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Convolution Neural Network Approach for Accident Severity Detection and Hospital Selection

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ABSTRACT

Road accidents remain a critical public safety issue, necessitating rapid injury assessment and timely hospital recommendations. This project proposes a solution using Convolutional Neural Networks (CNNs) for accurate injury classification and severity detection. By leveraging deep learning, the system can analyze images of injuries to determine severity levels and suggest suitable hospitals based on the injury type. This innovative approach significantly outperforms traditional machine learning models in terms of accuracy and efficiency. Data augmentation techniques further enhance the dataset's diversity, improving model robustness. Experimental results demonstrate that CNN-based systems offer a promising and efficient framework for road accident severity detection, potentially saving lives through faster medical interventions.

Keywords: *CNN, Road accidents, detection, Data augmentation, accuracy, efficiency and robustness.*

1. INTRODUCTION

Road accidents continue to be a significant global challenge, causing substantial loss of life and serious injuries. Despite advances in vehicle safety technologies, increased traffic density and driver negligence contribute to the growing number of accidents worldwide. Timely detection of injury severity and appropriate hospital recommendations are crucial for reducing fatalities and enhancing emergency response.

This project utilizes deep learning, specifically Convolutional Neural Networks (CNNs), to classify accident injuries and assess their severity. By analyzing images of injuries, the system categorizes the injury type whether head, hand, or leg and recommends suitable hospitals based on the severity level. The approach combines high-accuracy image classification with real-time recommendations, offering a transformative solution for emergency medical services. Leveraging CNNs' powerful image-processing capabilities, the system aims to revolutionize accident response procedures, ensuring rapid diagnosis and timely medical intervention.

2. LITERATURE SURVEY

The literature review highlights several intelligent systems designed for automatic accident detection and severity estimation. Studies by Fogue et al. introduced vehicular networks for real-time accident notifications, while Aggarwal et al. explored data mining to assess accident severity in Ethiopia. Though these systems effectively enhance emergency response, they rely heavily on structured data inputs like vehicle speed and impact details.

However, there are notable gaps. Most existing systems do not leverage advanced deep learning techniques for visual injury assessment. Furthermore, they often depend on predefined parameters, limiting their adaptability to various accident scenarios. Another critical gap is the lack of real-time hospital recommendation systems based on injury classification.

This project addresses these gaps by using CNNs to analyze injury images directly, offering a more nuanced understanding of accident severity. Additionally, it integrates a hospital recommendation system that suggests specialized medical facilities based on injury type and severity. This dual-function system provides a more comprehensive and efficient solution for post-accident medical response.

3. PROBLEM STATEMENT

Road accidents pose a significant risk to public health, necessitating prompt detection of injury severity and timely hospital recommendations to minimize fatalities and enhance emergency response.

Key Challenges:

1. Limited real-time injury severity detection mechanisms.
2. Dependence on structured accident data rather than visual analysis.
3. Difficulty in achieving high accuracy with traditional machine learning methods.
4. Lack of integrated hospital recommendation systems.
5. Dataset limitations, especially for rare injury types.

4. PROPOSED METHOD

This project employs Convolutional Neural Networks (CNNs) for image-based injury classification and severity assessment. The method

