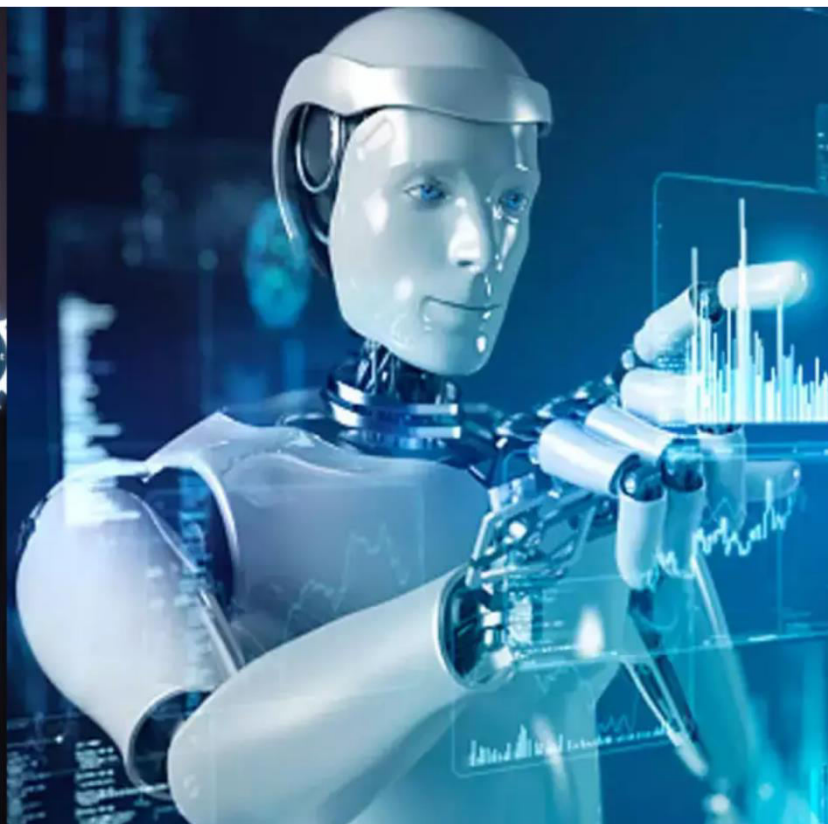




International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.699

Volume 14, Issue 4, April 2025

A CNN-Powered Framework for Injury Classification and Hospital Navigation in Emergency Response Systems

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ABSTRACT - Effective and precise injury evaluation is imperative in emergency scenarios to provide prompt medical treatment and enhance patient care. This work introduces a CNN-based Injury Detection and Hospital Suggestion System using deep learning and computer vision that can automatically detect the type and severity of injury from medical images. The system particularly identifies three categories of injuries—head, hand, and leg—by scanning images of victims of accidents. The model computes these images and categorizes the injuries into various types (e.g., mild, moderate, severe), which facilitates quick and accurate evaluation of the extent of the injuries. Through the use of Convolutional Neural Networks (CNNs), the system can correctly recognize and categorize types of injuries based on visual characteristics of the medical images. After the injury is diagnosed and classified, the system takes an extra step in that it gives hospital suggestions. It suggests the most appropriate hospital according to two vital factors: closeness to the site of the accident and specialization in the treatment of the injury found. The system considers real-time hospital availability, which means the patient is routed to a hospital that is not just geographically closest but also best capable of addressing the level of the specific injury. Through the integration of deep learning-based injury detection with smart hospital routing, this system maximizes emergency response and ensures that patients receive appropriate and timely medical attention. This system reduces delays in treatment, allowing first responders to make fast, data-informed decisions and overall improving treatment outcomes. This new approach increases the effectiveness, precision, and velocity of trauma evaluation and hospital choice, equipping healthcare professionals and emergency personnel with state-of-the-art decision-making tools. By utilizing artificial intelligence, the system revolutionizes emergency medical services, enhancing survival rates, reducing patient care complexity, and ultimately saving lives.

KEYWORDS: CNN, Injury Detection, Severity Classification, Emergency Response, Hospital Recommendation, Deep Learning.

