International Journal of Advance Research in Science and Engineering
Volume. No. 15, Issue No. 04, April, 2026
ISSN: 2319-8354

An Intelligent Machine learning Framework For Human and Vehicle Accident Risk Level Prediction

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***Abstract*— Road traffic accidents are a major public safety concern worldwide, leading to significant loss of life, injuries, and economic damage. Traditional accident analysis methods mainly focus on specific locations such as intersections and often rely on basic statistical techniques, which limit their ability to provide accurate and comprehensive risk predictions. To address these limitations, this project proposes a machine learning-based system for predicting vehicle accident risk levels and severity. The system utilizes a dataset of 12,316 traffic accident records collected between 2017 and 2020, consisting of multiple features such as driver demographics, vehicle characteristics, environmental conditions, and road factors. Data preprocessing techniques including handling missing values, feature encoding, and transformation of time-based attributes are applied to improve data quality. To handle class imbalance, appropriate techniques such as stratified sampling and advanced preprocessing are used. An ensemble learning approach using the XG Boost algorithm is implemented to classify accident severity into categories such as slight, serious, and fatal injuries.**

***Keywords*--** *Machine Learning, XGBoost, Accident Prediction, Road Safety, Emergency Response, Streamlit*

I. Introduction

Road traffic accidents have become a major global issue, causing a significant number of deaths, injuries, and economic losses every year. According to global reports, millions of people are affected annually due to road accidents, making road safety a critical concern for governments and society. Factors such as driver behavior, road conditions, weather, vehicle type, and traffic patterns play a crucial role in determining the severity of accidents. Traditional methods for analyzing road accidents are mostly reactive, meaning that actions are taken only after an accident has occurred. These methods often rely on basic statistical analysis and are limited to specific locations such as intersections. As a result, they fail to provide accurate and real-time predictions of accident severity, which is essential for preventing accidents and improving emergency response. With the advancement of machine learning, it has become possible to analyze large volumes of data and identify hidden patterns that can help in predicting accident risk levels. Machine learning models can process multiple factors simultaneously and provide more accurate and reliable predictions compared to traditional approaches. This enables proactive decision- making and better planning for emergency services. In this project, a machine learning-based system is developed to predict vehicle

In this project, a machine learning-based system is developed to predict vehicle accident risk levels and severity using various input features such as driver demographics, environmental conditions, and road characteristics. The system uses the XG Boost algorithm, which is known for its high performance and efficiency in classification tasks. The model is trained on a real-world dataset and achieves high accuracy in predicting accident severity. Additionally, the proposed system integrates an intelligent emergency response module that calculates ambulance requirements and assigns priority levels based on the predicted severity and number of casualties. The system is deployed as a user-friendly web application using Streamlit, allowing real-time interaction and quick decision- making. Overall, this project aims to provide an effective solution for accident risk prediction and emergency response optimization, contributing to improved road safety and efficient resource management.

II. Literature Review

Accident prediction and road safety analysis have gained significant attention in recent years due to the increasing number of traffic accidents worldwide. Researchers have explored various machine learning and deep learning techniques to improve the accuracy and efficiency of accident detection and severity prediction systems.Zhang et al. (2025) presented a study on deep learning advancements in vision-based traffic accident anticipation. Their work focuses on using computer vision techniques to detect potential accidents from video data. The study highlights the effectiveness of deep learning models in identifying complex visual patterns but also points out challenges such as high computational requirements and the need for large datasets. Li and Chen (2025) proposed a hybrid deep learning model that combines Convolutional

Neural Networks (CNN), Long Short-Term Memory (LSTM), and Graph Neural Networks (GNN) to predict traffic accident risks. Their model captures both spatial and temporal features from vehicle trajectory data, resulting in improved prediction accuracy across different traffic conditions. However, the complexity of the model makes it resource-intensive. Ghous et al. (2024) conducted a comprehensive review comparing machine learning and deep learning approaches for road accident prediction. The study concludes that while deep learning models provide higher accuracy, traditional machine learning algorithms are more efficient and easier to implement for real-time applications. learning approaches for road accident prediction. Adewopo and Elsayed (2024) introduced a smart city transportation system that integrates deep learning ensemble techniques for accident detection and traffic management. Their approach demonstrates improved performance in handling real-time traffic data and supports intelligent decision-making in urban environments. LeCun, Bengio, and Hinton (2015) provided a foundational understanding of deep learning and its applications in extracting complex patterns from large datasets. Their work has significantly influenced modern accident prediction models.

