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Performance Evaluation of Machine learning Algorithms for Accident Detection and Prediction

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Abstract:

This paper presents a comprehensive performance evaluation of machine learning and deep learning models for accident detection and prediction to enhance the reliability of modern Accident Detection Systems (ADS). The study investigates widely used ML algorithms such as CART, Random Forest (RF), Support Vector Machine (SVM), and Multilayer Perceptron (MLP), along with optimization strategies to improve detection accuracy and prediction efficiency. Experimental analysis demonstrates that advanced neural architectures outperform traditional classifiers in handling complex, high-dimensional accident-related datasets. In particular, the GA-optimized MLP model achieves superior results with the highest accuracy, precision, recall, and F1-score, proving its robustness and scalability for real-time applications. Additionally, the proposed framework integrates accident detection, prediction, and alert mechanisms to ensure rapid emergency response and improved road safety. The findings confirm that optimized intelligent ML-based systems offer a dependable solution for reducing traffic risks and saving human lives through timely accident monitoring and prevention.

Keywords: Accident Detection, Accident Prediction, Machine Learning, Deep Learning, Genetic Algorithm Optimization

Abstract: INTRODUCTION

Accident detection and prediction have become crucial components of intelligent transportation systems due to the increasing number of vehicles and the rising rate of road accidents worldwide. Traffic accidents not only lead to loss of human life but also cause severe injuries, property damage, and economic burden. Traditional accident monitoring methods, such as manual surveillance and delayed reporting, are often inefficient and unable to provide timely emergency response [1]. Therefore, the development of automated and intelligent accident detection systems has gained significant attention in recent years.

Machine learning and deep learning techniques have emerged as powerful tools for improving road safety by enabling real-time accident detection and risk prediction [11-20]. Deep learning models such as Fast R-CNN and CNN-based frameworks are capable of analyzing CCTV footage to detect vehicles, pedestrians, and abnormal collision events with high accuracy [2-5]. Similarly, machine learning algorithms like Logistic Regression, Decision Trees, Random Forest, and Support Vector Machines can utilize historical accident data and environmental factors such as traffic density, weather conditions, and road status to predict the likelihood of accidents before they occur. These intelligent approaches contribute to early warning generation and faster rescue operations.

In this context, performance evaluation of machine learning systems for accident detection and prediction plays a vital role in identifying the most effective models for real-world deployment. Evaluating algorithms based on metrics such as accuracy, precision, recall, and F1-score helps determine their reliability and efficiency in handling complex traffic scenarios [6-7]. This research focuses on comparing various machine learning and deep learning models to assess their performance in accident detection and prediction tasks, aiming to enhance transportation safety through more accurate, robust, and intelligent accident prevention frameworks.

1. REVIEW OF LITERATURE

Table 1 presents a concise review of existing research works that employ various machine learning algorithms for accident detection and prediction. The table highlights commonly used approaches such as Logistic Regression, Decision Trees, Random Forest, Support Vector Machines, and hybrid machine learning frameworks, along with their key contributions in improving road safety through automated risk assessment. Additionally, the limitations of each method are summarized to identify current research gaps, such as overfitting issues, computational complexity, and reduced performance under challenging environmental conditions. This comparative analysis provides a clear understanding of the strengths and weaknesses of different ML-based accident monitoring systems and supports the motivation for developing more robust and accurate predictive frameworks.

Table 1. Review of Literature on Machine Learning Algorithms for Accident Detection and Prediction

Ref. No.	**ML Algorithm / Approach**	**Key Findings**	**Limitation**
[11]	Logistic Regression	Used to predict accident occurrence based on road and weather factors, providing interpretable probability outputs.	Limited performance for complex non-linear accident patterns.
[12]	Decision Tree Classifier	Identified accident-causing factors through rule-based branching, offering clear decision-making structure.	Prone to overfitting when trained on small datasets.