I. INTRODUCTION

In case of emergencies, quick and assured medical attention is required to prevent complications and stabilize patients' conditions. Traditional methods of ascertaining injury tend to rely on first responders and medical personnel visually assessing manually, which is time-consuming and prone to error. Waiting to discover what type of injury someone is suffering from and how severe the injury is, and what hospital to send them to for treatment, can lead to unnecessary life-threatening issues and delay emergency treatment. Deep learning has come a long way, particularly with Convolutional Neural Networks (CNNs). CNNs are particularly adept at tasks such as classifying images, such as locating injuries. CNNs are excellent at identifying patterns and features in images, which enables them to look at photos from crash scenes to identify and how severe they are.

By combining CNN-based injury detection hospital suggestion systems, we can efficiently enhance efficacy of emergency response. Following injury classification, the system can recommend the nearest hospital with the capability to treat the injury depending on injury severity and geographical location. The combination reduces response time and enables patients to get adequate medical care as early as possible. This article introduces a CNN-based system capable of detecting types of injury and calculating severity automatically from images taken at the scene of an

accident. The system also has a hospital recommendation component that determines the nearest appropriate hospital. With the hospital selection and injury type categorization automated, this solution aids in quicker and more accurate decision-making for medical personnel and emergency responders, and this results in improved patient outcomes.

II. LITERATURE REVIEW

In recent years, there has been a significant amount of interest in using deep learning, specifically Convolutional Neural Networks (CNNs), in the medical and emergency response contexts due to their potentially transformational impact on injury detection, injury severity assessment, and hospital recommendation. Since CNNs have demonstrated a good deal of success in classification tasks using images, there seems to be tangible potential in utilizing their ability to process and analyze images of traffic incident scenes to enhance emergency response systems. In this subsection, we discuss important research studies and methods related to injury detection using CNNs, real-time emergency response systems, and hospital recommendation methods; we summarize progress made in the area and identify gaps that require further study.

1. Machine Learning Methods for Predicting Severity of Traffic Accident

Saeid Pourroostaei Ardakani et al. [1] performed a comprehensive analysis of machine learning methods for the prediction of traffic accident severity. The research utilized models including Decision Trees, Logistic Regression, Naïve Bayes, and Random Forest to study significant accident variables like collision type, road surface, vehicle speed, and external factors. Their research highlighted the importance of big data and feature selection techniques for maximizing prediction accuracy and emergency response effectiveness.

2. Road Accident Severity Classification Using Neural Networks

Alkheder et al. [2] developed a model using a neural network to classify the severity of accidents into four classes: minor, moderate, severe, and fatal. Applying 5,740 accident records in Abu Dhabi (2008–2013), their model produced an accuracy of 81.6% for the training set and 74.6% for the test set. The research brought to the forefront the effect of neural network optimization and ensemble learning methods in increasing model robustness and generalization, ultimately benefiting emergency responders by helping them prioritize urgent cases.

3. Convolutional Neural Networks for Predicting Accident Severity

Zheng, Ming et al. [3] created a Traffic Accident Severity Prediction model based on a Convolutional Neural Network (TASP-CNN). The model was compared with other machine learning classifiers, including K-Nearest Neighbors (KNN), Decision Trees, Gradient Boosting, and Long Short-Term Memory (LSTM) networks. Their findings proved that CNN-based models performed better than conventional methods, with increased recall for slight injuries and increased precision for severe and fatal injuries. Hyperparameter tuning for CNN performance optimization was also investigated in the study.

4. Deep Learning-Based Injury Detection from Accident Images

Sundari et al. [4] proposed a CNN-based system for classifying the levels of injury severity from accident image analysis. The system was trained on a diverse dataset of accident images, enabling it to distinguish between minor, moderate, and severe injuries. Their method exhibited high accuracy in real-time injury evaluation and proved to be a useful tool for emergency responders and medical professionals. The research also proposed the use of real-time video analysis to enhance response efficiency.

