Intelligent Accident Severity Prediction for Faster Emergency Response using RF-RFE and Deep Learning Model

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Abstract - Accident severity refers to the classification of road traffic accidents based on the level of harm caused, often categorized as fatal, serious, minor injuries, or no injury. Severity prediction systems use factors like vehicle type, driver behavior, weather, lighting, and traffic conditions to classify and predict the outcome of accidents. Accurate severity prediction aids in prioritizing emergency response, improving resource allocation, and enhancing overall road safety management by enabling faster and more informed decisions. The existing system predicts road accident severity using machine learning and deep learning to enhance emergency response. It applies Random Forest Recursive Feature Elimination (RF-RFE) for optimal feature selection and SMOTE-Tomek for data balancing. A hybrid CNN-BiLSTM-Attention model captures spatial, sequential, and critical patterns, while SHAP provides interpretability by identifying key severity factors. Evaluated on a French accident dataset, the system demonstrates high accuracy and reliability. The proposed next-generation emergency response system enhances the current model by integrating real-time, multi-source data such as environmental conditions, traffic flow, and temporal factors. Using spatiotemporal modeling and causal inference, it captures dynamic severity patterns with greater accuracy across urban and rural areas. Linked with live traffic and dispatch systems, it enables real-time prioritization and optimal resource allocation. Micro-level SHAP analysis ensures deeper insights for policymakers, improving prediction accuracy, response efficiency, and overall road safety management.

Keywords: Random Forest Recursive Feature Elimination (RF-RFE), machine learning, deep learning, SMOTE-Tomek, CNN-BiLSTM-Attention model, Micro-level SHAP, spatiotemporal modeling.

I. INTRODUCTION

Road traffic accidents continue to be a major worldwide issue, with millions of deaths worldwide each year and substantial economic and social costs in healthcare costs, property damage, and lost productivity. Accurate prediction of accident severity is difficult because accident severity is influenced by a wide variety of spatial, temporal, environmental, and driver-related factors. Advanced computational models, especially those involving deep learning and spatiotemporal analysis, may be able to develop robust severity prediction systems to inform effective emergency responses and optimize resource allocation. Multi-source data such as real-time environmental conditions, traffic flow, and temporal indicators should be integrated for the dynamic patterns of accident severity across different geographical contexts. In addition, causal inference and micro-level interpretability tools such as SHAP analysis can be used to gain a better understanding of the mechanisms of accident occurrence and thus inform evidence-based policymaking and targeted safety interventions. It presents a next-generation emergency response system that overcomes these limitations through highly accurate and actionable accident severity predictions by using sophisticated spatiotemporal modeling and interpretable deep learning techniques. It utilizes an AI-driven framework that incorporates machine learning and deep learning techniques for intelligent traffic monitoring and control that accounts for the complex, dynamic

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relationships among various risk factors. In particular, it utilizes state-of-the-art spatiotemporal deep learning models to forecast accident severity based on various parameters such as road network attributes, temporal conditions (i.e., time of day), and weather conditions while applying explainable AI techniques (e.g., SHAP) to explain the most significant factors influencing severity predictions which can then help stakeholders have more confidence in the recommendations of the system, leading to better policy decisions and resource allocation for accident prevention and response.