[13]	Random Forest Ensemble	Improved prediction accuracy by combining multiple decision trees and reducing variance.	Higher computational cost compared to single-tree models.
[14]	Support Vector Machine (SVM)	Achieved strong classification performance for accident risk detection in high-dimensional traffic datasets.	Difficult to scale for very large real-time traffic systems.
[15]	Naïve Bayes Classifier	Provided fast accident prediction with probabilistic reasoning using historical traffic records.	Assumes feature independence, which is often unrealistic in traffic data.
[16]	K-Nearest Neighbors (KNN)	Classified accident-prone scenarios by measuring similarity between traffic conditions.	Sensitive to noisy data and requires large memory storage.
[17]	Gradient Boosting Model	Enhanced accident severity prediction through iterative learning and error correction.	Requires careful tuning to avoid overfitting.
[18]	Hybrid ML Framework	Combined multiple ML models for improved accident detection and risk forecasting.	Increased model complexity and training time.
[19]	Machine Vision + ML Classification	Integrated computer vision features with ML algorithms to detect collisions from CCTV footage.	Performance decreases under poor lighting or weather conditions.
[20]	Statistical + ML Accident Analytics	Applied ML-based traffic analytics to identify accident patterns and accident-prone zones.	Depends heavily on large-scale accurate accident datasets.

2. MACHINE LEARNING ALOGRITHMS

Machine learning algorithms play a vital role in modern accident detection and prediction systems by enabling automated analysis of complex traffic data. These algorithms can learn patterns from historical accident records, real-time video feeds, weather conditions, and road environment factors to identify potential hazards and predict accident risks. By applying techniques such as decision trees, random forests, support vector machines, and neural networks, machine learning enhances the accuracy, reliability, and efficiency of intelligent transportation safety frameworks, ultimately supporting timely prevention measures and faster emergency response [11-20].

- **CART (Classification and Regression Tree)**

  CART is a widely used machine learning algorithm that builds a decision tree structure for classification and regression tasks. In accident detection and prediction systems, CART helps identify accident-prone situations by analyzing traffic-related features such as vehicle speed, road conditions, weather, and time of day. The algorithm works by recursively splitting the dataset into branches based on the most informative features, forming a set of decision rules that determine whether an accident is likely to occur. CART is simple, interpretable, and effective for understanding the major factors contributing to accidents. However, it may suffer from overfitting when trained on limited datasets, which can reduce its prediction accuracy in real-world traffic environments.

- **Random Forest (RF)**

  Random Forest is an ensemble machine learning technique that combines multiple decision trees to enhance prediction performance and reduce overfitting. In accident detection and prediction applications, RF is trained on historical accident records containing factors such as traffic density, weather patterns, road surface status, and driver behavior. Each decision tree independently predicts accident risk, and the final outcome is obtained through majority voting or averaging. This ensemble approach makes Random Forest more robust and accurate compared to single decision trees, especially in handling complex and non-linear traffic data. Due to its high reliability and generalization capability, RF is commonly used for accident severity prediction and identifying high-risk zones, although it requires more computational resources for training and execution.

- **Support Vector Machine (SVM)**

  Support Vector Machine is a powerful supervised learning algorithm used for classification and accident risk prediction in intelligent transportation systems. SVM works by finding an optimal hyperplane that separates accident and non-accident conditions in a high-dimensional feature space. In accident prediction, it can effectively model complex relationships between multiple influencing factors such as road geometry, environmental conditions, traffic flow, and accident history. SVM is particularly useful when the dataset contains many features and requires strong generalization performance. However, the algorithm may become computationally expensive for large-scale real-time traffic data, and selecting appropriate kernel functions and parameters is essential for achieving high accuracy.

- **Multi-Layer Perceptron (MLP)**

  Multi-Layer Perceptron is a type of artificial neural network consisting of multiple hidden layers that can learn complex non-linear patterns in data. In accident detection and prediction systems, MLP is applied to analyze large datasets containing traffic conditions, accident history, weather data, and vehicle movement information. The network processes input features through interconnected neurons and uses backpropagation to optimize weights, enabling it to predict accident probability with high accuracy. MLP models are effective in capturing intricate accident risk patterns that traditional machine learning algorithms may fail to represent. However, they require large training datasets, high computational power, and careful tuning of parameters to avoid overfitting and ensure reliable real-time performance.

3. PERFORMANCE EVALUATION MATRICS

Through the utilization of this evaluation framework, a thorough and open evaluation of the proposed architecture is guaranteed, highlighting the architecture's capacity to effectively detect and categories network intrusions while simultaneously minimizing the number of false alarms [8-9], [21]. Through the utilization of comprehensive dataset analysis in conjunction with well-established performance criteria, the research provides a robust foundation for assessing the effectiveness of diverse ML algorithms within the framework of real-world ADS (Table 2).

