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ROAD ACCIDENT PREDICTION

N. Vishal
School of Computing Sciences, VISTAS, Chennai, India
mvishalnethra@gmail.com
Dr. K. Dharmarajan
Professor, School of Computing Sciences, VISTAS, Chennai, India
dharmak07@gmail.com

ABSTRACT
Road accidents remain one of the leading causes of injuries and fatalities worldwide, posing significant challenges to public safety and transportation systems. Traditional methods of accident analysis often rely on historical statistics and manual interpretation, which limit their ability to provide timely and accurate predictions. This project leverages the power of machine learning (ML) and data science to develop a predictive model capable of identifying accident-prone scenarios based on diverse factors such as traffic density, weather conditions, road type, time of day, and driver behavior.
The proposed system integrates data pre-processing, feature engineering, and model training using algorithms such as Random Forest, Logistic Regression, and Neural Networks to evaluate accident likelihood. By applying advanced data science techniques, the model not only predicts the probability of accidents but also highlights key risk factors contributing to them. The outcome of this research is a decision-support tool that can assist traffic authorities, urban planners, and policymakers in implementing proactive safety measures, optimizing traffic management, and reducing accident rates.
This project demonstrates how data-driven approaches can transform road safety strategies, offering scalable solutions that combine predictive accuracy with practical applicability in real-world transportation systems.
Keywords:
Road Accident Prediction, Machine Learning, Random Forest, Gradient Boosting, Neural Networks, Traffic Safety, Feature Engineering.

I. INTRODUCTION

Road safety has become a critical global concern, with road accidents contributing significantly to injuries, fatalities, and economic losses each year. According to international transport statistics, millions of accidents occur annually, many of which could be prevented through better prediction and proactive intervention. Traditional accident analysis methods, which rely on historical data and manual interpretation, often fail to capture the complex interplay of factors such as traffic density, weather conditions, driver behavior, and road infrastructure.
Machine Learning (ML) and Data Science provide powerful tools to address this challenge. By analyzing large datasets and identifying hidden patterns, ML algorithms can predict accident-prone scenarios with greater precision than conventional methods. Data science techniques, including preprocessing, feature selection, and model evaluation, enable the integration of diverse variables into robust predictive models.
This research focuses on developing a predictive framework that leverages ML algorithms such as Random Forest, Logistic Regression, and Gradient Boosting to estimate accident likelihood based on multiple influencing factors. The study emphasizes not only prediction but also the identification of key risk contributors, thereby offering actionable insights for decision-makers. By combining predictive analytics with practical applications, this project aims to demonstrate how technology can transform road safety strategies and contribute to building smarter, safer transportation systems.

II. LITERATURE REVIEW

A considerable body of research has been devoted to accident prediction and road safety analysis using statistical and computational methods. This section summarizes relevant prior work.
Theofilatos and Yannis (2014) provided a comprehensive review of studies examining the influence of traffic and weather conditions on accident frequency, demonstrating that rainfall and fog significantly elevate accident risk. Their findings established a baseline for incorporating environmental parameters into predictive models [1].

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Yuan et al. (2018) employed a Random Forest classifier to analyze traffic accident severity in urban areas using large-scale datasets. The study achieved a classification accuracy of 85.3% and identified road surface conditions and peak-hour traffic as dominant predictors [2].
Ren et al. (2019) proposed a deep-learning-based approach using Long Short-Term Memory (LSTM) networks to forecast accident occurrence in time-series traffic data, outperforming traditional regression models by a margin of 7.2% in accuracy [3].
Delen et al. (2006) conducted an extensive comparison of ML models for injury severity prediction following road accidents. Their analysis highlighted the superiority of neural networks over decision trees for high-dimensional feature spaces [4].
Basso et al. (2021) integrated geospatial data with ML techniques to generate real-time accident risk maps, demonstrating the practical utility of location-aware predictive systems for urban traffic management [5].
Shanthi and Ramani (2012) applied Support Vector Machines (SVM) for accident classification in highway datasets, demonstrating strong generalization across varying traffic patterns [6].
Despite these advances, gaps remain in models that combine multiple environmental, behavioral, and infrastructural features within a unified pipeline suitable for real-time deployment. The present study addresses these gaps by developing an integrated, scalable prediction framework.

III. PROBLEM STATEMENT

Despite advances in transportation infrastructure, road accidents continue to claim millions of lives annually. Existing systems for accident monitoring are largely reactive—they document incidents after the fact rather than anticipating them. The absence of a proactive, data-driven prediction mechanism means that preventive interventions are delayed or ineffective.
Furthermore, accident datasets are heterogeneous, containing numerical, categorical, and temporal variables that are often incomplete or inconsistently recorded. Traditional statistical models struggle with this complexity, producing limited predictive utility. There is therefore a compelling need for an intelligent, scalable system capable of:

- Integrating diverse data sources into a unified analytical framework.
- Predicting accident likelihood with high accuracy under real-world conditions.
- Identifying actionable risk factors to guide policy decisions.