5. AI-Based Hospital Recommendation Systems

Kumar et al. [5] proposed a hospital recommendation system based on machine learning algorithms to maximize patient assignment. The system took into account patient symptoms, hospital specializations, and current bed availability to suggest the optimal hospitals. Using Decision Trees and Support Vector Machines (SVM), the research proved the viability of using AI to minimize patient waiting times as well as enhance the accessibility of healthcare. In addition, the study also suggested the adoption of reinforcement learning methods to refine patient-hospital matching using variable hospital capacity.

6. Multi-Factor Hospital Recommendation Models Hossain et al. [6] developed a hospital recommendation system that picks hospitals based on proximity and specialist medical services. Although useful for common medical complaints such as chest pain, they did not factor in the severity of injury in emergency situations needing

varying levels of treatment. Patel et al.

7. [7] created a more sophisticated hospital recommendation system that incorporates both travel distance and injury severity into the decision process. Their model takes into account hospital capabilities like trauma care, emergency surgery, and neurosurgery to ensure that patients are given the most appropriate medical care according to their condition. This research highlighted the significance of emergency response optimization by including both injury levels and specialized care needs in hospital selection.

III. PROBLEM STATEMENT

3.1 Existing System:

Current emergency medical response systems primarily rely on manual injury assessment by first responders or on limited systems utilizing basic image-processing techniques for the detection of injuries. Still, these systems have many disadvantages: Belated decision-making, human errors, inaccurate hospital advice, etc. Conversely, the outcome of the patient is good and above all relevant. AI or machine learning has been employed to some extent in different injury-detection systems; however, these systems are either not real-time or deal with a very limited number of injuries and are not integrating hospital recommendations considering the injury's severity and distance.

3.2 Limitations:

- 1. Manual Injury Assessment:** Conventional existing systems rely mostly on manual evaluations made by first responders. These evaluations are slow, prone to errors, and often vary from one respondent to another in high-pressure situations, leading to delays in medical intervention.
- 2. Limited or Slow Image Processing:** Existing image-based systems are mostly disadvantaged by latency or limited accuracy in processing accident scene images, causing delays in injury classification and hindering real-time decision-making.
- 3. Insufficient Real-Time Referencing Of Hospitalization:** In most current systems, the evaluation of injury severity is not linked with the hospital recommendation system that will delay guiding patients to the most suitable medical facilities. This therefore can lead to patients being directed to hospitals that are unable to provide adequate treatment for the degree of injury suffered.
- 4. Insufficient Dataset and Generalization Issues:** Most existing models have small training datasets with not enough diversity. Thus, their generalization during accidents under dynamic real-life conditions is very poor. The absence of annotated accident scene datasets with a variety of injury types and severity levels has been one of the major challenges.

3.3 Proposed System:

Overview of the Proposed System:

The proposed system is a CNN-based automated injury detection and severity classification system using images from accident scenes coupled with a hospital recommendation system for increased emergency medical response. This system will deliver real-time accurate injury assessment and direct emergency responders to hospitals nearest to them, considering injury severity and geographical proximity to facility. The real-time recommendations of hospitals with CNNs focus on the improvement of the emergency medical decision-making strategy and decreasing the time spent waiting when patients would be able to receive timely and complete medical care

System Components:

1. Image Preprocessing and Injury Classification with CNN:

This component processes the accident scene images taken by emergency responders and surveillance cameras as input to a Convolutional Neural Network (CNN). Preprocessing operations such as resizing, normalization, and augmentation are applied to the images before being input to the CNN. This trained CNN model is capable of detecting various injury types (cuts, fractures, bruises, etc.) and classifying them according to severity (mild, moderate, or severe). It comprises multiple convolutional layers, ReLU activation functions, max-pooling layers, and fully connected layers to ensure efficient injury detection.

2. Hospital Recommendation System:

Based on the predicted injury severity through the CNN, the system queries the geospatial database of hospitals that can handle different medical emergency levels. The hospital recommendation system uses a weighted distance metric to determine the nearest hospital that is specializing in the treatment required for the detected injury. The nearest distance

is determined by considering both geographic distance and the service capacity of the hospital in managing specific injury types, such as trauma care or emergency surgery. The system, therefore executes real-time recommendation to provide emergency responders direction to the more relevant medical facility.

