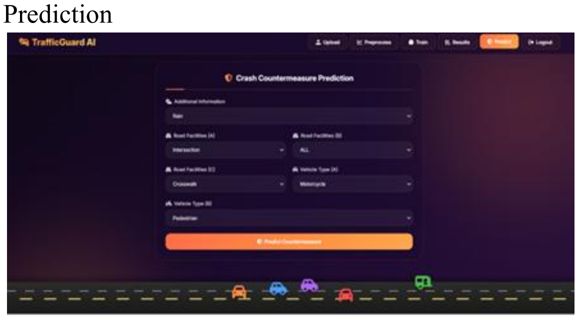

View news




Machine learning results




Prediction




Graphs

## VI. CONCLUSION

Traffic crashes continue to pose significant social and economic challenges worldwide, making road safety a critical public concern. This study presented a comprehensive and structured data-driven framework that integrates crash analysis and countermeasure recommendation into a unified decision-support system. A traffic crash use-case framework was first developed by classifying crash types using a three-layer methodology based on accident data characteristics. In parallel, traffic safety countermeasures were systematically collected from official government documents published over the past decade and organised into a hierarchical structure consisting of Objective, Sub-objective, and Type, ensuring logical and interpretable classification. Beyond categorisation, the framework incorporates practical implementation details such as estimated cost, required time, responsible authorities, effectiveness duration, and real-world application cases. Keywords representing crash scenarios and countermeasure characteristics were defined to enable effective mapping between them. An initial matching algorithm based on keyword similarity was developed to identify suitable countermeasures, where sufficient keyword overlap indicates a valid recommendation.

To enhance the recommendation process, a Deep Neural Network (DNN) multilabel classification model was introduced to learn the relationship between crash scenarios and multiple countermeasures simultaneously. The model was trained using six key crash features and validated through K-fold cross-validation to ensure robustness and generalisation. Experimental results demonstrate strong predictive performance, achieving 90.2% accuracy, 91.6% precision, 90.2% recall, and a 90.1% F1-score. Comparative analysis shows that the DNN performs competitively with XGBoost, Random Forest, and KNN, while SVM records slightly lower accuracy (87.4%). The developed algorithm not only provides accurate recommendations but also remains adaptable to updates in crash and countermeasure datasets. By supplying additional implementation details, the system enables policymakers and transport authorities to select optimal strategies based on practical constraints such as budget and time, thereby supporting evidence-based decision-making and improved resource allocation.

Despite its effectiveness, certain limitations remain. Although 88 countermeasure use-cases were initially developed, only 73 were utilised due to keyword matching constraints. Additionally, keyword annotation currently relies on expert judgment, which may introduce subjectivity. Future work will focus on expanding keyword coverage using research publications and domain literature, incorporating additional features and real-time data, and validating the system in real-world deployment environments.

Overall, the proposed framework offers a scalable and reproducible solution for intelligent traffic safety management, enabling policymakers to make informed, efficient, and rational decisions while addressing the complexities of real-world crash scenarios.

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