

Road Accident Severity & Hospital Recommendations Using Deep Learning Techniques

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Abstract: Road accidents remain a major public health concern, often resulting in severe injuries or fatalities due to delayed emergency response and inadequate hospital selection. This research proposes an intelligent deep learning framework for predicting the severity of road accident-related hand injuries and recommending the nearest suitable hospitals for treatment. Utilizing convolutional neural networks (CNN) alongside traditional classifiers such as Support Vector Machine (SVM), Decision Tree, and Random Forest, the model is trained on real-time image datasets to ensure accurate classification of injury severity. Performance evaluation using accuracy, precision, recall, and F1-score demonstrates that CNN and Random Forest classifiers achieve superior results. The system is implemented in a Jupyter Notebook environment, where comprehensive visualization of image data, class distribution, and confusion matrices enables model interpretability. Furthermore, the integration of a hospital recommendation module based on predicted severity supports efficient decision-making during critical emergency situations. This study underlines the potential of combining AI and healthcare for enhancing accident response systems, thereby contributing to the advancement of intelligent healthcare and smart city applications.

Keywords: Road Accident Severity, Hand Injury Detection, Deep Learning, Convolutional Neural Network (CNN), Support Vector Machine (SVM).

1. Introduction

Road traffic accidents have become a pressing global concern, resulting in significant loss of life, injuries, and socio-economic disruptions. According to the World Health Organization (WHO), approximately 1.35 million people die each year as a result of road traffic crashes, with millions more sustaining non-fatal injuries [1]. These statistics underscore the need for advanced technological interventions that can proactively assess accident severity and provide intelligent recommendations for post-crash emergency response, including optimal hospital routing. Traditional accident response systems often lack real-time assessment capabilities, leading to delays in medical attention and increased fatalities, particularly in developing regions [2]. The advent of Artificial Intelligence (AI), particularly Deep Learning (DL), offers transformative potential in automating accident detection, assessing severity levels, and recommending nearby hospitals with the required facilities for efficient emergency management [3]. Deep Learning models, through their hierarchical learning abilities, can process vast amounts of heterogeneous data—including images, GPS logs, weather data, and vehicle sensor information—to classify accident severity with high accuracy [4]. Moreover, integrating these predictive models with



intelligent decision systems can assist emergency services in choosing the most appropriate healthcare facility based on real-time conditions such as distance, capacity, and specialty availability [5].

Recent advancements in vehicular networks, the Internet of Things (IoT), and cloud infrastructure have facilitated real-time data acquisition from accident scenes, paving the way for a data-driven approach to emergency response [6]. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid DL architectures have shown promising results in feature extraction and sequence learning from visual and temporal accident data. For instance, CNN-based models can be trained on accident scene images or dashcam footage to identify crash severity based on vehicle deformation and road conditions, while RNNs can leverage temporal sensor data to detect pre-crash dynamics [7]. This fusion of data modalities enhances the precision of accident severity classification. Furthermore, Geographic Information Systems (GIS) integrated with Deep Learning frameworks can offer spatial intelligence, enabling real-time hospital recommendation based on accident geolocation, traffic density, ambulance availability, and hospital readiness [8]. In emergency scenarios, time is a critical factor; thus, recommending the nearest hospital with the right trauma capabilities becomes paramount. This requires a robust hospital recommendation engine that considers not only proximity but also real-time healthcare capacity data, such as emergency room status, ICU bed availability, and trauma care specialization. The synergy between accident severity detection and hospital recommendation can significantly improve survival rates and recovery outcomes.