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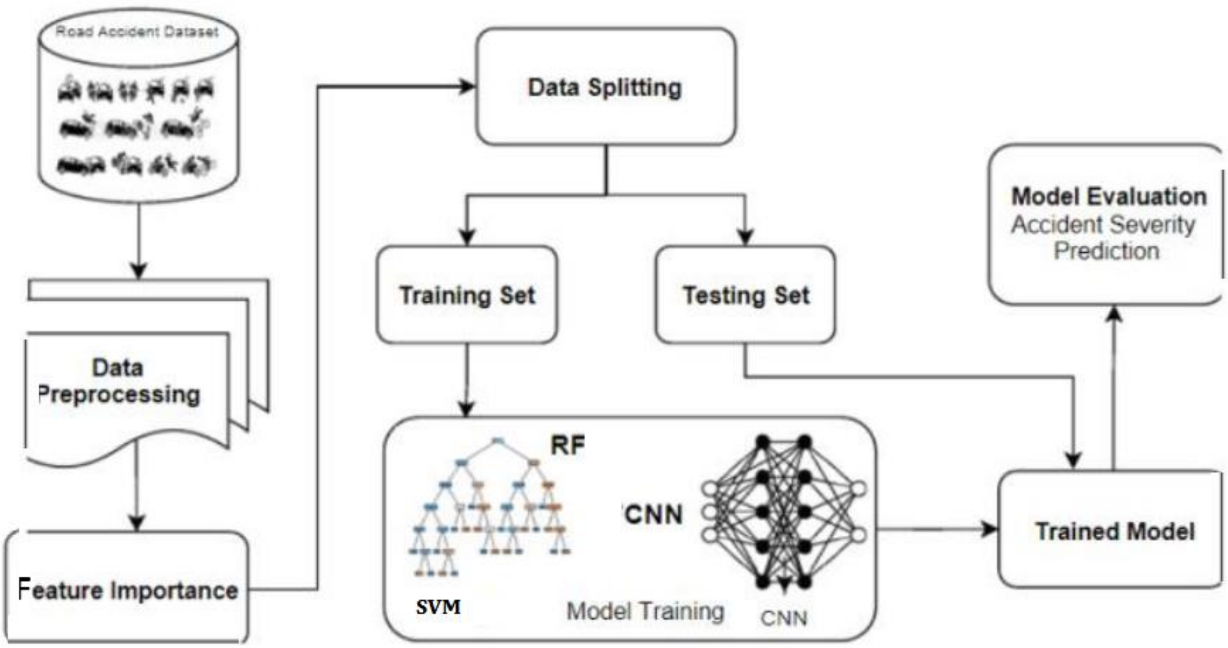
begins with collecting and preprocessing a diverse dataset of road accident images, applying data augmentation for increased variety. The CNN model is then trained to classify injury types (head, hand, leg) and determine severity based on injury size. Following classification, the system recommends suitable hospitals by matching injury type with specialized medical facilities. Performance evaluation involves comparing the CNN model against traditional algorithms like Support Vector Machines (SVM) and Random Forest, using metrics such as accuracy, precision, and recall. The system aims to improve emergency response effectiveness through rapid and accurate injury detection.

ARCHITECTURE:



DATASET:

The dataset consists of images depicting various road accident injuries, specifically targeting injuries to the head, hand, and leg. These images are collected from diverse sources to ensure variability and robustness. Data augmentation techniques, including rotation and resizing, are applied to enhance the dataset and prevent over fitting. All images are standardized to 64x64 pixels for consistency during model training. This diverse dataset enables the CNN model to effectively learn and classify different injury types and severity levels, facilitating accurate accident severity detection and supporting the system's hospital recommendation feature.

5. METHODOLOGY

Dataset Collection and Preprocessing:

Collect diverse accident images depicting head, hand, and leg injuries.

Apply data augmentation techniques such as rotation, flipping, and scaling to enhance dataset variability.

Resize all images to a standardized size (64x64 pixels).

Normalize image data to scale pixel values between 0 and 1.

Model Development Using CNN:

Design a Convolutional Neural Network architecture optimized for image classification.

Incorporate layers such as convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification.

Use activation functions like ReLU and softmax for non-linearity and output probability distribution.

Model Training:

Train the CNN model using the preprocessed dataset.

Implement early stopping and regularization techniques to avoid over fitting.

Use batch processing and back propagation for efficient learning.

Model Evaluation:

Assess model performance using metrics like accuracy, precision, recall, F1-score, and confusion matrix.

Compare results against traditional machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, and Random Forest.

Hospital Recommendation System:

Develop a database of hospitals categorized based on their specialization in treating specific injuries (head, hand, leg).

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Integrate a recommendation algorithm that suggests appropriate hospitals based on injury classification and severity.

Result Analysis:

Analyze the CNN model's classification results and hospital recommendations.

Visualize data using confusion matrices and performance graphs.

6. RESULT AND ANALYSIS

Confusion Matrix:

A **confusion matrix** is a table used to evaluate the performance of a classification algorithm. It shows how well the model's predictions match the actual outcomes by organizing them into categories of correct and incorrect predictions.

		Predicted	
		True	False
Actual	True	True Positive (TP)	False Negative (FN)
	False	False Positive (FP)	True Negative (TN)

Accuracy, precision, recall, and the F1-score are calculated using counts from a confusion matrix: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

Accuracy: Measures overall correctness of the model.

