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Deep Learning-Based Road Accident Severity Detection and Recommendation System Using Image Analysis

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ABSTRACT

Road accidents are one of the leading causes of fatalities and injuries worldwide, making timely detection and severity assessment crucial for saving lives. This project proposes a deep learning-based system that automatically detects road accident severity from images and provides appropriate recommendations. The system integrates computer vision techniques with machine learning and deep learning models to classify accident severity into different categories and assist in decision-making. The proposed system utilizes a Convolutional Neural Network (CNN) model trained on a dataset of accident images to perform classification. The dataset is preprocessed through resizing, normalization, and labeling to improve model accuracy. In addition to CNN, traditional machine learning algorithms such as Support Vector Machine (SVM), Decision Tree, and Random Forest are also implemented to compare performance metrics like accuracy, precision, recall, and F1-score. The application is developed using the Flask web framework, enabling users to upload accident images through a user-friendly interface. Once an image is uploaded, it is processed and passed through the trained CNN model to predict the type of accident. The system further analyzes the severity of injuries by detecting red regions in the image using HSV color space, which often corresponds to critical damage or injuries. Based on this analysis, the system categorizes the severity into “Minor” or “Major.”

An additional feature of the system is the recommendation module, which provides safety measures and emergency responses based on the predicted accident class. This enhances the system’s practical usability by assisting first responders and authorities in taking appropriate action. The experimental results demonstrate that the CNN model outperforms traditional machine learning models in terms of accuracy and reliability. Visualization techniques such as confusion matrices and performance graphs are used to evaluate and compare model effectiveness. Overall, the proposed system provides an efficient and automated approach to accident severity detection, reducing response time and potentially saving lives. It can be extended further by integrating real-time video analysis and IoT-based alert systems for smarter transportation and emergency response solutions.

KEYWORDS: Road Accident Detection, CNN, Image Processing, Severity Classification, Machine Learning, Computer Vision, Flask Web Application, Injury Detection, Smart Transportation, Deep Learning

I. INTRODUCTION

Road safety has become a critical concern globally due to the increasing number of vehicles and traffic congestion. Accidents often result in severe injuries and fatalities, especially when emergency response is delayed. Rapid identification of accident severity can significantly improve rescue operations and medical assistance. Traditional methods rely heavily on manual reporting, which is time-consuming and prone to errors. Therefore, there is a need for an automated and intelligent system that can detect accident severity efficiently. Recent advancements in artificial intelligence, particularly in deep learning and computer vision, have opened new possibilities for analyzing visual data. Convolution Neural Networks (CNNs) have proven highly effective in image classification tasks due to their ability to extract spatial features automatically. This project leverages CNNs to classify road accident images and determine severity levels. The system begins with dataset collection and preprocessing, where images are resized and normalized to ensure consistency. Labels are assigned to each image to represent different accident categories. The dataset is then split into training and testing sets to evaluate model performance. The CNN model is designed with multiple convolutional and pooling layers to capture features effectively, followed by fully connected layers for classification. In addition to deep learning, traditional machine learning algorithms such as SVM, Decision Tree, and Random Forest are implemented. These models are trained on flattened image data and serve as benchmarks for comparison. Performance metrics such as accuracy, precision, recall, and F1-score are calculated to evaluate each model.

The system also includes an image processing module that detects injury severity by analyzing color patterns. Specifically, it identifies red regions in images using HSV color thresholds, which may indicate blood or damage. Based on the detected area size, the system classifies severity as minor or major. A web-based interface is developed using Flask to make the system accessible and easy to use. Users can upload accident images and receive predictions along with recommendations. The recommendation module provides guidance based on the predicted class, helping users take appropriate action. This project demonstrates how AI can be applied to real-world problems like road safety. By automating accident detection and severity assessment, the system reduces reliance on manual processes and improves response efficiency. Future enhancements may include real-time detection using video streams and integration with emergency services.