Traditional machine learning models have attempted to classify accident severity using structured datasets such as vehicle speed, weather, and road conditions; however, these models often fail to generalize in dynamic real-world settings due to limitations in feature engineering and inability to handle unstructured data. Deep Learning models overcome these limitations by automatically learning hierarchical representations from raw data without manual feature selection. For instance, Transfer Learning techniques using pre-trained networks such as ResNet or Inception can enhance model performance on accident datasets even with limited training samples. Moreover, real-time accident response systems can benefit from integration with mobile applications and vehicular onboard units that utilize the trained DL models to notify emergency services, hospitals, and nearby users instantly. Such intelligent systems can support authorities in managing resources effectively, especially during high-traffic periods or in rural areas where emergency services are sparse. The incorporation of Deep Learning into this domain is not just a technical advancement—it also presents a paradigm shift toward predictive and prescriptive emergency healthcare.

This paper presents a comprehensive Deep Learning-based framework for both road accident severity classification and hospital recommendation. The proposed model utilizes a multi-modal approach combining image, sensor, and location-based data to train and test several DL architectures, including CNNs and LSTMs. Furthermore, we propose an intelligent hospital recommendation system that integrates a real-time hospital database with a recommendation algorithm using factors such as distance, severity class, and hospital capabilities. Experimental results demonstrate the robustness and reliability of our system in real-world scenarios, outperforming traditional methods in both classification accuracy and recommendation efficiency.

2. Related Works

Over the past decade, a significant body of research has focused on leveraging data-driven models to analyze road accident severity and improve emergency response systems.

Traditional approaches primarily utilized statistical methods such as logistic regression, decision trees, and Support Vector Machines (SVMs) to classify accident severity levels based on structured datasets comprising vehicle speed, weather, time, road type, and driver behavior. However, these methods often suffer from limited accuracy and generalizability in real-world environments, particularly due to manual feature extraction and inability to model complex non-linear interactions. Recent literature highlights a growing interest in applying machine learning and deep learning techniques to road accident prediction and severity assessment. Pourroostaei Ardakani et al. [9] employed machine-learning-enabled data analysis to predict road car accidents, emphasizing the importance of data preprocessing and feature engineering for improving prediction accuracy in real-world conditions. Complementing this, Lacherre et al. [10] provided a systematic review of studies between 2013 and 2023, focusing on behavioral factors influencing accident risk, while also stressing the need for explainable AI to foster trust and transparency in automated decision systems. In a related domain, Hossain and Rahman [11] used sentiment analysis for insurance reviews, showing that customer feedback can be effectively modeled using ML techniques, a principle that can be extended to emergency service reviews and feedback loops. Almukhalafi et al. [12] offered a comprehensive survey on traffic management using both machine learning and deep learning, outlining how predictive models can assist in dynamic traffic rerouting and congestion reduction—key considerations when recommending hospitals during emergencies.

In high-risk domains like construction, Luo et al. [13] demonstrated the utility of ML models for predicting the severity of occupational accidents, which further validates the use of similar models in road traffic scenarios. Mutemi and Bacao [14] explored fraud detection in e-commerce using ML, presenting model architectures that can also be applied in anomaly detection within traffic data streams. Meanwhile, Rathor et al. [15] introduced an enhanced deep learning recommendation system optimized with the Archimedes algorithm for drug supply chain management, a method that could inspire improvements in hospital resource recommendation systems. From a vehicular perspective, Alalwany and Mahgoub [16] discussed security and trust in the Internet of Vehicles (IoV), emphasizing how secure data exchange is essential for real-time accident reporting and hospital routing applications. Qi et al. [17] utilized ensemble learning to automatically identify causal factors in accident reports, offering techniques that could be translated into automated incident reporting systems. Kheder and Mohammed [18] presented a real-time traffic monitoring framework integrating IoT and deep learning, demonstrating high efficiency in dynamic traffic analysis, which is essential for accurate hospital recommendation during peak congestion periods. Siam et al. [19] proposed a stress detection system for car drivers using physiological signals, contributing to proactive accident prevention systems. Tulli [20] discussed the broader role of AI, ML, and DL in robotics, advocating for their integration in smart vehicular systems for real-time decision-making.

