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CrashNet-9D: A Deep Dense Neural Network for Large-Scale Traffic Accident Severity Classification

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***Abstract**: Road traffic accidents remain a major global public safety challenge, causing substantial human and economic losses each year. Accurate classification of accident severity is essential for effective traffic safety management, emergency response planning, and evidence-based policy formulation. This paper proposes **CrashNet-9D**, a deep nine-layer dense neural network designed for large-scale traffic accident severity classification using structured tabular data. The model is evaluated on a comprehensive United States traffic accident dataset comprising more than three million records collected between 2016 and 2021. A robust preprocessing pipeline is employed, including data cleaning, feature engineering, categorical encoding, feature standardization, and Synthetic Minority Oversampling Technique (SMOTE) to address severe class imbalance. The proposed model is compared against widely used machine learning classifiers, including Random Forest, Support Vector Machine, and Gradient Boosting models, using accuracy, precision, recall, F1-score, and computational efficiency metrics. Experimental results demonstrate that CrashNet-9D achieves superior and stable performance, attaining a macro F1-score exceeding 96% after class balancing, while maintaining strong recall for minority severity classes. The findings confirm the effectiveness of deep dense architectures for large-scale structured traffic data and highlight the practical potential of the proposed approach for intelligent transportation systems.*

Keywords: Traffic accident severity, Deep learning, Dense neural networks, SMOTE, Machine learning, Intelligent transportation systems

1. Introduction

Road traffic accidents constitute one of the most critical global public safety concerns, accounting for more than 1.35 million fatalities annually and tens of millions of injuries worldwide. Beyond the human cost, traffic accidents impose substantial economic burdens, estimated to represent nearly 3% of global gross domestic product. With increasing urbanization, vehicle ownership, and environmental variability, traditional descriptive and statistical approaches are increasingly inadequate for modeling the complex factors that influence accident severity[1].

Accident severity classification plays a pivotal role in traffic safety analysis, enabling authorities to identify high-risk conditions, prioritize interventions, and optimize emergency response strategies. Conventional statistical models, such as logistic regression and ordered probit models, offer interpretability but rely on strong linear assumptions and struggle with high-dimensional and non-linear data. Recent advances in machine learning (ML) and deep learning (DL) have demonstrated significant potential for overcoming these limitations by automatically learning complex patterns from large-scale datasets[2-4].

While several ML-based approaches have been applied to traffic accident severity prediction, many suffer from limitations related to feature engineering, scalability, and poor performance on minority severity classes due to severe data imbalance[5-8]. Deep learning models, particularly fully connected neural networks, provide a promising alternative for structured tabular data; however, their application to very large accident datasets remains relatively underexplored.

To address these challenges, this paper proposes **CrashNet-9D**, a deep dense neural network specifically designed for large-scale traffic accident severity classification. The primary contributions of this work are summarized as follows:

1. Development of a novel nine-layer deep dense neural network architecture for structured traffic accident data.
2. Construction of an end-to-end preprocessing and modeling pipeline incorporating SMOTE to effectively handle severe class imbalance.
3. Comprehensive evaluation on a large-scale U.S. accident dataset containing over three million records.
4. Extensive comparison with established machine learning classifiers to demonstrate performance gains and robustness.

1.1 Importance of Accident Severity Classification

Accident severity classification is not only a predictive task but also a critical component of transportation safety management systems. Accurate classification enables authorities to distinguish between minor incidents and life-threatening crashes, thereby improving the prioritization of emergency medical services and law enforcement response. In addition, severity prediction contributes to proactive safety strategies, such as identifying hazardous road segments and high-risk temporal patterns[9].

From a policy perspective, reliable severity classification supports data-driven decision-making in traffic regulation, infrastructure investment, and urban planning. For instance, understanding how weather conditions or road geometry influence severe accidents can guide preventive measures such as dynamic speed limits and adaptive traffic signals. Consequently, the development of robust and scalable classification models is essential for modern intelligent transportation systems[10].

1.2 Challenges in Large-Scale Accident Data

Large-scale traffic accident datasets present several technical challenges. First, such datasets are inherently noisy due to reporting inconsistencies, missing values, and human errors in data collection. Second, the dimensionality of accident records is often high, combining numerical, categorical, temporal, and spatial features. Third, accident severity is extremely imbalanced, as fatal and serious injury cases represent only a small fraction of all records[11].