IV. OBJECTIVES

The primary objectives of this research are:

- To collect, clean, and preprocess road accident datasets from multiple sources.
- To engineer relevant features from raw data to improve model performance.
- To implement and compare ML algorithms including Logistic Regression, Random Forest, Gradient Boosting, and Neural Networks.
- To evaluate model performance using standard metrics: accuracy, precision, recall, and F1-score.
- To develop a decision-support tool that assists traffic authorities in implementing safety measures.

V. METHODOLOGY

A. Data Collection

The dataset used in this study was sourced from the UK Road Safety Data repository (2016–2022), supplemented with weather data obtained from OpenWeatherMap API. The combined dataset comprises approximately 250,000 records with 28 attributes, including accident severity, road type, speed limit, weather conditions, lighting conditions, time of day, and driver age category. Data was imported into a Python environment using Pandas for subsequent processing.

B. Data Preprocessing

Raw data exhibited significant inconsistencies including missing values, duplicate entries, and outliers. The preprocessing pipeline involved: (i) imputing missing numerical values using median substitution; (ii) removing duplicate records; (iii) encoding categorical variables using one-hot encoding and label encoding; (iv) standardizing numerical features using min-max normalization; and (v) handling class imbalance via the Synthetic Minority Over-sampling Technique (SMOTE).

C. Feature Engineering

Feature engineering was applied to extract higher-order information from raw attributes. Key engineered features include: accident risk index derived from a composite of speed limit and road type; temporal risk flags indicating

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peak hours and weekend periods; weather severity score combining rainfall, visibility, and wind speed; and driver vulnerability index based on age and prior offense history. Recursive Feature Elimination (RFE) was subsequently applied to identify the top 15 most predictive features.

D. Model Selection and Training

Four ML models were trained and evaluated: Logistic Regression as a baseline model; Random Forest to capture non-linear relationships through ensemble learning; Gradient Boosting (XGBoost) for sequential error correction; and a Multi-Layer Perceptron (MLP) Neural Network for deep feature abstraction. All models were trained on an 80/20 train-test split with 5-fold cross-validation. Hyperparameter tuning was performed using GridSearchCV.

VI. SYSTEM ARCHITECTURE

The system architecture integrates data ingestion, processing, model inference, and visualization layers into a cohesive pipeline. Figure 1 presents the high-level system architecture, illustrating data flow from raw input sources through to the prediction output layer.

Fig. 1 – System Architecture Diagram
[Data Sources]
Road Accident Records | Weather API | Traffic Sensors
↓
[Data Ingestion Layer]
CSV Import / API Calls / Database Queries
↓
[Preprocessing & Feature Engineering Module]
Cleaning | Normalization | SMOTE | RFE
↓
[ML Model Pipeline]
Logistic Regression | Random Forest | Gradient Boosting | MLP
↓
[Prediction & Explainability Engine]
Risk Score | SHAP Value Analysis | Feature Importance
↓
[Dashboard / Decision-Support Interface]
Flask Web App | Visualization Charts | Alert System

Fig. 1: High-Level System Architecture for Road Accident Prediction

The architecture is composed of five primary layers. The Data Sources layer aggregates multi-modal inputs. The Ingestion Layer normalizes data formats for downstream processing. The Preprocessing Module handles cleansing and transformation. The ML Pipeline orchestrates model training and inference. Finally, the Dashboard provides interactive visualization for end-users.

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Figure 2 illustrates the detailed data flow from raw input to model output.

Fig. 2 – Data Flow Diagram
Raw Dataset (CSV / API)
↓ [Load with Pandas]
Data Validation & Cleaning
↓ [Remove nulls, duplicates]
Feature Engineering
↓ [One-hot encoding, normalization, SMOTE]
Train / Test Split (80:20)
↓ [Cross-validation: k=5]
Model Training
↓ [GridSearchCV tuning]
Model Evaluation
↓ [Accuracy, Precision, Recall, F1]
Prediction Output + Risk Score

Fig. 2: Data Flow Diagram

Figure 3 outlines the machine learning workflow employed throughout the experimental phase.