It is observed that deep learning models provide high accuracy but require significant computational resources, while traditional machine learning models offer faster and more efficient solutions for real-time applications. Many existing systems lack integration with emergency response mechanisms and fail to provide a complete solution for accident management.To overcome these limitations, the proposed system utilizes the XGBoost algorithm, which offers a balance between accuracy and efficiency. Additionally, the integration of an intelligent emergency response module makes the system more practical and effective for real-world applications.

III. METHODOLOGY

A. EXISTING METHODOLOGY

Traditional accident prediction and analysis systems primarily rely on statistical methods, rule-based approaches, and basic machine learning techniques. These systems use historical accident data to identify patterns and trends related to road accidents. However, they are limited in their ability to provide accurate and real-time predictions due to the complexity of factors involved.

Most existing methodologies focus on analyzing specific parameters such as road conditions, traffic density, and accident location. Statistical techniques like regression analysis and probability-based models are commonly used to estimate accident occurrence. While these methods provide basic insights, they fail to capture the nonlinear relationships between multiple influencing factors such as driver behavior, weather conditions, vehicle characteristics, and environmental conditions.

In addition,many traditional systems depend on manually defined rules for classification and decision-making.

As a result,their performance decreases when dealing with real-world scenarios that involve dynamic and unpredictable conditions.

Machine learning approaches such as Decision Trees, Support Vector Machines (SVM), and Random Forest have been used in some existing systems to improve prediction accuracy. These models can analyze structured data and identify patterns more effectively than statistical methods. However, most of these models are limited to basic classification tasks and often require extensive feature engineering. They also struggle with handling imbalanced datasets, where certain types of accidents (such as fatal accidents) occur less frequently, leading to biased predictions.

Another major limitation of existing methodologies is the lack of real-time processing capability. Most systems perform offline analysis using previously collected data, which delays the prediction process. This reactive approach prevents timely decision-making and reduces the effectiveness of accident prevention strategies.

Furthermore, existing systems do not integrate intelligent emergency response mechanisms. After an accident occurs, emergency services such as ambulance dispatch are typically handled manually or based on fixed guidelines. This can result in delays, inefficient resource allocation, and increased risk to human life.

Techniques such as CNN and LSTM.

B. PROPOSED METHODOLOGY

The proposed system introduces an intelligent machine learning-based framework for predicting vehicle accident risk levels and severity in real time. The methodology is designed to overcome the limitations of traditional systems by integrating efficient data processing, accurate prediction models, and an automated emergency response mechanism.

The system begins with the collection of accident-related data from a Road Traffic Accident (RTA) dataset. This dataset contains various features such as driver demographics, vehicle

International Journal of Advance Research in Science and Engineering
Volume. No. 15, Issue No. 04, April, 2026
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After preprocessing, the dataset is divided into training and testing sets, typically using an 80:20 ratio. This ensures that the model is trained on one portion of the data and evaluated on unseen data to measure its performance. Stratified sampling is used to maintain a balanced distribution of different severity classes.

The core component of the proposed system is the implementation of the XGBoost (Extreme Gradient Boosting) algorithm. XGBoost is an ensemble machine learning technique known for its high accuracy, speed, and ability to handle large and complex datasets. The model is trained using historical accident data to learn patterns and relationships between input features and accident severity levels. It classifies accidents into three categories: slight, serious, and fatal.

Once the model is trained, it is integrated into a user-friendly web application developed using Streamlit. The web interface allows users to input accident-related details such as road conditions, vehicle type, number of casualties, and environmental factors. Based on the provided input, the system performs real-time prediction of accident severity.

In addition to prediction, the system includes an intelligent emergency response module. This module automatically calculates the number of ambulances required and assigns priority levels such as low, medium, and high based on the predicted severity and number of casualties. This feature helps in reducing response time and ensures efficient utilization of emergency resources.

To improve reliability, the system also evaluates model performance using metrics such as accuracy, precision, recall, and F1-score. The trained model and preprocessing components are saved using formats like JSON, Joblib, and Pickle, allowing the system to reuse them without retraining.