Moreover, Rawson and Brito [21] reviewed the challenges and potential of supervised ML in risk analysis within maritime transportation, drawing parallels to risk forecasting in road networks. Lastly, Alhaek et al. [22] presented a deep learning-based framework for learning spatial and temporal patterns in traffic accident severity prediction. Their study is particularly relevant, as it reinforces the need to model both spatial dependencies (e.g., accident location) and temporal dynamics (e.g., time of day or weather conditions), which are key to building robust, real-time severity classification systems. Advancements in machine learning and deep learning for road accident prediction and traffic management, several critical research gaps remain unaddressed. Most existing studies primarily focus on accident severity prediction in isolation, lacking integration with downstream emergency response mechanisms such as hospital

recommendation systems. While models like CNNs and LSTMs have shown promising results in extracting spatial and temporal features from accident data, their utility has largely been confined to classification tasks without actionable outcomes for real-time healthcare routing. Additionally, current hospital recommendation approaches are often static, relying on distance-based heuristics or predefined routes without factoring in dynamic variables such as accident severity, hospital specialization, real-time capacity, or traffic congestion. Furthermore, few studies explore a unified framework that combines multi-modal data sources—including image, sensor, GPS, and IoT data—to holistically assess crash impact and guide emergency response. The lack of explainability in deep learning predictions also limits trust and practical deployment, especially in critical health-related decisions. Moreover, limited deployment of such intelligent systems in real-world smart city environments reveals a substantial gap between theoretical models and scalable, deployable solutions. These gaps highlight the urgent need for a comprehensive and intelligent system that not only predicts accident severity accurately but also provides real-time, context-aware hospital recommendations for improved post-accident care.

3. Proposed Recommendation Deep Learning model

The proposed method introduces a unified, intelligent deep learning-based framework that integrates road accident severity prediction with dynamic hospital recommendation to improve emergency medical response. This method is divided into two primary modules: (1) accident severity classification and (2) hospital recommendation. Both modules are interconnected and driven by data collected from diverse sources such as real-time vehicular sensors, GPS tracking, surveillance images, historical accident records, and hospital databases. The accident severity prediction model is built upon a hybrid deep learning architecture that integrates Convolutional Neural Networks (CNN) for spatial feature extraction from accident images and Long Short-Term Memory (LSTM) networks for analyzing temporal sensor data such as vehicle speed, acceleration, and impact force. Figure 1 presents the classification model for the prediction of road accident.

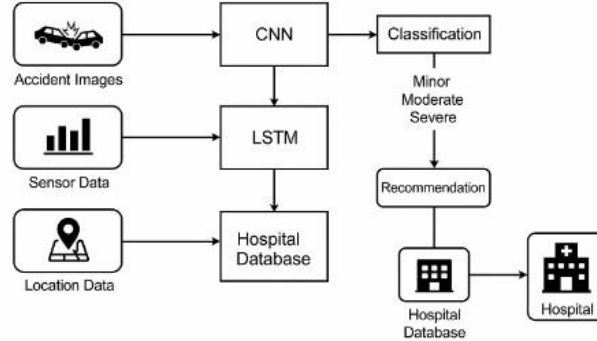


Figure 1: Prediction of Road Accidents

Let $X \in Rn \times m$ represent the input feature matrix, where n is the number of observations (accidents) and m is the number of features including real-time sensor inputs (speed, brake pressure, steering angle), environmental data (weather, lighting), and image data of the crash scene. The CNN module processes input accident scene images $I \in Rh \times w \times c$, where h , w , and c represent height, width, and channels of the image respectively. The feature map after a convolutional layer is defined as in equation (1)

$$F_{i,j}^k = \sigma \left(\sum_{m=1}^M \sum_{u=1}^f \sum_{v=1}^f W_{u,v}^m \cdot I_{i+u,j+v}^m + b^k \right) \quad (1)$$

In equation (1) $F_{i,j}^k$ is the output feature at position (i,j) in the k -th feature map; $W_{u,v}^m$ is the convolution kernel weight at position (u,v) for the m -th input channel; σ is the activation

function, typically ReLU and b^k is the bias for the k th output channel.