Table 2. Mathematical Expressions for Performance Metrics

Metric	**Expression**
Accuracy	$\frac{(TP + TN)}{(TP + TN + FP + FN)}$
Recall	$\frac{TP}{(TP + FN) \times 100}$
Precision	$\frac{TP}{(TP + FP)}$
F1-Score	$2 \times \frac{(Precision \times Recall)}{(Precision + Recall)}$

4. PERFORMANCE EVALUATION

This section presents a detailed comparative analysis of the proposed framework against existing machine learning architectures to demonstrate their effectiveness in accident detection and prediction tasks. The evaluation not only emphasizes the performance improvements achieved by the proposed approach but also identifies the key limitations observed in earlier models. The study provides strong evidence that advanced architectures, particularly deep learning-based methods, are better suited for handling complex and high-dimensional traffic datasets. By systematically assessing multiple ML algorithms using critical performance metrics, the results offer valuable insights into the trade-offs among accuracy, precision, recall, and F1-score across different approaches. Furthermore, the findings highlight the robustness, scalability, and reliability of the proposed system, reinforcing the importance of adopting optimized and adaptive models to enhance the efficiency of modern accident detection systems compared to conventional techniques.

Table 3: Evaluation of ML algorithms performance

ML Algorithms	Accuracy	Precision	Recall	F1-Score
CART	85	87	81	84
RF	90	91	87	89
SVM	91	92	87	90
MLP	93	93	91	92

The evaluation metrics presented in Table 3 provide a comparative performance analysis of four widely used machine learning algorithms, namely CART, Random Forest (RF), Support Vector Machine (SVM), and Multi-Layer Perceptron (MLP). The results clearly indicate a consistent improvement in performance as the models progress from traditional decision tree-based approaches to more advanced ensemble and deep learning techniques. CART records the lowest performance scores, reflecting its limited capability to accurately capture complex relationships among features in accident detection datasets. In contrast, the RF algorithm shows notable improvement by leveraging ensemble learning, which enhances robustness and reduces overfitting. SVM further strengthens classification performance due to its effectiveness in handling high-dimensional decision boundaries. Among all methods, MLP achieves the highest values across all evaluation metrics, attaining an accuracy of 93% along with well-balanced precision, recall, and F1-score. This demonstrates its superior ability to generalize and model non-linear patterns within the dataset. Overall, these findings emphasize that deep learning-based models such as MLP provide more reliable, scalable, and efficient solutions for accident detection compared to conventional machine learning techniques, as illustrated in Figure 1.

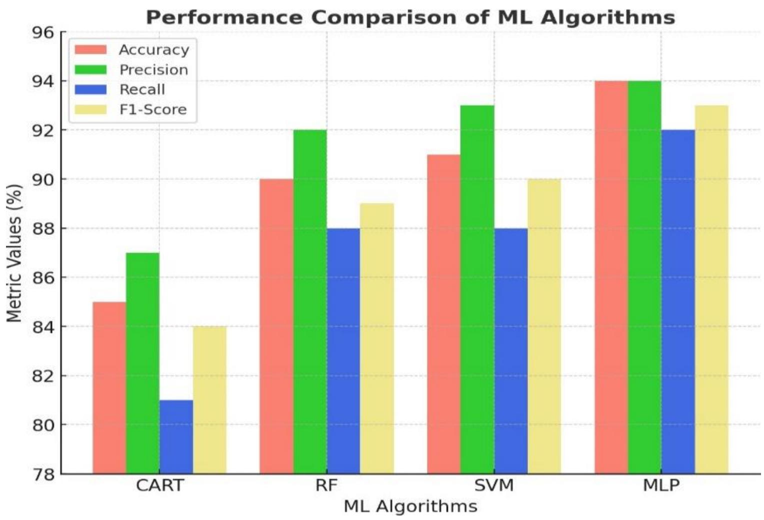


Figure 1: Performance Comparison of ML Algorithms

The figure above illustrates the comparative effectiveness of four machine learning models—CART, Random Forest (RF), Support Vector Machine (SVM), and Multi-Layer Perceptron (MLP)—based on key performance metrics. The results clearly show that CART performs the weakest across all evaluation criteria, indicating its limited ability to capture complex and non-linear accident patterns. In contrast, RF and SVM demonstrate notable improvements, particularly in precision and overall classification reliability, due to their strengths in ensemble learning and margin maximization, respectively. Among all models, MLP achieves the best performance with the highest accuracy (94%), precision (94%), recall (92%), and F1-score (93%), consistently outperforming the other algorithms. This superior outcome highlights the capability of deep neural architectures to effectively model intricate relationships within high-dimensional accident detection datasets. While traditional methods like CART provide baseline results, the analysis confirms that advanced models such as MLP are more suitable for robust and scalable accident detection, especially in dynamic and heterogeneous traffic environments.