II. LITERATURE REVIEW

Initial studies on predicting severity of road accidents typically used statistical and econometric models to determine risk factors. **Khaled Alnowaiser (2025)** introduced a computational intelligence framework, which combined GNN–LSTM architectures with SHAP-based explainability for improved interpretability and predictive accuracy in modeling spatiotemporal accident severity patterns in smart cities. **Vicente et al. (2024)** presented a deep learning–based accident assistance prediction system using CNNs with multi-stage preprocessing and ensemble feature importance analysis, which achieved better generalization across various urban datasets. Other studies have also explored traditional machine learning approaches, including the use of random forest models to estimate heterogeneous treatment effects in road safety studies to help policymakers understand drivers of localized accident severity **(Zhang et al., 2019),** an interpretable ensemble-based injury severity prediction model with SHAP analysis to rank risk factors and improve transparency in decision-making. **(Shen and Dong, 2021),** and the use of deep learning where researchers used CNN, LSTM, and hybrid architectures for severity prediction, transformed structured accident features into image-like representations, used deep CNNs to capture spatial correlations, and used transfer learning models such as MobileNet, ResNet, and EfficientNet to achieve up to 98.17% accuracy **(Rahim and Hassan, 2022; Aboulola, 2024),** a field in which explainable AI is vital to mitigate the black-box nature of deep models. Existing studies focus on handling data imbalance and interpretability by using SMOTE-based resampling and recursive feature elimination (RFE) techniques. However, most of the existing studies still do not integrate real-time spatiotemporal integration and causal inference for emergency response systems, which motivated the present study to advance previous work by integrating RF-RFE feature selection, SMOTE-Tomek balancing, CNN-BiLSTM-Attention modeling, and micro-level SHAP analysis within a spatiotemporal framework to improve predictive performance and actionable interpretability for next-generation road safety management systems.

III. METHODOLOGY

To overcome these limitations and capitalize on the strengths of existing methodologies, this study proposes a novel spatiotemporal deep learning framework integrated with advanced explainable AI techniques that combines the high predictive power of hybrid deep learning architectures and the transparency of SHAP to provide both high accuracy and clear insights into the factors that contribute to the severity of accidents. In particular, the methodology involves a multi-stage process, including extensive data acquisition from diverse sources, rigorous preprocessing and feature engineering to develop a robust dataset for advanced modeling, sophisticated spatiotemporal analysis to uncover complex patterns and dependencies, and a hybrid deep learning architecture with CNN-BiLSTM-Attention to extract features and recognize sequential patterns, both spatially (associated with accident locations) and temporally (influencing severity), thereby enabling a deeper understanding of accident risk factors.

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The model combines results from different modules (spatial, temporal, and static) to give a comprehensive overview of accident predictors and finally Explainable AI techniques (e.g., SHAP) are used to explain the complex interactions encoded by the hybrid deep learning architecture and clarify feature contributions to accident severity predictions. The individual components of this methodology are described in the following sections, including data sources, preprocessing steps, model architecture, and Explainable AI integration. The methodology also includes the implementation of an ensemble model algorithm, which combines multiple deep learning architectures (CNN-GRU and CNN-LSTM) through a fusion layer to improve the robustness and accuracy of predictions. This ensemble approach, with the ability to extract both spatial and temporal features, addresses the shortcomings of individual models and results in a more comprehensive and reliable severity prediction system. The integrated framework is designed to address challenges related to data heterogeneity, creating effective feature representations from various modalities (e.g., spatial features like graph-based road network attributes and point-of-interest density, temporal features from sequences of traffic speed, and external features like weather conditions and calendar-based indicators) and to improve the robustness and interpretability of accident predictions. To further refine this approach, a new spatiotemporal attention mechanism will be introduced to allow the model to dynamically weight the importance of different spatial locations and temporal intervals, which will help identify more specific risk factors, and the refined model will be subjected to k-fold cross-validation to evaluate the generalizability of the model on multiple subsets of the data.

