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Insurance amount prediction based on accidental car damage level using AI

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Abstract

Accurately estimating insurance payouts for car damage is crucial for fair and efficient claim processing. This project uses Convolutional Neural Networks (CNNs) to predict insurance amounts based on vehicle damage images. The system combines visual features extracted by CNNs with structured data like vehicle details and repair costs to improve prediction accuracy. Data augmentation techniques enhance model performance and generalization. This AI-driven approach automates damage assessment, reduces fraud, and streamlines the insurance claim process.

Keywords: A CNN-based image classification system was developed to detect the severity of car damage from images

Introduction

For the insurance sector to ensure equitable, open, and effective claim processing, it is essential to forecast the claim amount based on the extent of Traditional assessment methods are time-consuming, susceptible to human error, and often constrained by limited data, leading to potential inaccuracies. With the advancement of artificial intelligence, deep learning techniques such as Convolutional Neural Networks (CNNs) offer a powerful solution for automating damage assessment and insurance amount estimation. This project proposes the use of CNNs to analyze car damage images and predict the corresponding insurance claim amounts. A regression model is used to estimate the insurance payout based on these features. By leveraging CNNs for feature extraction and predictive analysis, this AI-driven approach streamlines the claims process, improves accuracy, reduces fraud, and ensures consistent insurance evaluations, making claim settlements faster and more reliable.

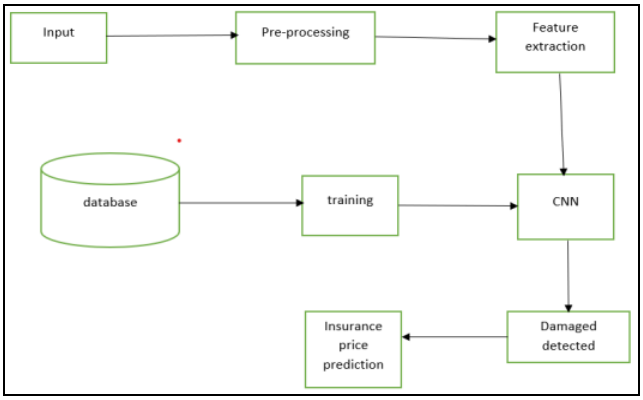

Fig 1: System Architecture

Literature Review

Numerous approaches have been explored in the domain of automated vehicle damage analysis. Van Ruitenbeek *et al*. [1] demonstrated CNNs for vehicle damage classification. Parhizkar *et al*. [3] used deep learning for detecting vehicle surface damage. GANs, introduced by Goodfellow *et al*., are a recent innovation allowing effective dataset augmentation.

Proposed System

The system integrates two AI models:

- **CNN for Classification:** Trained to classify damage severity (normal, minor, moderate, severe).
- **GAN for Augmentation:** Increases training data diversity by generating synthetic damage images.
- **CNN Architecture:** Includes Conv2D, MaxPooling, ReLU activation, Dropout, and fully connected layers.

Existing System: Machine learning models like Random Forests, Support Vector Machines (SVM), and Decision Trees are used in current insurance claim systems to estimate damage and forecast claim amounts. To determine the cost of repairs, these models use characteristics taken from photos of auto damage, such as the make and extent of the damage. However, because these algorithms rely on labeled data, they have trouble generalizing to different damage circumstances. Furthermore, complex patterns in photographs are difficult for typical machine learning models to recognize, which results in inaccurate results