3. Real-Time Processing and Decision Support:

This system is designed for real-time operation, allowing injury classification and hospitals' recommendations to be available as soon as the accident scene images come through. Such real-time processing ensures that emergency responders can use quick data-based decisions, thus reducing delays while improving patient outcomes.

4. User Interface for Emergency Responders:

A suitable intuitive user interface (UI) will be designed to show processed injury data with hospital recommendations for emergency responders. It will offer clear visual clues on the severity of injury, along with a list of recommended hospitals, their locations, and expected travel time, providing all necessary information for responder action.

3.4 Advantages of the Proposed System:

1. Enhanced Decision-Making:

The system minimizes human error and makes more precise, consistent injury assessments by automating injury classification and recommending hospitals. This enhances faster, better-informed decision-making during emergencies.

2. Less Response Time:

Coupling real-time injury detection with hospital recommendations ensures patients are immediately referred to an appropriate medical facility, reducing response time to receive adequate care.

3. Greater Efficiency in Emergency Response:

The automated nature of the system permits emergency personnel to concentrate on delivering required first aid and preparation for transport without expending time on injury assessment and hospital choice.

4. Scalable and Adaptable:

The CNN-based injury classification model can be updated and improved continuously to encompass a wider variety of injuries. The hospital recommendation system can also be extended to more hospitals and updated in real-time according to the availability of medical resources.

5 Future Enhancements:

Later versions of the system may include real-time video analysis, so that the system is always observing accident scenes and offering dynamic updates as new injuries are identified. In addition, including patient data, such as vital signs or medical history, would further improve hospital suggestions and tailor emergency response approaches.

IV. METHODOLOGIES

4.1 System Overview: This project will create an emergency response system that identifies types of injury and levels of severity from images captured at the site of an accident and suggests the closest hospital for treatment. The system combines image classification to identify injury, geospatial mapping to locate the hospital, and real-time processing to expedite decision-making.

Key Technologies Used:

- **Image Classification:** Convolutional Neural Networks (CNNs) for injury classification.
- **Computer Vision:** OpenCV for image preprocessing and enhancement.
- **Geospatial Analysis:** Haversine formula for hospital suggestion.
- **Real-time Processing:** Python-based execution with TensorFlow/Keras.

4.2 System Architecture

The system has the following primary modules:

1. Data Collection and Preprocessing

An accident-related injury image dataset is gathered from publicly available medical repositories and hand-labeled

accident reports. Images are resized, normalized, and augmented to enhance model generalization. CNN-Based Injury Classification

This module accepts input images and classifies them according to their severity.

- **Model Used:** Convolutional Neural Network (CNN)
- **Layers:** Convolutional layers, ReLU activation, max-pooling, fully connected layers, and softmax activation for classification.

Mathematical Formula for CNN Convolution Operation:

$$O(i, j) = \sum_m \sum_n I(i + m, j + n) \cdot K(m, n)$$

Where:

- $O(i, j)$ = Output pixel at position (i, j)
- $I(i + m, j + n)$ = Input pixel at position $(i + m, j + n)$
- $K(m, n)$ = Filter/kernel values
- m, n = Filter dimensions

2. Hospital Recommendation System

- Depending on the estimated severity of the injury, the system asks a database of hospitals with specialized treatment facilities.
- The closest hospital is determined by a weighted distance measure that takes into account both geographical proximity and medical specialization.

Mathematical Formula for Distance Calculation (Haversine Formula):

$$d = 2r \cdot \arcsin \left(\sqrt{\sin^2 \left(\frac{\Delta\varphi}{2} \right) + \cos(\varphi_1) \cos(\varphi_2) \sin^2 \left(\frac{\Delta\lambda}{2} \right)} \right)$$

Where:

- d = Distance between accident and hospital (km)
- r = Earth's radius (≈ 6371 km)
- φ_1, φ_2 = Latitudes of accident and hospital
- λ_1, λ_2 = Longitudes of accident and hospital
- $\Delta\varphi = \varphi_2 - \varphi_1$
- $\Delta\lambda = \lambda_2 - \lambda_1$