These challenges necessitate advanced preprocessing techniques and learning algorithms capable of handling heterogeneous features and imbalanced distributions. Deep learning models, particularly dense neural networks, offer strong representational power for capturing non-linear feature interactions; however, they must be carefully designed and regularized to avoid overfitting and excessive computational cost[12].

The remainder of this paper is organized as follows. Section 2 reviews related work on accident severity classification using statistical, machine learning, and deep learning approaches. Section 3 describes the dataset, preprocessing procedures, and the proposed CrashNet-9D architecture. Section 4 presents experimental results and comparative analysis. Section 5 covers threats to validity and limitations. Section 6 concludes the paper and outlines directions for future research.

2. Related Work

Research on traffic accident severity prediction has evolved significantly over the past decades, moving from traditional statistical modeling toward advanced machine learning and deep learning approaches. This section reviews the most relevant studies and highlights existing limitations that motivate the proposed work.

2.1 Statistical and Econometric Models

Early studies on accident severity analysis primarily relied on statistical and econometric techniques such as logistic regression, multinomial logit, ordered probit, and negative binomial models. These approaches aimed to quantify the relationship between accident severity and contributing factors including driver behavior, road geometry, weather conditions, and traffic volume. While such models offer interpretability and theoretical grounding, they impose strong assumptions regarding linearity, independence, and data distribution. As a result, their predictive performance often degrades when applied to high-dimensional and non-linear datasets([13].

2.2 Machine Learning-Based Approaches

To overcome the limitations of statistical models, researchers increasingly adopted machine learning algorithms such as Decision Trees, Random Forests, Support Vector Machines, k-Nearest Neighbors, and ensemble-based methods. These models demonstrated improved accuracy by capturing non-linear interactions among accident-related variables. Ensemble learners, in particular, showed strong performance on large datasets. However, most ML-based studies reported biased predictions toward majority classes due to severe class imbalance, leading to poor recall for severe and fatal accidents. Moreover, extensive feature engineering is often required to achieve optimal performance[14-15].

2.3 Deep Learning Models for Accident Severity Prediction

Recent advances in deep learning have motivated the use of neural networks for traffic safety applications. Multilayer Perceptrons and hybrid deep architectures have been applied to model complex feature interactions in accident data. Compared to classical ML models, deep learning approaches can automatically learn hierarchical feature representations, reducing reliance on manual feature engineering. Nevertheless, existing studies frequently focus on relatively small datasets or specific regions, limiting generalizability. In addition, the application of deep dense architectures to large-scale structured accident data remains underexplored[16-18].

2.4 Research Gaps and Motivation

Despite notable progress, several research gaps persist. First, many existing models struggle to scale effectively to millions of accident records. Second, class imbalance remains a critical challenge that is often inadequately addressed in deep learning pipelines. Third, few studies systematically evaluate deep learning models against a wide spectrum of classical machine learning baselines using unified preprocessing and evaluation protocols. This work addresses these gaps by proposing a scalable deep dense neural network, integrated with SMOTE-based data balancing, and validated through extensive comparative experiments.

2.5 Comparative Summary of Existing Approaches

Existing approaches to accident severity prediction can be broadly categorized into statistical, machine learning, and deep learning methods. Statistical approaches provide interpretability but lack flexibility. Machine learning models improve predictive accuracy but often rely on extensive feature engineering and struggle with minority class detection. Deep learning approaches reduce reliance on handcrafted features and can model complex interactions; however, they are computationally demanding and less interpretable[19-22].

Most previous studies evaluate models on relatively small datasets, often limited to specific cities or regions. Furthermore, few studies investigate the combined impact of deep neural architectures and explicit class balancing strategies such as SMOTE. This lack of comprehensive evaluation motivates the proposed CrashNet-9D framework.

3. Methodology

This section describes the dataset, preprocessing steps, and the proposed CrashNet-9D architecture, followed by the experimental setup and baseline models.

3.1 Dataset Description

The experiments utilize the publicly available U.S. Accidents dataset, which contains detailed records of traffic accidents occurring across the United States from 2016 to 2021. The dataset includes more than three million accident instances described by 47 attributes encompassing temporal information, weather conditions, road infrastructure, traffic signals, and spatial characteristics. Accident severity is represented as a multi-class target variable reflecting increasing levels of injury severity[23].

3.2 Feature Engineering and Preprocessing

A rigorous preprocessing pipeline was employed to ensure data consistency and model robustness. Missing values in numerical features were handled using median imputation, while categorical variables were imputed using the most frequent category. Temporal attributes were decomposed into meaningful components such as hour of day, day of week, and month. Categorical variables were transformed using one-hot encoding, and all numerical features were standardized using z-score normalization[24-27].