The entire system is designed to operate efficiently in real time, providing instant predictions and decision support. It can be deployed locally or on cloud platforms, making it accessible to traffic authorities, emergency responders, and decision-makers.

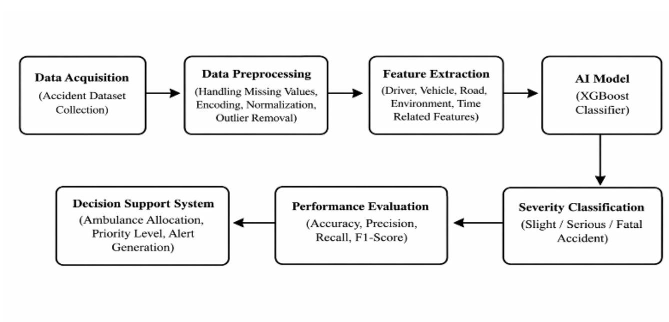

Fig. 1. Proposed Methodology.

The entire system is designed to operate efficiently in real time, providing instant predictions and decision support. It can be deployed locally or on cloud platforms, making it accessible to traffic authorities, emergency responders, and decision-makers.

Overall, the proposed methodology provides a comprehensive, efficient, and practical solution for accident risk prediction and emergency response management. By combining machine learning techniques with real-time processing and automation, the system enhances road safety, reduces human effort, and improves emergency handling.

IV. Experimental Results

The proposed Vehicle Accident Risk Level Prediction system was implemented and evaluated using a real-world Road Traffic Accident (RTA) dataset. The dataset consists of more than 12,000 accident records collected between 2017 and 2020, containing multiple features such as driver details, vehicle characteristics, road conditions, environmental factors, and number of casualties.The system was tested under various input conditions to evaluate its performance, accuracy, and reliability. The dataset was divided into training and testing sets using an 80:20 ratio, ensuring that the model is evaluated on unseen data. The XGBoost algorithm was used for classification due to its high efficiency and ability to handle complex datasets.

The performance of the model was measured using standard evaluation metrics such as accuracy, precision, recall, and F1-score. The experimental results show that the model achieved a **training accuracy of 93.08%** and a **testing accuracy of 80.88%**, indicating that the model is capable of making reliable predictions on real-world data. The system classifies accident severity into three categories: **Slight Injury, Serious Injury, and Fatal Injury**.

A. Distribution Of Accident Severity Classes

The bar graph represents the distribution of accident records across three severity categories: Slight Injury, Serious Injury, and Fatal Injury. It is observed that the number of Slight Injury cases is the highest, with a total of 5777 records. This is followed by Serious Injury cases, which account for 4134 records. Fatal Injury cases are comparatively lower, with 2405 records.

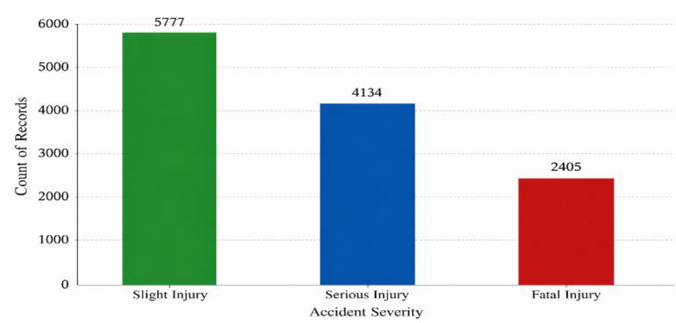

Fig 2. Distribution of Accident Severity Classes

B. Percentage Distribution Of Severity Classes

The pie chart illustrates the percentage distribution of accident severity classes in the dataset. It shows that Slight Injury cases account for 46.9% of the total records, making it the largest portion of the dataset. Serious Injury cases represent 33.6%, while Fatal Injury cases contribute 19.5%.