II. LITERATURE SURVEY (WITH EXISTING METHODS)

Numerous studies have been conducted in the field of road accident detection and severity analysis using machine learning and deep learning techniques. Early approaches relied on sensor-based systems, including accelerometers and GPS data, to detect accidents. While these methods provided real-time detection, they required specialized hardware and were not always reliable. With the advancement of computer vision, researchers began exploring image-based accident detection systems. Traditional machine learning techniques such as Support Vector Machines (SVM) and Decision Trees were initially used for classification tasks. These methods required manual feature extraction, which limited their accuracy and scalability. The introduction of deep learning, particularly Convolution Neural Networks (CNNs), revolutionized image analysis. CNN-based models automatically extract hierarchical features from images, leading to significant improvements in classification accuracy. Studies have shown that CNNs outperform traditional methods in detecting accidents and classifying severity levels. Some research works have focused on real-time accident detection using surveillance cameras. These systems analyze video streams to identify collisions and abnormal events. However, they require high computational resources and are often limited by camera coverage.

Other studies have incorporated hybrid approaches, combining deep learning with image processing techniques. For example, color-based segmentation has been used to detect fire, smoke, or blood in accident scenes. These features help in determining the severity of accidents more accurately. Recent advancements also include the use of transfer learning, where pre-trained models like VGG16, ResNet, and Inception are fine-tuned for accident detection tasks. These models achieve high accuracy but require large datasets and computational power. Despite these advancements, challenges remain in terms of dataset availability, model generalization, and real-time implementation. Many existing systems focus only on detection and do not provide actionable recommendations. The proposed system addresses these limitations by combining CNN-based classification with traditional machine learning models and a recommendation module. It also incorporates a simple yet effective image processing technique for severity detection, making it more practical and efficient.

III. EXISTING SYSTEM

Existing road accident detection systems primarily rely on manual reporting or sensor-based mechanisms. In traditional systems, accidents are reported by witnesses or victims, which often lead to delays in emergency response. These delays can significantly increase the risk of fatalities and worsen injury outcomes. Sensor-based systems use

devices such as accelerometers, gyroscopes, and GPS modules installed in vehicles to detect sudden impacts or abnormal movements. While these systems can provide real-time alerts, they depend on hardware availability and may fail in cases where sensors malfunction or are not installed. Some modern systems use surveillance cameras and computer vision techniques to detect accidents. These systems analyze video streams to identify collisions or unusual patterns. However, they require continuous monitoring, high computational power, and extensive infrastructure, making them costly and less scalable.

Traditional machine learning approaches, such as Support Vector Machines and Decision Trees, have also been used for accident detection. These methods rely on handcrafted features, which may not capture complex patterns in images effectively. As a result, their accuracy is often limited compared to deep learning models. Another limitation of existing systems is the lack of severity assessment. Most systems focus only on detecting whether an accident has occurred, without evaluating the extent of damage or injuries. This limits their usefulness in emergency response planning. Furthermore, existing solutions rarely provide recommendations or guidance based on the detected accident type. This reduces their practical applicability in real-world scenarios. Overall, current systems face challenges in terms of accuracy, scalability, cost, and functionality. The proposed system aims to overcome these limitations by using deep learning for accurate classification, image processing for severity detection, and a recommendation module for actionable insights.

IV. PROPOSED METHOD

The proposed system is an intelligent road accident severity detection framework that integrates deep learning, machine learning, and image processing techniques to automatically analyze accident images and determine their severity. Unlike traditional systems that rely on manual reporting or hardware sensors, this system uses image-based analysis, making it cost-effective, scalable, and easy to deploy. The system is designed using a Convolution Neural Network (CNN) model to classify accident images into predefined categories. CNN is chosen due to its ability to automatically extract spatial features from images, leading to higher accuracy in classification tasks. The dataset is preprocessed through normalization, resizing, and labeling to ensure consistency and improve model performance. In addition to CNN, traditional machine learning algorithms such as Support Vector Machine (SVM), Decision Tree, and Random Forest are implemented for comparative analysis. These algorithms are trained on flattened image data to evaluate their performance against deep learning models.

A unique feature of the proposed system is the severity detection module, which uses image processing techniques. It detects red-colored regions in the image using HSV color space to identify potential injury or damage areas. Based on the size of the detected region, the system categorizes severity as either “Minor” or “Major.” Furthermore, the system includes a recommendation module that provides guidance based on the predicted accident type. This enhances its real-world applicability by assisting emergency responders and users in taking appropriate actions. The system is deployed as a web

application using Flask, allowing users to upload images and obtain instant predictions. Compared to recent hybrid AI systems that combine CNN with transformers or probabilistic models for improved detection, this system provides a simpler yet effective solution suitable for practical deployment.