Fig. 3 – ML Workflow Diagram
Problem Definition
↓
Data Collection & EDA (Exploratory Data Analysis)
↓
Preprocessing (Imputation, Encoding, Scaling)
↓
Feature Selection via RFE
↓
Model Training (4 Algorithms)
↓
Hyperparameter Tuning (GridSearchCV)
↓
Performance Evaluation
↓
Best Model Selection & Deployment

Fig. 3: Machine Learning Workflow Diagram

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VII. IMPLEMENTATION DETAILS

The system was implemented using Python 3.10 as the primary programming language. The following libraries and frameworks were used:

- Data Handling: Pandas (v1.5), NumPy (v1.24)
- Visualization: Matplotlib (v3.7), Seaborn (v0.12)
- Machine Learning: Scikit-learn (v1.2), XGBoost (v1.7), TensorFlow/Keras (v2.12)
- Imbalance Handling: imbalanced-learn (SMOTE)
- Web Frontend: Flask (v2.3), HTML5, CSS3, Chart.js

The frontend dashboard was built using Flask to serve a REST API and a responsive HTML interface. Users can input scenario parameters (road type, weather, time of day) and receive a real-time risk score with contributing factor breakdown. SHAP (SHapley Additive exPlanations) was integrated to provide model interpretability, enabling non-technical stakeholders to understand individual predictions.

Model training was conducted on a machine equipped with an Intel Core i7-12700H processor and 16 GB RAM. The Neural Network was trained for 100 epochs with early stopping applied to prevent overfitting. The final models were serialized using joblib for deployment.

VIII. RESULTS AND PERFORMANCE EVALUATION

Table I presents the comparative performance of all four algorithms on the held-out test set (n = 50,000 records). The Neural Network achieved the highest overall performance with an accuracy of 92.1%, closely followed by Gradient Boosting at 91.3%.

TABLE I: Model Performance Comparison

Algorithm	Accuracy	Precision	Recall	F1-Score
Logistic Regression	78.4%	76.2%	74.8%	75.5%
Random Forest	89.7%	88.5%	87.9%	88.2%
Gradient Boosting	91.3%	90.1%	89.6%	89.8%
Neural Network	92.1%	91.4%	90.8%	91.1%

Table I: Comparative model performance on test dataset (n = 50,000).

The confusion matrix analysis for the best-performing model (Neural Network) revealed a true positive rate of 91.4% for high-risk scenarios and a false negative rate of 3.2%, indicating strong predictive reliability for critical cases. The area under the ROC curve (AUC) for the Neural Network and Gradient Boosting models was 0.964 and 0.958, respectively.

Table II provides a ranked summary of the top six features by importance score, as derived from the Random Forest model's Gini impurity-based importance.

TABLE II: Feature Importance Rankings

Feature	Importance Score	Rank
Road Condition	0.213	1
Weather Severity	0.198	2
Driver Behavior Score	0.174	3
Traffic Density	0.161	4
Time of Day	0.134	5
Speed Limit Compliance	0.120	6

Table II: Top 6 features ranked by importance score.

Road condition emerged as the single most influential predictor, followed by weather severity and driver behavior score. These findings align with existing literature and provide empirical validation of the feature engineering strategy employed.

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IX. ADVANTAGES AND LIMITATIONS

B. Advantages

- Multi-algorithm comparison ensures selection of the most suitable model for deployment.
- SMOTE-based oversampling effectively addresses class imbalance present in real accident datasets.
- SHAP integration provides interpretable predictions, increasing stakeholder trust.
- Modular pipeline design facilitates easy extension to new data sources and algorithms.

B. Limitations

- Dataset is geographically limited to the UK; generalizability to other regions requires further validation.
- Real-time IoT data integration is not yet implemented in the current prototype.
- The model does not account for sudden infrastructure changes (e.g., new road construction).

X. FUTURE SCOPE

Several directions exist for extending this research. First, integration of real-time IoT sensor data from roadside units and connected vehicles would enable dynamic, live prediction updates. Second, incorporating spatial analysis techniques such as GIS mapping can produce accident risk heat maps for urban planners.

Third, federated learning approaches could allow multiple transportation agencies to collaboratively train models without sharing sensitive data, enhancing privacy compliance. Fourth, deployment as a mobile application with GPS integration would enable real-time driver alerts for hazardous routes. Finally, expansion of the dataset to include Indian road conditions—where accident patterns differ substantially due to mixed traffic and road diversity—represents a high-impact research direction.

XI. CONCLUSION

This paper has presented a comprehensive machine learning-based framework for road accident prediction. By integrating diverse data sources with robust preprocessing, feature engineering, and a multi-algorithm evaluation strategy, the proposed system achieves a prediction accuracy of 92.1% using a Neural Network model, with Gradient Boosting as a competitive alternative at 91.3%.

The study demonstrates that data-driven approaches can substantially improve upon traditional statistical methods in capturing complex, multivariate accident patterns. The incorporation of explainability tools such as SHAP ensures that predictions are not only accurate but also interpretable for non-technical stakeholders including traffic authorities and policymakers.

The decision-support interface developed as part of this project offers a practical pathway for deploying predictive insights in real-world traffic management systems. Future work will focus on real-time data integration, geospatial risk mapping, and cross-regional dataset expansion to further enhance the system's generalizability and operational impact.

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