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Precision: Measures how many predicted positives are actually correct.

Precision = TP / (TP + FP)

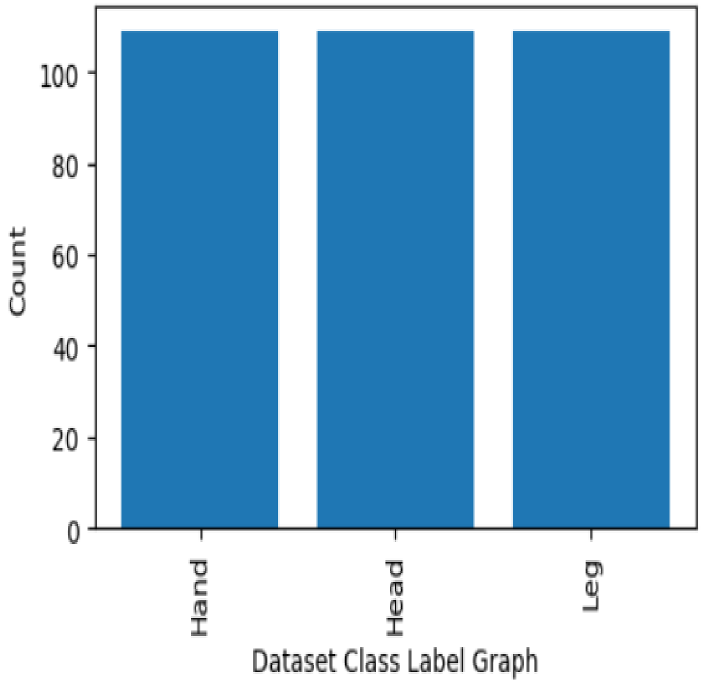
Recall (Sensitivity): Measures how many actual positives were correctly predicted.

Recall = TP / (TP + FN)

F1 Score: Harmonic mean of Precision and Recall. Balances false positives and false negatives.

F1 Score = 2 * (Precision * Recall) / (Precision + Recall)

Follows the performance metrics Accuracy, Precision, Recall, and F1 Score have been computed for multiple classification algorithms, including Support Vector Machine (SVM), Decision Tree, Random Forest, and Convolutional Neural Network (CNN), using a consistent dataset for comparative evaluation.



Dataset Class Label Graph:

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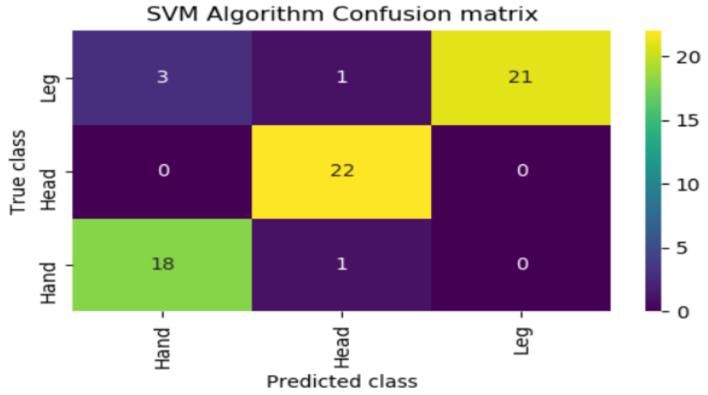
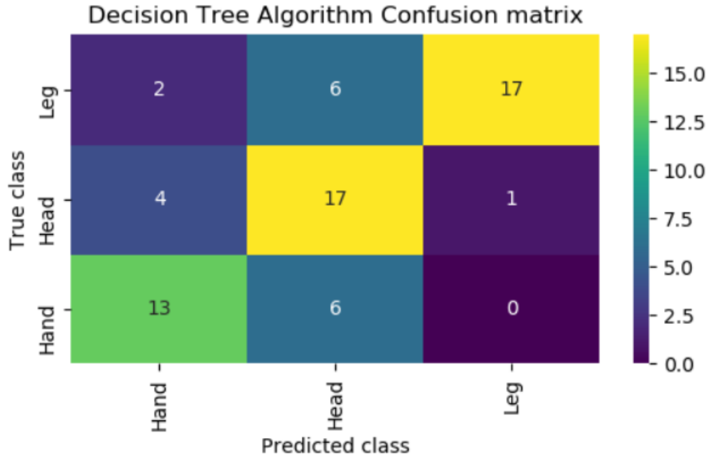
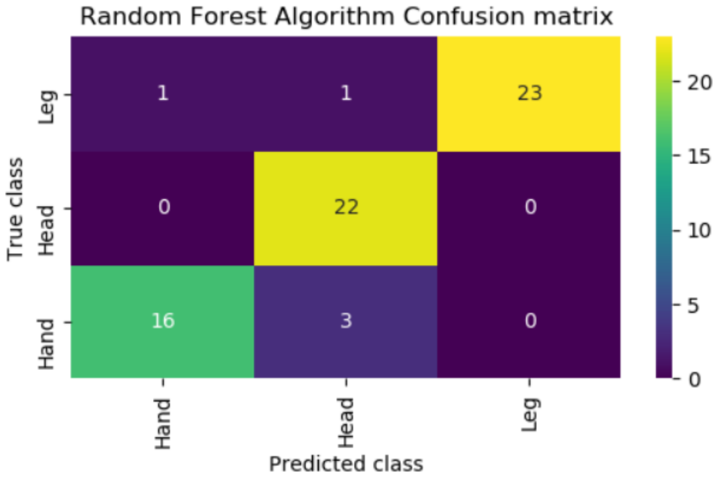