Table 4: Performance Evaluation of Optimized ML Algorithms

	GS	GBO	SA	GA
Accuracy (%)				
CART	86	86	87	89
RF	91	92	92	93
SVM	92	92	93	94
MLP	93	93	94	96
Precision (%)				
CART	88	88	89	91
RF	93	94	94	95
SVM	94	94	95	96
MLP	95	95	96	97
Recall (%)				
CART	82	82	83	85
RF	87	88	88	89
SVM	88	88	89	90
MLP	89	89	90	92
F1-Score (%)				
CART	85	86	87	89
RF	90	92	92	93
SVM	91	92	93	94
MLP	92	93	94	96

Table 4 presents a comparative performance evaluation of four conventional machine learning algorithms CART, Random Forest (RF), Support Vector Machine (SVM), and Multi-Layer Perceptron (MLP) after optimization using four metaheuristic approaches: Grid Search (GS), Gradient-Based Optimization (GBO), Simulated Annealing (SA), and Genetic Algorithm (GA). The results clearly indicate that MLP consistently delivers the highest performance across all evaluation metrics, with its best outcome achieved under GA optimization, attaining an accuracy of 96%, precision of 97%, recall of 92%, and an F1-score of 96%, thereby outperforming all other techniques. SVM also demonstrates strong performance, particularly with GA, achieving high precision (96%) and an F1-score of 94%. RF shows balanced improvements across all optimization strategies, reflecting its robustness as an ensemble method. Although CART remains the weakest performer overall, it still benefits from optimization, achieving its best F1-score of 89% under GA.

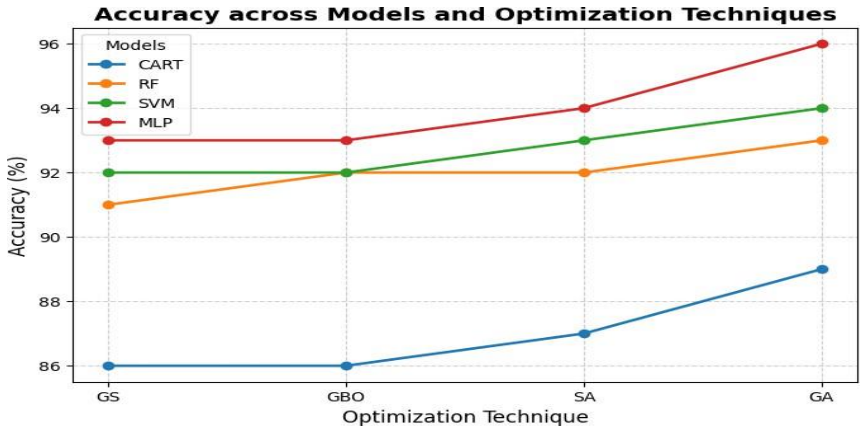
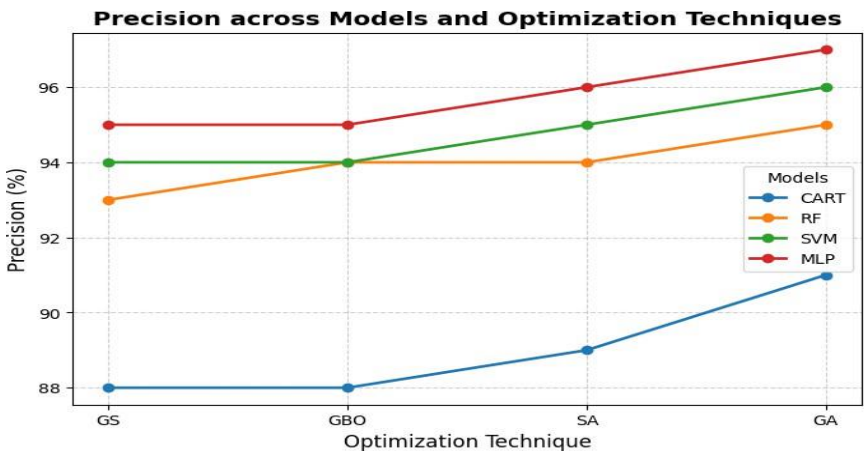