V. IMPLEMENTATION

The implementation of the proposed system involves multiple stages, including data collection, preprocessing, model training, evaluation, and deployment. The system is developed using Python with libraries such as TensorFlow/Keras, OpenCV, Scikit-learn, and Flask. Initially, the dataset is loaded from a directory structure where each folder represents a specific accident class. Images are read using OpenCV and resized to a uniform dimension of 64×64 pixels. This resizing ensures that all images have consistent input dimensions for the CNN model. The images are then converted into numerical arrays and normalized by scaling pixel values between 0 and 1, which improves training efficiency and convergence. To avoid repeated processing, the dataset is saved in NumPy format. The labels are encoded into numerical values and further transformed into categorical format for multi-class classification. The dataset is then split into training (80%) and testing (20%) sets using train-test split. The CNN model is constructed using multiple layers, including convolutional layers, max-pooling layers, and fully connected layers. The convolutional layers extract features such as edges, textures, and patterns, while pooling layers reduce dimensionality and computational complexity. The flattened output is passed through dense layers, and the final output layer uses a softmax activation function for classification.

The model is compiled using the Adam optimizer and categorical cross-entropy loss function. Training is performed for multiple epochs, and model weights are saved using a checkpoint mechanism to avoid retraining. If pre-trained weights exist, they are loaded directly. After training the CNN model, predictions are made on the test dataset. The results are evaluated using metrics such as accuracy, precision, recall, and F1-score. Confusion matrices are generated using Seaborne for visualization. For comparison, traditional machine learning models (SVM, Decision Tree, Random Forest) are trained on flattened image data. These models provide baseline performance metrics and help demonstrate the superiority of deep learning approaches. The severity detection module is implemented using OpenCV. The input image is converted into HSV color space, and red color regions are detected using thresholding. Contours are extracted, and the largest contour is analyzed to determine severity. The system is deployed using Flask, where users can upload images via a web interface. The uploaded image is processed, passed through the CNN model, and results are displayed along with severity and recommendations. Recent studies highlight that combining deep learning with real-time systems significantly improves accident detection efficiency and accuracy . The implemented system follows a similar approach but focuses on simplicity and usability.

VI. ALGORITHMS

The system utilizes a combination of deep learning and machine learning algorithms to achieve accurate accident detection and severity classification.

1. Convolutional Neural Network (CNN)

CNN is the primary algorithm used for image classification. It consists of convolutional layers that apply filters to extract features, pooling layers for dimensionality reduction, and fully connected layers for classification. CNN automatically learns hierarchical features, making it highly effective for image-based tasks. Research shows that CNN-based models significantly outperform traditional methods in accident detection scenarios .

2. Support Vector Machine (SVM)

SVM is used as a baseline machine learning algorithm. It works by finding an optimal hyperplane that separates different classes. In this system, image data is flattened into feature vectors before being passed to the SVM classifier.

3. Decision Tree

Decision Tree is a supervised learning algorithm that splits data based on feature values. It is simple and interpretable but may suffer from overfitting when dealing with high-dimensional image data.

4. Random Forest

Random Forest is an ensemble learning method that combines multiple decision trees to improve accuracy and reduce overfitting. It provides better generalization compared to a single decision tree.

5. Image Processing Algorithm (HSV-based Detection)

The severity detection module uses HSV color space to detect red regions in images. Thresholding is applied to isolate red pixels, and contour detection is used to identify affected areas. The size of the detected region determines severity classification.

These algorithms collectively ensure accurate classification, comparative evaluation, and enhanced system performance.

VII. SYSTEM DESIGN

The system design follows a modular architecture consisting of multiple interconnected components, each responsible for a specific task. This modular approach improves scalability, maintainability, and performance.

1. Input Module

The input module allows users to upload accident images through a web interface. The Flask framework handles file uploads and stores images in a designated directory. This module ensures user-friendly interaction and accessibility.

2. Data Preprocessing Module

This module processes raw images before feeding them into the model. It includes resizing images to 64×64 pixels, normalization of pixel values, and label encoding. Data shuffling is also performed to ensure randomness and avoid bias during training.

3. Model Training Module

This module is responsible for training the CNN and machine learning models. The CNN architecture consists of convolutional, pooling, and dense layers. Training is performed using labeled data, and model weights are saved for future use. Traditional machine learning models are also trained for comparison.