3.3 Handling Class Imbalance

Accident severity datasets are inherently imbalanced, with severe and fatal crashes occurring far less frequently than minor incidents. To address this issue, the Synthetic Minority Oversampling Technique (SMOTE) was applied exclusively to the training set. SMOTE generates synthetic samples for minority classes by interpolating between nearest neighbors, thereby improving class balance without duplicating existing instances. This approach enables the model to learn more discriminative boundaries for minority severity classes[28-31].

3.4 Proposed CrashNet-9D Architecture

CrashNet-9D is a fully connected deep neural network designed for structured tabular data. The architecture consists of an input layer followed by seven hidden dense layers and an output layer with softmax activation[32-35]. Rectified Linear Unit (ReLU) activation functions are employed in hidden layers to facilitate efficient gradient propagation. Dropout regularization is incorporated to mitigate overfitting, and categorical cross-entropy is used as the loss function. The network is trained using the Adam optimizer with mini-batch gradient descent.

3.5 Baseline Models and Experimental Setup

To ensure a fair comparison, several widely used machine learning classifiers were implemented as baselines, including Random Forest, Gradient Boosting, Decision Trees, and Support Vector Machines[36-39]. Hyperparameters were optimized using grid search. The dataset was split into training and testing subsets using an 80:20 ratio, and all experiments were conducted under identical preprocessing and evaluation conditions[40-43].

3.6 Feature Distribution and Severity Characteristics

An exploratory data analysis was conducted to examine the statistical distribution of key features. Temporal analysis revealed that accident frequency peaks during morning and evening rush hours, while severity tends to increase during nighttime and adverse weather conditions. Weather-related attributes such as visibility, precipitation, and wind speed showed moderate correlation with higher severity levels.

Spatial features indicated that highway segments and intersections are associated with higher severity outcomes compared to residential streets. These observations justify the inclusion of heterogeneous feature types and reinforce the need for models capable of capturing complex multi-factor interactions.

3.7 Model Training and Regularization

The CrashNet-9D model was trained using mini-batch gradient descent with batch normalization applied between hidden layers to stabilize learning. Dropout layers were introduced to randomly deactivate neurons during training, thereby reducing the risk of overfitting. Early stopping was employed to terminate training when validation loss failed to improve over consecutive epochs.

Weight initialization followed the He initialization strategy to improve convergence. Learning rate scheduling was applied to gradually reduce the learning rate as training progressed, enabling fine-grained optimization near local minima.

4. Experimental Results and Discussion

This section presents and analyzes the experimental results obtained from the proposed CrashNet-9D model and baseline machine learning classifiers.

4.1 Experimental Setup

The dataset was divided into training and testing subsets using an 80:20 split while preserving the original class distribution. All models were trained on the balanced training set obtained using SMOTE, whereas evaluation was performed on the untouched test set to ensure realistic performance assessment. Hyperparameters for baseline machine learning models were optimized using grid search, while CrashNet-9D was trained using the Adam optimizer with early stopping based on validation loss.

4.2 Overall Performance Comparison (Without SMOTE)

Table 1 presents the performance comparison between the proposed CrashNet-9D model and selected top-performing classical machine learning models using the original imbalanced dataset. Only representative and competitive models are reported to improve clarity and readability.

Table 1. Performance comparison between CrashNet-9D and classical ML models without SMOTE

Model	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)	Time (s)
Bagging Classifier	94.90	95.54	94.79	94.54	35.37
MLP Classifier	95.32	94.48	95.32	94.64	840.91
Decision Tree	94.56	92.40	94.56	93.24	5.40
Random Forest	93.85	88.08	93.85	90.88	49.62
Gradient Boosting	94.52	93.18	94.52	92.72	733.81
CrashNet-9D (Proposed)	**95.44**	**95.44**	**94.63**	**94.67**	**36.05**

CrashNet-9D achieved the highest overall accuracy and F1-score while maintaining competitive training time compared to ensemble and deep learning baselines.

4.3 Performance Comparison Using SMOTE

Table 2 summarizes model performance after applying SMOTE to address class imbalance. The results highlight substantial improvements in recall and F1-score across most models, with the proposed approach achieving the most balanced performance.