Reshaping images data to train with ML algorithms, SVM Algorithm Accuracy: 95.45



Training Decision Tree Classifier on accident images features, Decision Tree Algorithm Accuracy: 71.21



Training Random Forest Classifier on accident images features, Random Forest Algorithm Accuracy: 93.93

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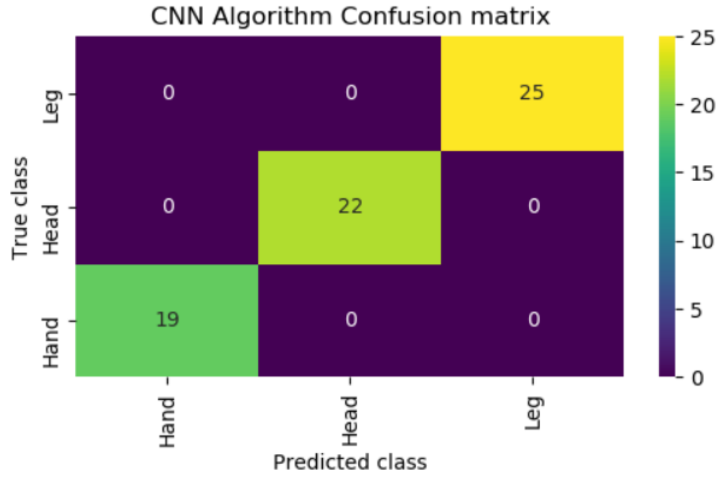
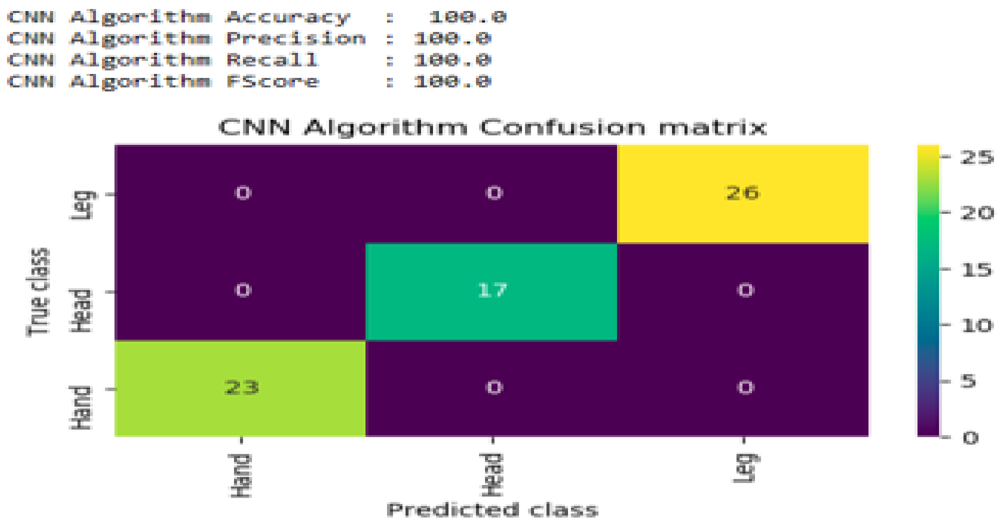