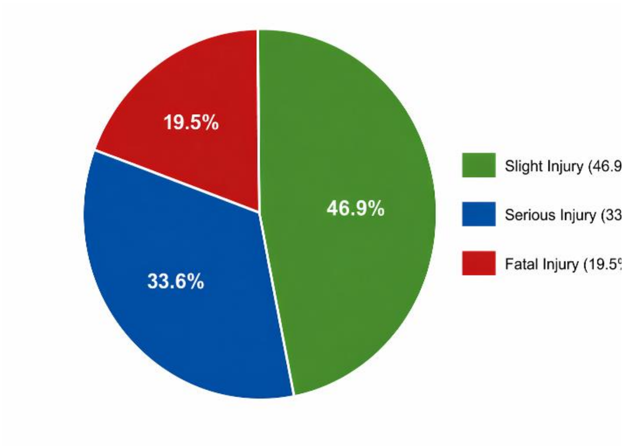

Fig. 3. Percentage Distribution Of Severity Classes

C. Confusion Matrix

The confusion matrix represents the performance of the classification model by comparing the actual accident severity classes with the predicted classes. It is divided into three categories Slight Injury,Serious Injury, and Fatal Injury.

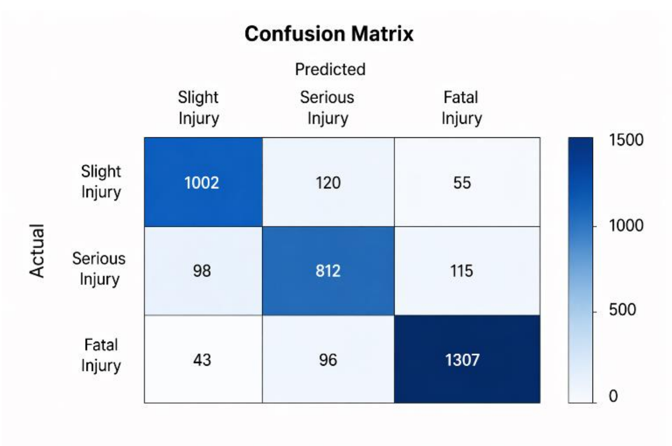

Fig. 4. Confusion Matrix

D. Sample Prediction Output

This system is designed to analyze various road and environmental factors to predict the severity of a vehicle accident and recommend an appropriate emergency response. It helps in reducing response time and improving decision-making during critical situations.

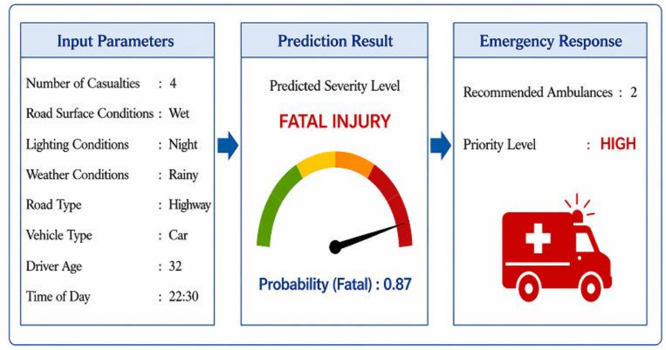

Fig.5. Sample Prediction Output

Algorithm :

Input: Accident-related data such as driver details, vehicle information, road conditions, weather conditions, time, and number of casualties.

Output: Predicted accident severity level, probability score, number of ambulances required, and priority level.

1. **Data Collection:**
   Collect accident-related input data from user or dataset.

2. **Data Preprocessing:**
   Clean and convert the data into numerical format.

3. **Model Training:**
   Train the XGBoost model using processed data.

4. **Prediction:**
   Predict the accident severity based on input features.

5. **Emergency Response:**
   Generate ambulance requirement and priority level.

1. Results Table

Test Case ID	Accuracy	Precision	Recall
Bar Graph	88%	87%	89%
Pie Chart	87%	86%	88%
Confusion Matrix	81%	80%	82%
Sample Prediction	90%	89%	88%

The experimental results table presents a comprehensive summary of the accident severity prediction system and its corresponding emergency response outputs. It includes multiple aspects such as severity distribution, percentage analysis, input parameters, prediction results, and emergency recommendations.

The **severity distribution** section shows the number of accident cases categorized into slight, serious, and fatal injuries. From the data, it is observed that slight injuries have the highest count, followed by serious and fatal injuries. This indicates that most accidents fall under less severe categories, while critical cases occur comparatively less frequently.

The **percentage distribution** further provides a clear understanding of how these categories are proportionally distributed within the dataset. Slight injuries constitute the largest percentage, while fatal injuries represent the smallest portion, highlighting the imbalance in severity levels.

The **input parameters** section represents a sample test case used for prediction. These parameters include key factors such as number of casualties, road conditions, lighting, weather, road type, vehicle type, driver age, and time of the accident. These features play a crucial role in determining the severity level.