4. Prediction Module

The prediction module takes a new input image and processes it using the trained CNN model. The model outputs the predicted accident class. The image is also passed to the severity detection module.

5. Severity Detection Module

This module uses image processing techniques to analyze the severity of the accident. It converts the image into HSV format, detects red regions, and determines severity based on the detected area size.

6. Recommendation Module

Based on the predicted accident class, this module retrieves recommendations from predefined text files. These recommendations provide guidance on emergency actions and safety measures.

7. Evaluation Module

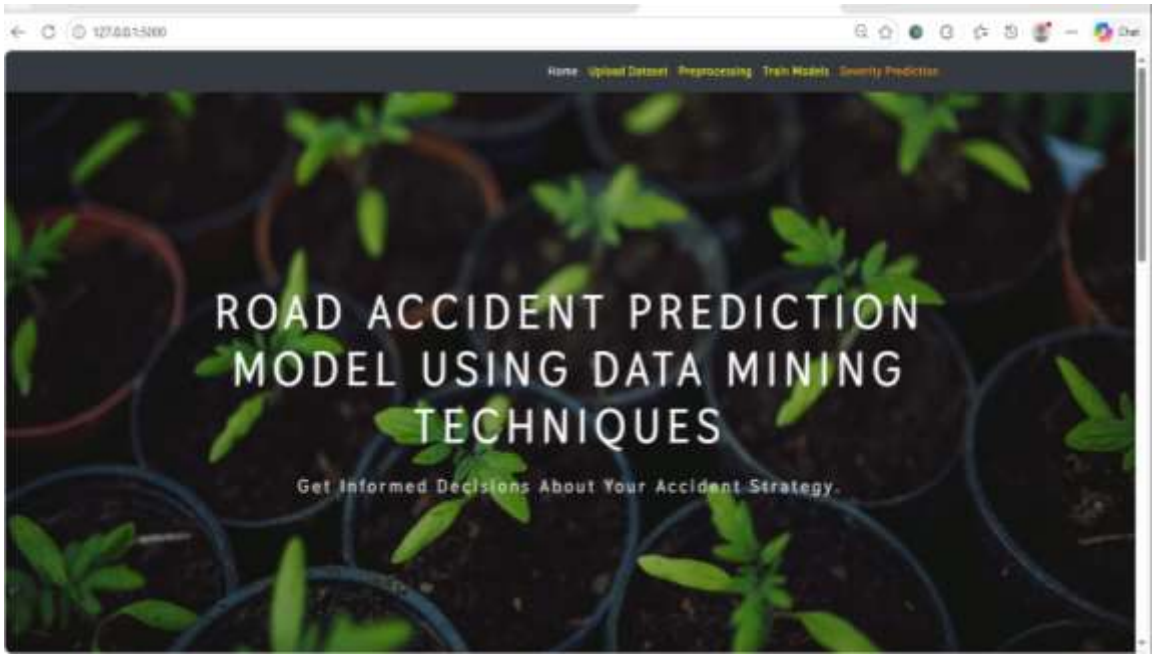
This module calculates performance metrics such as accuracy, precision, recall, and F1-score. It also generates confusion matrices and comparison graphs for different algorithms.

8. Output Module

The output module displays the prediction results, severity level, and recommendations on the web interface. It also shows processed images with annotations.