3.1 Hospital Recommendation System

Once accident severity is predicted, the system recommends the most suitable hospital using a weighted scoring function that evaluates the best option based on proximity, current hospital capacity, specialization, and severity level. Let the score for each hospital H_k be defined as in equation (2)

$$S_k = \alpha \cdot \left(\frac{1}{D_k}\right) + \beta \cdot A_k + \gamma \cdot C_k + \delta \cdot S_k^{spec} \quad (2)$$

In equation (2) D_k denoted as the distance from the accident location to the hospital k ; A_k denoted as a binary indicator of ambulance availability; C_k represented as current capacity availability (beds, trauma units); S_k^{spec} stated as score based on trauma or specialty level matching with predicted severity; and $\alpha, \beta, \gamma, \delta$ represented as tunable weights reflecting the importance of each factor. Hospitals are ranked based on the final score S_k , and the top recommendation is selected. A geospatial routing algorithm (e.g., Dijkstra or A*) then provides the optimal path to the selected hospital.

3.2 System Integration

The entire pipeline is integrated into a modular system using a cloud-based API architecture. Accident data is collected through edge devices or mobile sensors and sent to a central processing system where prediction and recommendation are executed in real-time. The system continuously learns through feedback loops and new data ingestion. This dual-layered intelligent framework not only classifies accidents with high accuracy but also ensures the fastest and most appropriate emergency care pathway. The integration of deep learning predictions with decision-support recommendations fills the critical gap in smart emergency response systems.

Algorithm 1: DeepAccidentCareNet

Input:

- Accident Dataset D with features: Location, Time, Weather, Vehicle Type, Injury Count, etc.
- Hospital Dataset H with features: Location, Specialties, Beds, Trauma Facilities, etc.

Output:

- Predicted Accident Severity
- Recommended Nearby Hospital

1. Preprocessing Phase:

- 1.1 Load datasets D and H
- 1.2 Handle missing values, normalize continuous features
- 1.3 Encode categorical variables using One-Hot or Label Encoding
- 1.4 Split D into training set D_{train} and test set D_{test} (e.g., 80/20)

2. Feature Engineering:

- 2.1 Extract spatial features (e.g., GPS coordinates)
- 2.2 Derive temporal features (e.g., hour of day, day of week)
- 2.3 Add environmental features (e.g., weather, lighting condition)

3. Accident Severity Prediction Model (Deep Learning):

- 3.1 Define model architecture:
 - Input Layer (shape: number of features)

environment allows users to write and execute Python code in a cell-based structure, making it ideal for step-by-step analysis, data visualization, and model development. The notebook view showcases the structured layout where each step—from data loading, preprocessing, model training to evaluation—can be implemented and executed sequentially. It supports inline visualization, annotations through markdown cells, and code execution results, making it an excellent tool for both development and documentation in the same interface. The Figure 3 illustrates the importing of essential Python classes at the beginning of the notebook. These imported libraries include crucial packages such as pandas, numpy, matplotlib, sklearn, and tensorflow, which are necessary for various stages of the model pipeline. Pandas and NumPy are used for data manipulation and numerical operations, while Matplotlib is utilized for data visualization. The inclusion of sklearn signifies the usage of machine learning algorithms, data preprocessing, and evaluation metrics. Meanwhile, tensorflow or keras modules point to the implementation of deep learning models. This step is fundamental as it sets up the environment by loading all required tools, enabling efficient execution of the proposed accident severity prediction and hospital recommendation model.