Figure 2: Accuracy across Models and Optimization Techniques

Figure 2 illustrates a clear and consistent upward trend in accuracy for all models when transitioning from Grid Search (GS) to Genetic Algorithm (GA) optimization. CART shows a gradual improvement, increasing from 86% under GS to 89% with GA, indicating modest gains despite its limited learning capacity. Similarly, RF demonstrates enhanced performance, rising from 91% to 93%, reflecting the benefit of optimization in strengthening ensemble-based predictions. SVM also exhibits steady progress, achieving its peak accuracy of 94% under GA, highlighting its effectiveness in handling complex decision boundaries. Most notably, the MLP model remains the strongest performer throughout, starting at 93% and reaching its highest accuracy of 96% with GA. Overall, the results emphasize that GA consistently delivers the most effective optimization across all algorithms, while MLP achieves the highest classification accuracy, confirming its dominance for accident detection and prediction tasks.



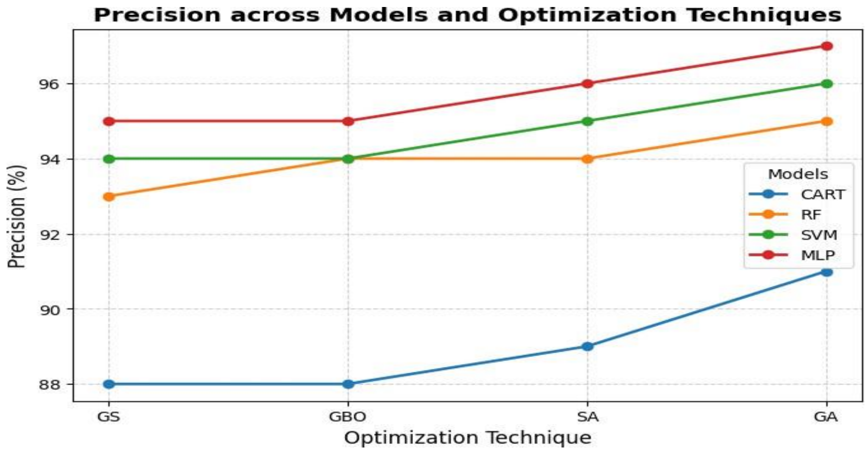


Figure 3: Precision across Models and Optimization Techniques

Figure 3 demonstrates that all models experience notable improvements in precision as a direct result of optimization. CART shows a moderate increase from 88% to 91%, while RF achieves a strong enhancement, reaching 95% under GA optimization. Similarly, SVM attains an even higher precision of 96% with GA, whereas MLP delivers the best overall performance, achieving the maximum precision of 97%. These findings clearly indicate that GA not only enhances the overall predictive capability of the models but also significantly reduces false positive rates, which is crucial for critical applications such as anomaly detection and accident identification.

In addition, recall trends further highlight improvements in model sensitivity. CART improves from 82% to 85%, and RF increases from 87% to 89%, reflecting better detection of true accident cases. SVM reaches a recall of 90% under GA, while MLP again outperforms all other methods with the highest recall of 92%. This superior performance confirms that the GA-optimized MLP model possesses the strongest ability to identify real positive events, ensuring minimal false negatives. Such a property is especially vital for high-stakes domains like defence, healthcare, and emergency response systems, where missing critical incidents can lead to severe consequences.