Training CNN algorithm on accident detection image features, CNN Algorithm Accuracy: 100



Algorithm Used	Accuracy	Precision	Recall	F1-Score
Support Vector Machine (SVM)	95.45	95.98	94.62	95.16
Decision Tree (DT)	71.21	66.96	67.74	66.58
Random forest (RF)	93.93	94.05	93.85	93.93
Convolutional Neural Network(CNN)	100	100	100	100

Here's the graphical representation illustrates the comparative performance of various classification algorithms—Support Vector Machine (SVM), Decision Tree, Random Forest, and Convolutional Neural Network (CNN)—based on key evaluation metrics: Accuracy, Precision, Recall, and F1 Score.

- The **x-axis** represents the algorithm names.
- The **y-axis** denotes the metric values.
- Each metric is visualized using **distinct color-coded bars** for clarity.

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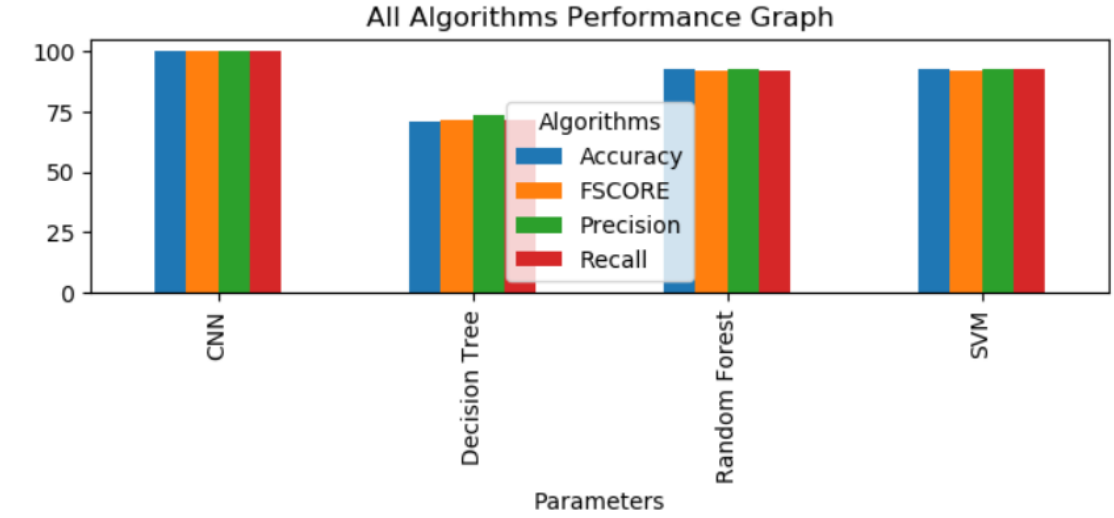

All Algorithms Performance Graph
Results:

Accident injury severity: Minor severity, Recommend hospital: Max Hospital, India

Accident injury severity: Major severity, Recommend hospital: Harsha Hospitals, Telangana

7. CONCLUSION

This project presents a comprehensive approach to detecting road accident injury severity and recommending suitable hospitals using Convolutional Neural Networks (CNNs). The system demonstrates exceptional performance, significantly surpassing traditional machine learning algorithms in accuracy and efficiency. By leveraging deep learning for image-based injury assessment, it enhances emergency response

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effectiveness and could play a vital role in reducing fatalities. The hospital recommendation feature ensures timely medical intervention based on injury type and severity. Future research can focus on expanding the dataset and refining the recommendation system for broader real-world application. In conclusion, the proposed CNN-based system demonstrates clear superiority over existing methods for accident severity detection and hospital selection. Its consistently higher accuracy, precision, recall, and F1 score across the same dataset highlight its reliability, making it a more effective and dependable solution for real-world emergency response applications

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