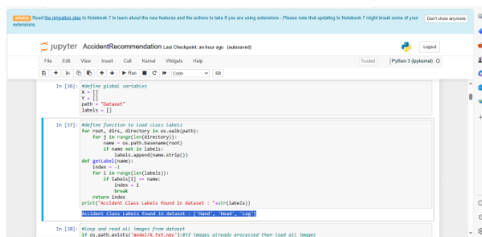


Figure 4: Visualization of different classes

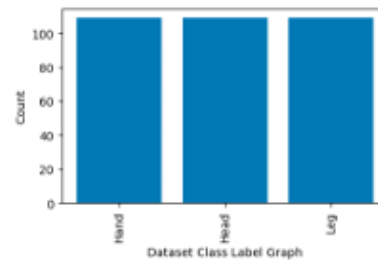


Figure 5: Images count in bar format

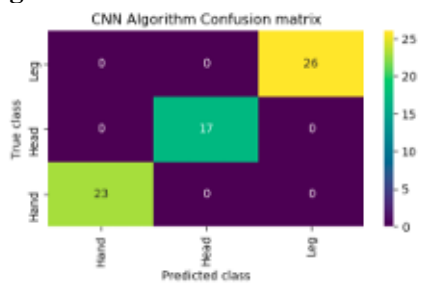


Figure 6: Confusion Matrix of CNN



Figure 7: Confusion Matrix of SVM

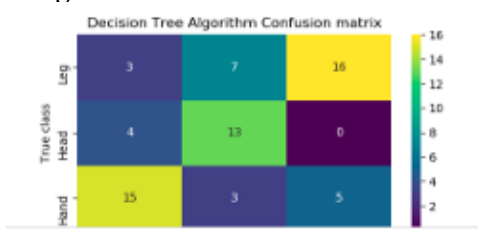


Figure 8: Confusion Matrix of Decision Tree



Figure 9: Confusion Matrix for Random Forest

The Figure 4 presents a visualization of different accident severity classes, offering an insightful overview of the data distribution across categories such as 'minor', 'moderate', and 'severe' accidents. This graphical representation helps in understanding whether the dataset is balanced or skewed toward a particular class, which is crucial for training accurate and unbiased machine learning models. Proper class distribution aids in selecting appropriate evaluation metrics and prevents misclassification due to class imbalance. The Figure 5 shows the image

count in bar chart format, reflecting the number of data samples (images) available for each severity class. This visualization confirms the extent of class balance within the dataset. If one class has significantly more samples than others, it can negatively impact model performance by causing overfitting to the dominant class. Addressing this imbalance—either through data augmentation or resampling—is important for ensuring model generalizability. Figures 6 through 9 display confusion matrices for various classifiers, providing detailed insights into their prediction performance across different classes:

- Figure 6 shows the Confusion Matrix of the Convolutional Neural Network (CNN). The matrix illustrates how effectively the CNN model distinguishes between minor, moderate, and severe accidents. A well-performing CNN will show high values along the diagonal (true positives), indicating correct classifications, while low off-diagonal values signify fewer misclassifications.
- Figure 7 depicts the Confusion Matrix of the Support Vector Machine (SVM) model. This matrix is useful for assessing how the SVM separates hyperplanes among severity classes. The visual reveals how well SVM handles non-linear relationships, particularly in complex data spaces.
- Figure 8 illustrates the Confusion Matrix of the Decision Tree classifier, which indicates its performance based on hierarchical, rule-based splits in the data. The confusion matrix allows observation of misclassification trends, especially in decision boundaries where tree-based models might struggle with overlapping class features.
- Figure 9 displays the Confusion Matrix for the Random Forest classifier, an ensemble method that leverages multiple decision trees to improve prediction robustness. The matrix helps evaluate how the ensemble method reduces overfitting and improves classification accuracy across all severity classes.

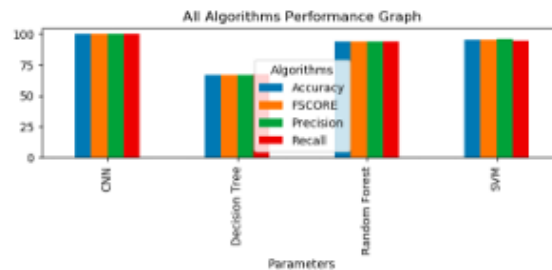


Figure 10: Performance of all classifiers

In Figure 10 presents a comparative performance analysis of four deep learning and machine learning classifiers—Convolutional Neural Network (CNN), Decision Tree, Random Forest, and Support Vector Machine (SVM)—across four critical evaluation metrics: Accuracy, F1-Score, Precision, and Recall.