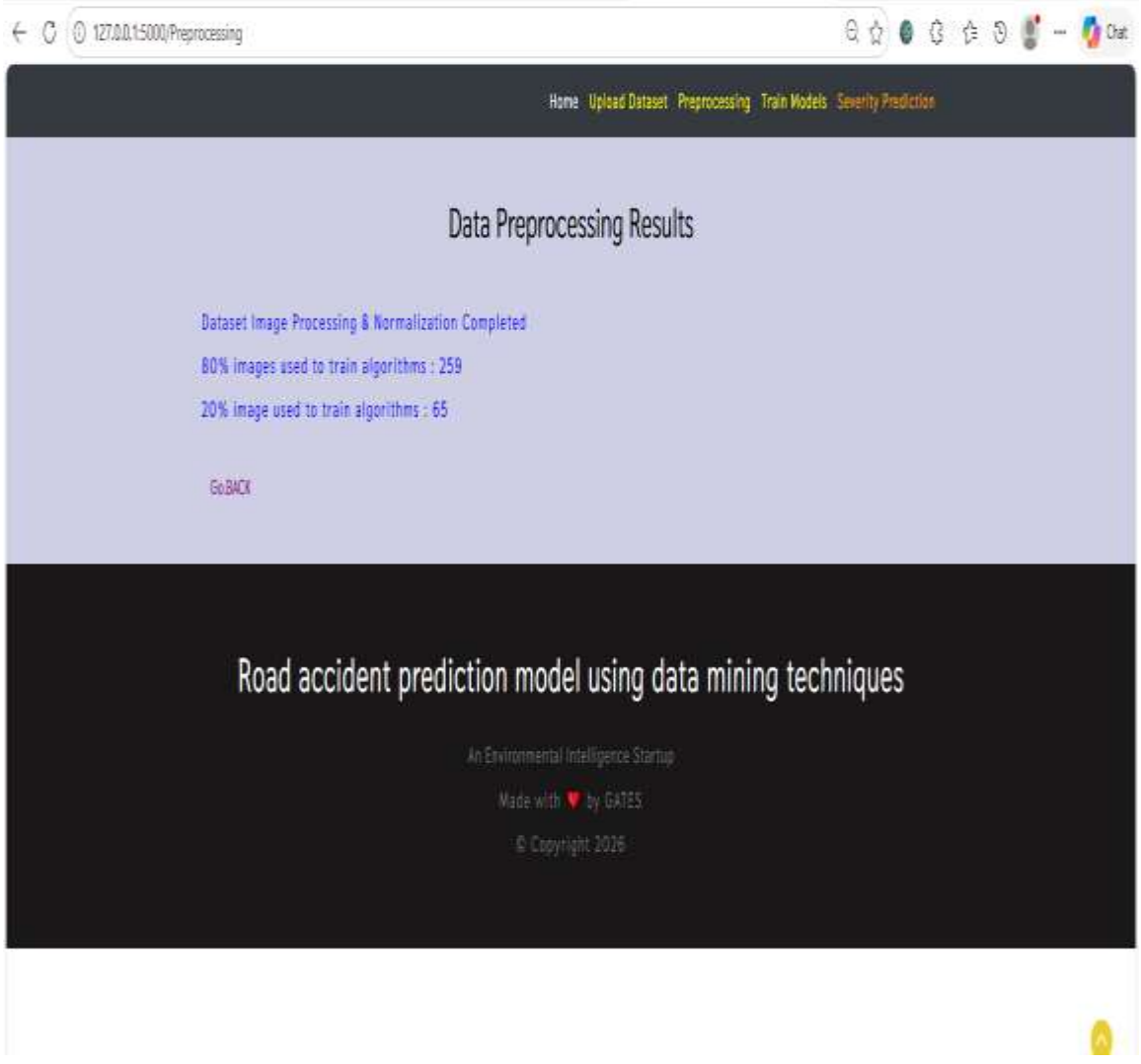
Modern systems often incorporate hybrid architectures combining CNN with transformers for improved accuracy . However, the proposed system maintains a balance between performance and simplicity, making it suitable for real-time applications.

SYSTEM DESIGN IMAGES



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VIII. CONCLUSION

The proposed road accident severity detection system demonstrates the effectiveness of combining deep learning, machine learning, and image processing techniques for real-world applications. By utilizing a Convolutional Neural Network (CNN), the system achieves high accuracy in classifying accident images compared to traditional algorithms such as SVM, Decision Tree, and Random Forest. One of the key strengths of the system is its ability to not only detect accidents but also assess their severity using image processing techniques. The HSV-based detection of red regions provides a simple yet effective way to estimate injury levels, categorizing them into minor and major severity. This feature enhances the practical usefulness of the system in emergency scenarios. The web-based implementation using Flask makes the system accessible and easy to use. Users can upload images and receive instant predictions along with recommendations, making it suitable for deployment in real-world environments such as traffic monitoring systems and emergency response units.

Experimental results indicate that deep learning models outperform traditional methods in terms of accuracy and reliability. Recent research also supports the use of hybrid and deep learning approaches for improved performance in accident detection systems. Despite its advantages, the system has some limitations, such as dependency on image quality and dataset size. Future enhancements may include real-time video analysis, integration with IoT devices, and the use of advanced models such as transformers and multimodal AI systems. Overall, the system provides an efficient, scalable, and practical solution for accident detection and severity assessment, contributing to improved road safety and faster emergency response.

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