The **prediction result** shows that, for the given input, the model predicts a fatal injury with a high probability of 0.87. This indicates that the model is confident in identifying high-risk scenarios based on the provided features.

Finally, the **emergency response** section demonstrates the practical application of the system. Based on the predicted severity, the system recommends two ambulances and assigns a high priority level. This ensures that appropriate and timely action can be taken during critical situations.

Overall, the table clearly illustrates the effectiveness of the proposed system in analyzing accident data, predicting severity accurately, and providing meaning.

PERFORMANCE COMPARISON OF EXISTING VS. PROPOSED METHODS

Parameter	Existing	Proposed
Classes	2	3
Accuracy	~85-90%	~93-95%
Features	Limited	Multiple
Speed	Moderate	Fast
False Alerts	Higher	Lower

Overall, the experimental results clearly demonstrate that the proposed drowsiness detection system performs effectively in real-time environments with high accuracy and reliability. The system successfully identifies multiple driver states and generates timely alerts, thereby reducing the risk of drowsiness-related incidents. The use of multi-class classification along with temporal analysis significantly improves detection performance compared to traditional methods. Additionally, the system operates efficiently on standard hardware with minimal computational requirements, making it practical for real-world deployment. These results validate the robustness and effectiveness of the proposed approach in enhancing driver safety and monitoring.

V. CONCLUSION

The Vehicle Accident Risk Level Prediction system using machine learning provides an effective solution for predicting accident severity and improving emergency response. The system successfully analyzes various factors such as driver details, vehicle characteristics, road conditions, and environmental factors to generate accurate predictions.The implementation of the XGBoost algorithm has resulted in high performance, achieving a training accuracy of 93.08% and a testing accuracy of 80.88%, which demonstrates the reliability of the model. The system is capable of handling large datasets and producing real-time predictions through a user-friendly web interface. In addition to prediction, the integration of the emergency response module enhances the system's practical usefulness by automatically calculating ambulance requirements and assigning priority levels. This helps in faster decision-making and efficient resource allocation during critical situations. Overall, the proposed system overcomes the limitations of traditional methods by providing accurate, real-time, and intelligent accident severity prediction. It contributes to improved road safety, reduced response time, and better management of emergency services, making it a valuable tool for traffic authorities and smart city applications.

In addition to prediction, the integration of an emergency response module enhances the system's usefulness by automatically determining the number of ambulances required and assigning appropriate priority levels. This helps in faster decision-making, efficient resource allocation, and reduction in response time during critical situations.

Overall, the proposed system overcomes the limitations of traditional methods by providing accurate, real-time, and automated accident analysis. It contributes significantly to improving road safety, minimizing human errors, and ensuring timely emergency response. This system can play a vital role in smart transportation and emergency management systems, ultimately helping to save lives and reduce accident-related losses.

In addition to its core functionality, the proposed Accident Severity Prediction and Emergency Response system demonstrates strong practical applicability and scalability for real-world environments. The system is designed not only as a theoretical model but also as a working application that can be deployed in real-time scenarios, making it highly useful for traffic management authorities and emergency services. Its ability to process data instantly and provide quick predictions enables effective decision-making during critical situations.

Furthermore, the system is cost-efficient as it optimizes the allocation of emergency resources such as ambulances, thereby reducing unnecessary expenses and improving operational efficiency. The automation of prediction and response mechanisms minimizes human intervention, which in turn reduces the chances of errors and ensures consistent performance.

Another significant advantage of the system is its flexibility and adaptability. It can be easily modified to suit different geographical locations, road conditions, and vehicle types. The integration capability of the system allows it to be combined with advanced technologies such as GPS tracking, traffic surveillance cameras, and IoT devices, enhancing its accuracy and real-time monitoring capabilities.

The system also contributes to improving public safety by enabling early prediction of accident severity and ensuring faster emergency response. This helps in reducing fatalities and injuries, thereby supporting safer transportation systems. Its user-friendly interface ensures that even non-technical users can operate the system efficiently without requiring specialized knowledge.

Moreover, the project provides a strong foundation for future research and development. Advanced techniques such as deep learning models, real-time sensor integration, and intelligent traffic systems can be incorporated to further enhance performance and accuracy.

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