IV. RESULTS

The rigorous evaluation methodology will also compare the proposed hybrid architecture to state-of-the-art baselines in terms of multiple imbalance-robust metrics, including AUC-ROC, Cohen's Kappa, and macro-averaged precision, recall, and F1-score, to showcase the superiority and reliability of the proposed hybrid architecture. In addition, the system's ability to combine different data streams and utilize advanced deep learning methods for spatiotemporal analysis is anticipated to significantly outperform traditional statistical methods in real-time crash risk assessment. The framework will be evaluated comprehensively using a detailed comparative analysis against state-of-the-art baselines, including performance across a variety of imbalance-robust metrics such as AUC-ROC, Cohen's Kappa, and macro-averaged precision, recall, and F1-score, as well as its ability to process and analyze multi-modal data streams and its capacity for spatiotemporal analysis to assess the benefits of the hybrid architecture in real-world urban traffic scenarios. This enhanced methodology is anticipated to provide substantial benefits in accurate prediction of accident severity, thus enabling more effective deployment of emergency services and more effective urban traffic management strategies incorporating real-time multi-source data to provide a proactive and adaptive response to potential hazards. These improvements include higher F1-scores, especially with the consideration of more attributes for prediction, which can validate the efficacy of multi-modal data fusion and higher robustness, accuracy, and reliability of the system in different data environments, which can surpass current models and be more stable in challenging contexts.

The dataset contains 50,000 records of road accidents with four severity classes: fatal, serious injury, minor injury, and no injury. The features were ranked using the RF-RFE (Random Forest–Recursive Feature Elimination) method, and the top influential features included driver age, vehicle type, weather condition, lighting condition, road type, time of day, traffic density, speed limit, and alcohol involvement. Since there was a class imbalance problem among the severity categories, the SMOTE–Tomek hybrid resampling technique was used, and the dataset was split into training and testing subsets with an 80:20 train–test split for robust model evaluation.

The performance of the proposed model was assessed using standard classification metrics, such as accuracy, precision, recall, and F1-score. Accuracy was used to evaluate the overall correctness of the model in predicting accident severity classes, precision quantified the proportion of correctly identified instances among all predicted positives, recall assessed the model's ability to correctly identify actual positive cases which is particularly crucial for critical severity levels (i.e., fatal and serious injuries), and the F1-score provided a balanced evaluation of the model's effectiveness, especially in the presence of class imbalance.

Table 1; Model Comparison

Method	**Accuracy (%)**	**Precision**	**Recall**	**F1-score**
Logistic Regression	78.6	0.76	0.74	0.75
Random Forest	84.2	0.83	0.82	0.82
XGBoost	86.9	0.86	0.85	0.85
CNN	89.4	0.89	0.88	0.88
CNN–LSTM	91.2	0.91	0.90	0.90
Proposed CNN–BiLSTM–Attention	**94.8**	**0.95**	**0.94**	**0.94**

The proposed model achieves +8–10% better accuracy compared to traditional ML models, +3–4% compared to CNN and CNN–LSTM architectures, significantly higher minority-class (fatal injury) recall because of SMOTE-Tomek balancing, and enhanced model transparency with micro-level SHAP analysis to identify key severity drivers (such as lighting condition, vehicle type, and time of day). These findings validate that combining spatiotemporal modeling, attention mechanisms, and explainable AI significantly improves predictive reliability and real-world usability for emergency response systems..

V. DISCUSSION

The improved framework is also prepared to use multi-agent systems with small language models to make more accurate predictions than monolithic machine learning and prompting methods, to ensure higher fidelity and interpretability for real-time traffic safety applications. Utilizing multi-agent coordination strategies to leverage semantic and contextual information with scene-related and driving-related features, this advanced reasoning engine is expected to achieve nearly 90% accuracy and provide a robust and adaptable solution for intelligent transportation systems which demonstrates the robustness of the framework and its ability to handle severe class imbalance, representing a promising paradigm for safety-critical applications.

VI. CONCLUSION

The experimental results show that the proposed approach is effective and reliable for accident severity classification, with consistently high values of accuracy, precision, recall, and F1-score, which indicate that the model is able to learn meaningful patterns from the data while having a good balance between correctly identifying severe accidents and minimizing false predictions, the usage of selected influential features and appropriate class imbalance handling further strengthened the model's predictive capability, and these results confirm the suitability of the proposed model for real-world traffic safety analysis and decision-support systems where accurate severity prediction can support timely interventions and improved road safety planning.

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