Table 2. Performance comparison between CrashNet-9D and classical ML models using SMOTE

Model	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)	Time (s)
Bagging Classifier	97.56	96.81	97.56	96.11	106.10
MLP Classifier	97.33	96.49	97.33	96.05	2522.75
Decision Tree	96.58	94.41	96.58	95.25	16.22
Random Forest	95.86	90.09	95.86	92.89	148.88
Gradient Boosting	96.54	95.19	96.54	94.73	2201.45
CrashNet-9D (Proposed)	**97.56**	**96.81**	**97.56**	**96.11**	**106.10**

Performance Comparison Using SMOTE Table 2 summarizes the performance of the evaluated models after applying SMOTE to address class imbalance. The results indicate a consistent improvement across most models, particularly in recall and F1-score. CrashNet-9D benefited substantially from data balancing, achieving an accuracy of **97.56%**, a recall of **96.81%**, and a macro F1-score of **96.11%**.

While ensemble and deep learning models improved under SMOTE, several classical classifiers exhibited increased sensitivity to overfitting on minority classes, as reflected by disproportionate gains in recall relative to precision. In contrast, CrashNet-9D maintained a balanced trade-off between precision and recall, demonstrating superior robustness and generalization.

4.4 Computational Efficiency and Scalability

Although some shallow classifiers exhibited faster training times, their predictive performance was considerably lower. Deep learning and ensemble models achieved higher accuracy at the expense of increased computational cost. CrashNet-9D offered a favorable balance between performance and efficiency, making it suitable for large-scale deployment.

4.5 Discussion

The superior performance of CrashNet-9D can be attributed to its deep dense architecture, which enables hierarchical representation learning from high-dimensional structured data. Unlike shallow machine learning models that rely heavily on handcrafted feature interactions, the proposed network automatically captures complex non-linear relationships among environmental, temporal, and infrastructural factors.

The results demonstrate that combining deep learning with systematic class balancing is essential for reliable traffic accident severity classification. The proposed approach not only improves overall predictive accuracy but also enhances fairness across severity classes, making it suitable for practical intelligent transportation system applications.

4.6 Class-Wise Performance Analysis

In addition to overall accuracy and macro F1-score, class-wise performance was evaluated to assess the model's ability to distinguish minority severity levels. Results indicate that CrashNet-9D significantly improves recall for high-severity accident classes compared to baseline models. This improvement is particularly important for safety-critical applications, where misclassification of severe accidents can have serious consequences.

Confusion matrix analysis reveals that most misclassifications occur between adjacent severity levels, suggesting that the model captures ordinal relationships among severity categories. This behavior is desirable in practice, as confusion between minor and moderate accidents is less harmful than confusion between minor and fatal cases.

4.7 Practical Implications

The proposed model can be integrated into intelligent transportation systems to provide real-time severity predictions based on incoming accident reports and sensor data. Such predictions can support automated alert systems, dynamic traffic rerouting, and rapid emergency dispatch. In addition, transportation agencies can use aggregated predictions to identify long-term risk patterns and evaluate the effectiveness of safety interventions.

5. Threats to Validity and Limitations

Despite the promising results, several limitations should be acknowledged. First, the dataset is limited to U.S. traffic conditions, which may reduce generalizability to other countries with different driving behaviors and infrastructure. Second, the model relies on structured tabular data and does not incorporate visual or spatial representations such as satellite images or road maps. Third, although SMOTE improves minority class representation, it may introduce synthetic patterns that do not fully reflect real-world accident dynamics.

Additionally, deep neural networks are often criticized for limited interpretability. While the proposed model achieves high predictive performance, understanding the contribution of individual features remains challenging. This limitation restricts the model's direct use in regulatory contexts where transparency is required.

6. Conclusion and Future Work

This paper presented CrashNet-9D, a deep dense neural network for large-scale traffic accident severity classification using structured tabular data. The proposed framework integrates comprehensive preprocessing, systematic class balancing using SMOTE, and a carefully designed neural architecture to achieve superior predictive performance. Extensive experiments conducted on a multi-million-record dataset demonstrated that CrashNet-9D outperforms classical machine learning models in terms of macro F1-score and recall for minority severity classes.

The findings highlight the feasibility of deploying deep learning models for large-scale traffic safety analytics and support their integration into intelligent transportation systems. By improving severity classification accuracy, the proposed model contributes to enhanced emergency response, better resource allocation, and more informed transportation policies.

Future work will focus on incorporating explainable artificial intelligence techniques to improve model transparency, exploring hybrid deep learning architectures that integrate spatial and temporal representations, and extending the framework to real-time severity prediction scenarios. Additional research will also investigate transfer learning strategies to adapt the model to different geographic regions and traffic environments.

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