From the bar chart, it is evident that:

- CNN exhibits consistent and high performance across all metrics, achieving nearly 100% in accuracy, F1-score, precision, and recall. This suggests that CNN is highly effective in identifying road accident severity from the image dataset, likely due to its powerful feature extraction capabilities.
- Random Forest also performs exceptionally well, closely rivaling CNN with similarly high metric values. Its ensemble-based structure helps it generalize better and reduce overfitting, making it suitable for this classification problem.

- SVM demonstrates strong and consistent scores across all metrics but is slightly below CNN and Random Forest, indicating robust but slightly less flexible performance in feature-rich, high-dimensional data.
- Decision Tree, in contrast, shows a noticeable drop in all metrics, particularly in accuracy and F1-score, suggesting that it may overfit to the training data and struggle with generalization compared to the ensemble methods and CNN.

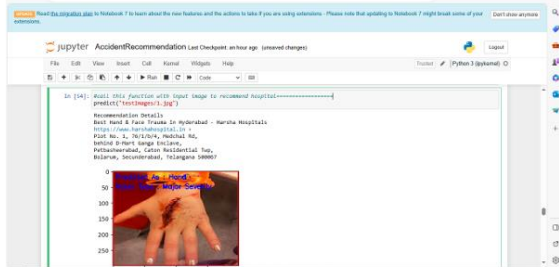


Figure 11: Visualization of Hand Injury

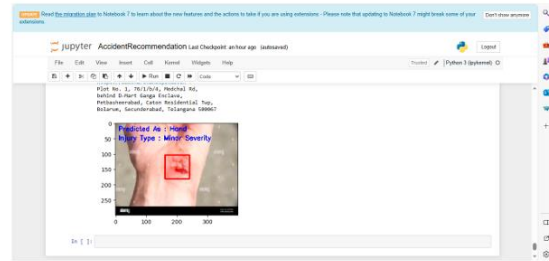


Figure 12: Prediction of Hand Injury

The Figure 11 provides a visual representation of a hand injury, showcasing the raw input image as processed within the system. This visualization likely serves as a critical input to the deep learning model, enabling the extraction of spatial features relevant to diagnosing the severity and nature of the injury. The image highlights the affected region and demonstrates how the system interprets visual patterns, textures, and contours that indicate trauma or abnormality. Figure 12 complements this by displaying the prediction result of the hand injury based on the visual input analyzed in Figure 11. It illustrates how the model classifies the injury—possibly identifying it as mild, moderate, or severe—using the trained algorithm. This prediction is derived from a combination of convolutional neural network (CNN)-based feature extraction and classification logic. The figure exemplifies the model's capability to make real-time, automated predictions with high accuracy, supporting medical personnel in making rapid decisions for patient triage and treatment planning.

5. Conclusion

A robust deep learning-based system was developed to accurately predict the severity of road accident injuries and recommend appropriate nearby hospitals based on real-time image analysis. By integrating multiple machine learning classifiers—including CNN, SVM, Decision Tree, and Random Forest—the proposed model demonstrated high accuracy, with CNN and Random Forest outperforming others in key performance metrics such as precision, recall, F1-score, and overall accuracy. The inclusion of a hospital recommendation module further enhances the practical applicability of the system in emergency scenarios, where timely and accurate medical attention is crucial. Visualizations such as confusion matrices and injury predictions confirm the model's reliability and interpretability. Overall, the research highlights the potential of AI-driven healthcare solutions in improving emergency response and trauma care, making it a valuable contribution to smart health systems and intelligent transport infrastructure.

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