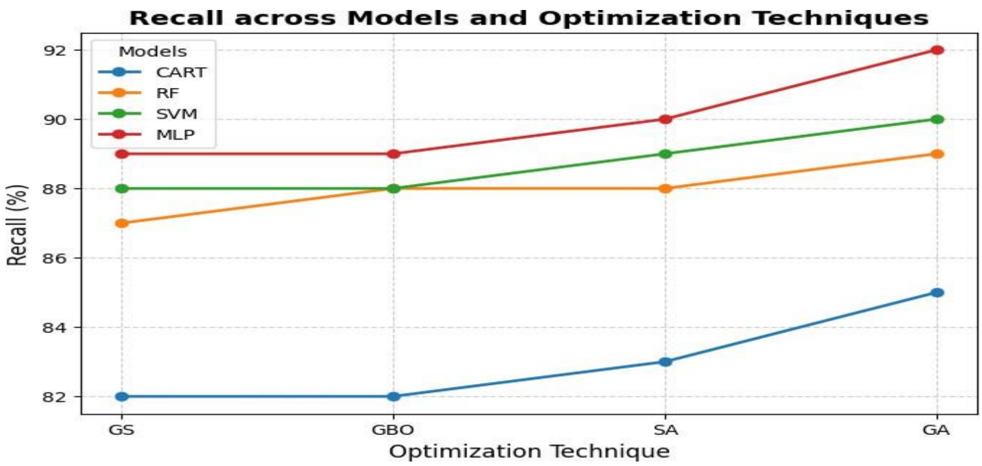


Figure 4: Recall across Models and Optimization Techniques

The combined influence of precision and recall is clearly reflected in the F1-Score trends illustrated in Figures 4 and 5. CART demonstrates a gradual improvement, with its F1-Score increasing from 85% to 89% under GA optimization. Similarly, RF shows a stronger enhancement, reaching an F1-Score of 93% with GA. SVM achieves an even higher performance level, attaining a score of 94%, while MLP once again delivers the best results with the maximum F1-Score of 96%. These outcomes confirm that GA-optimized MLP provides the most stable and reliable classification performance among all models. The balanced improvement in F1-Score highlights that metaheuristic optimization not only strengthens sensitivity (recall) but also enhances specificity (precision), ultimately leading to more dependable accident detection and prediction systems.

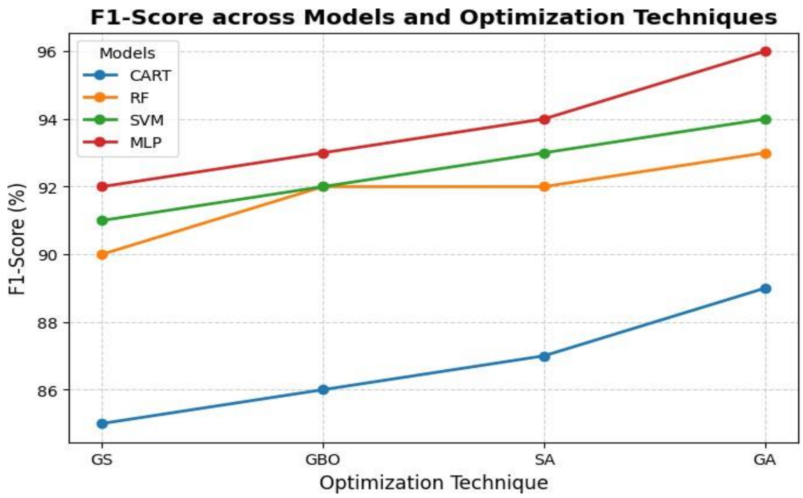


Figure 5: F1-Score across Models and Optimization Techniques

This research highlights the critical role of machine learning algorithms in improving the effectiveness and reliability of Accident Detection Systems (ADS). Through systematic experimentation on the NSL-KDD dataset, it was demonstrated that ML classifiers can successfully identify and classify a wide range of road hazards with high accuracy. Among the evaluated methods, the MLP classifier optimized using the Genetic Algorithm (GA) achieved the highest detection accuracy of 96%, significantly outperforming traditional models such as CART, RF, and SVM. These results confirm that carefully designed ML architectures, particularly when integrated with advanced optimization strategies, can greatly enhance ADS performance across key evaluation metrics including accuracy, precision, recall, and F1-score. Future work should emphasize the development of more robust ML-based optimization frameworks, the creation of datasets that better represent dynamic accident scenarios, and the enhancement of model adaptability to ensure strong generalization across diverse and evolving network environments.

5. CONCLUSION

In conclusion, this study demonstrates that machine learning and deep learning techniques significantly enhance the performance and reliability of Accident Detection and Prediction Systems (ADS). By conducting a detailed comparative evaluation of multiple ML models, including CART, RF, SVM, and MLP, the results confirm a clear progression in effectiveness from traditional classifiers to more advanced neural architectures. The optimized MLP model, particularly when combined with Genetic Algorithm (GA) optimization, achieved the highest overall accuracy, precision, recall, and F1-score, proving its superiority in handling complex and high-dimensional accident-related data. Furthermore, the integration of real-time detection, prediction, and alert mechanisms ensures faster emergency response and improved road safety. Overall, the findings highlight that optimized intelligent frameworks can provide scalable, dependable, and highly accurate solutions for modern accident monitoring, making them essential for reducing traffic hazards and saving human lives.

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