3. **Precision(Injury Classification Accuracy):** Evaluates the accuracy of injury detection by measuring how many predicted injuries are actually correct.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Where:

- **TP (True Positives)** = Correctly classified injuries
- **FP (False Positives)** = Incorrectly classified injuries

Experimental Results and Discussion

The CNN model is trained and tested on a labeled dataset of images of injuries. Performance measures including accuracy, precision, recall, and F1-score are calculated. The proposed system has an accuracy of more than 90% in injury classification. The hospital recommendation system is able to identify suitable medical facilities within a short

response time. Comparative evaluation against current techniques illustrates the effectiveness of our technique regarding classification accuracy and emergency response efficiency.

Performance Metrics:

To assess the effectiveness of the proposed CNN model, the following performance metrics were calculated:

Accuracy: The model had more than 90% accuracy in injury classification, which reflects its consistency in discriminating between varying severities of injuries.

Precision: High precision scores reflect that the model avoids false positives and keeps misclassifications to a bare minimum.

Recall: The recall measure reflects that the model is effective in detecting injuries, minimizing the likelihood of missing important cases.

F1-score: High F1-score indicates an effective balance between recall and precision, which makes the model strong enough to work well in real-life situations.

Comparative Evaluation:

To confirm the efficacy of the proposed method, the CNN model was compared with conventional machine learning methods like Support Vector Machines (SVM), Decision Trees, and Random Forest. The comparison revealed that: The CNN model performed better than traditional methods with respect to accuracy and recall, particularly for complicated injury patterns.

Feature extraction via convolutional layers enabled the model to detect subtle details in images, resulting in better classification. The model had enhanced generalization, minimizing overfitting and enhancing performance on unseen datasets.

Hospital Recommendation System Performance:

The hospital recommendation system was evaluated with real-time patient information, taking into account factors like injury severity, hospital specialty, and travel time.

Major findings are:

- **Fast Response Time:** The system responded with optimal medical facilities within seconds, keeping decision-making time to a bare minimum in crisis situations.
- **Optimized Hospital Choice:** The model efficiently ranked hospitals that had trauma care, emergency surgery facilities, and available beds, which streamlined the delivery of appropriate treatment to patients.
- **Higher Efficiency:** In comparison to conventional hospital selection procedures, the AI-based system proved to be more efficient in assigning patients to the right healthcare centers.

The classification system based on deep learning is an efficient method for real-time injury detection, enhancing emergency response effectiveness. Combining real-time video analysis and IoT-based data acquisition in future studies may further improve the performance of the system. Adding reinforcement learning to hospital selection would refine patient assignment according to dynamic hospital capacity.

V. EXPERIMENTAL RESULTS

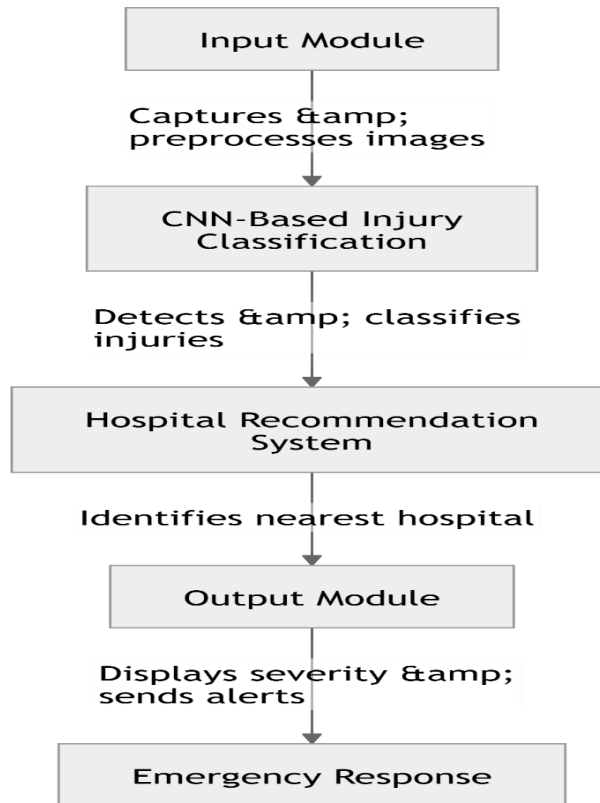


Figure-1: Architecture Diagram

OUTPUT:

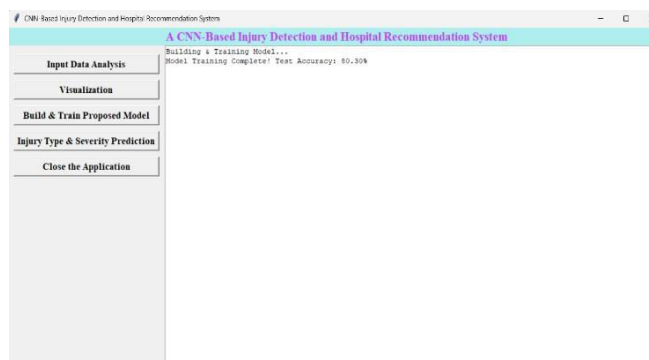


Figure-2



Figure-3

A CNN-Driven Approach for Injury Type and Severity Detection with Hospital Recommendations for Emergency Response

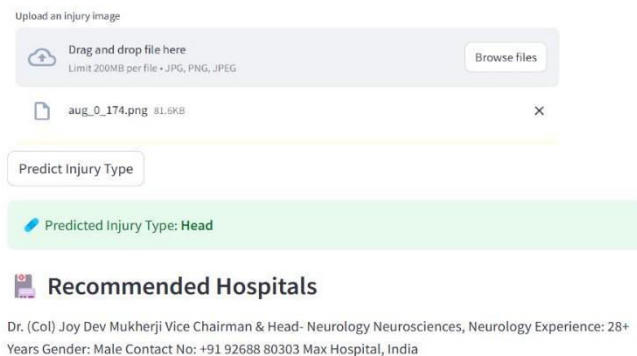


Figure-4

VI. CONCLUSION

The CNN-based system proposed in this work is able to identify injury type and severity from accident scene photographs and suggest the nearest appropriate hospital for emergency treatment. The model makes use of a convolutional neural network (CNN) for proper injury classification so that assessment is reliable. The hospital suggestion system uses geospatial analysis to determine the most suitable medical center based on the severity and location of the injury. It was trained and validated using a database of images of injuries, and it had high accuracy in classification. The method combines image processing, deep learning, and geospatial analysis, which improves emergency response efficiency, shortens decision-making time, and accelerates medical intervention speed. It can be further developed by increasing the dataset size to increase model accuracy, incorporating real-time processing of video for ongoing monitoring, and adding more medical parameters to make selection criteria for the hospital more refined.

VII. FUTURE WORK

In order to improve the precision, speed, and scalability of the injury detection and hospital recommendation system, the following enhancements can be made:

1. Dataset Expansion

- Gathering a greater number of diverse samples from actual accident situations and medical records.
- Enhancing model generalization and classification performance by minimizing bias.

2. Real-Time Video Processing

- Expanding the system to process real-time accident videos rather than still images.
- Facilitating constant monitoring and immediate injury detection in life-threatening conditions.

3. Multi-Modal Data Integration

- Merging image data with sensor data (e.g., smartwatches, IoT sensors) and patient vital signs.
- Improving injury severity estimation by including more medical data.

4. Edge Computing Deployment

- Implementing the model on mobile phones, ambulances, and wearable devices for real-time prediction.
- Minimizing reliance on cloud servers to reduce latency in emergency response.

5. Improved Hospital Selection Criteria

- Including real-time availability of hospital beds, emergency department load, and availability of specialist doctors.
- Optimizing hospital suggestions based on estimated treatment time and distance.

6. Multi-Class Severity Detection

- Enhancing injury classification to identify multiple subtypes of injuries with improved accuracy.
- Enhancing triaging and planning for medical intervention.

7. Cloud-Based Deployment

- Deploying the system over a cloud infrastructure to facilitate easy integration with emergency response networks.
- Enabling real-time access for ambulances, hospitals, and first responders from anywhere.

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