Accuracy

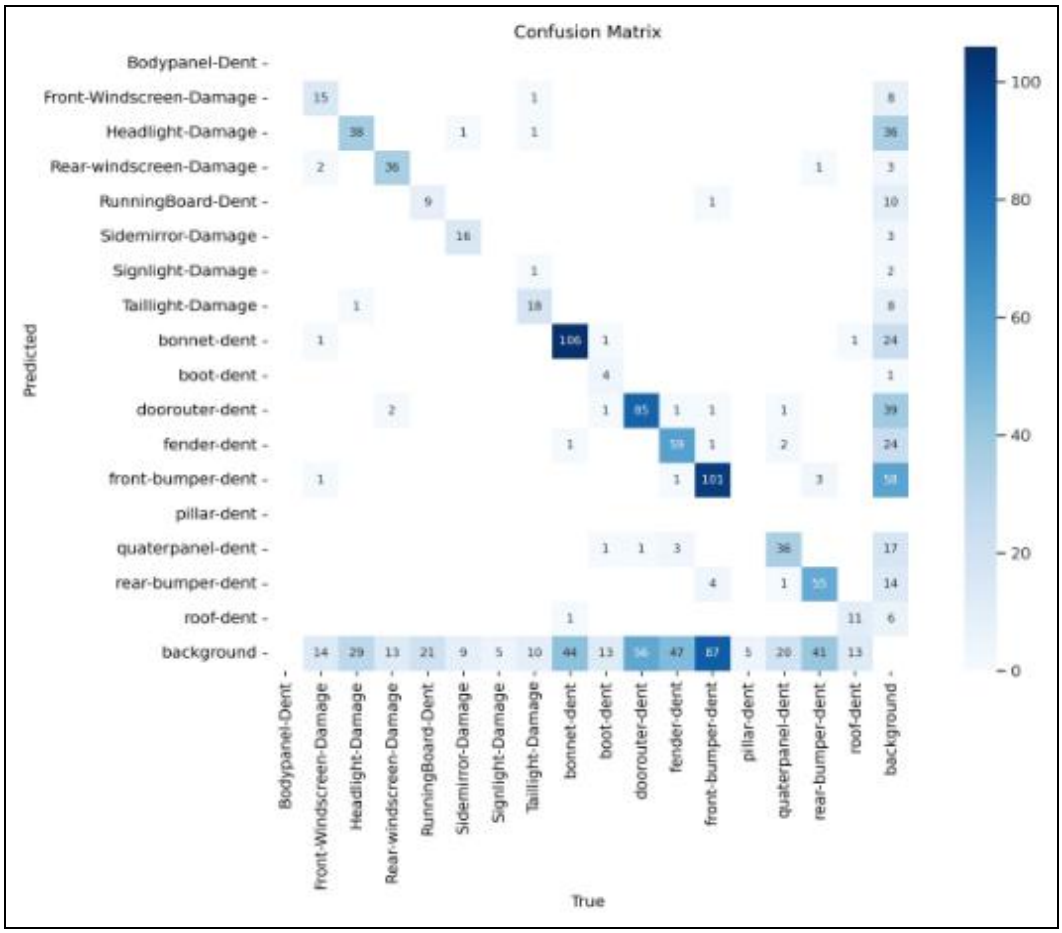

Fig 2: Matrix for defects

Implementation Model

1. **Input as Image**
   - The system takes an image of the damaged vehicle as input, either captured via a camera or uploaded from a database.
   - The input images include various types of damage such as dents, scratches, cracks, and broken parts.

2. **Preprocessing**
   - Resizing and Normalization: Standardizing image dimensions to ensure consistency in CNN input.
   - Noise Removal: Applying filters like Gaussian Blur to reduce unwanted noise and improve image clarity.
   - Data Augmentation: Enhancing the dataset using techniques such as rotation, flipping, contrast adjustment, and brightness correction, helping the CNN model generalize better.

3. **Training and Test Data Splitting**
   - The dataset is divided into training (80%) and testing (20%) sets to ensure balanced learning.
   - Stratified Sampling is used to maintain an even distribution of damage severity levels in both training and testing datasets.

4. **Feature Extraction**
   - CNN-based Deep Feature Extraction: The CNN model extracts significant features such as dent size, scratch depth, structural deformation, and broken glass regions.
   - Edge Detection and Contour Analysis: Helps in detecting cracks and damage severity.
   - Texture and Color Variations: Identifies damage intensity by analyzing variations in texture and color shifts due to scratches or dents.

Convolutional Neural Network

Convolutional Neural Networks (CNNs) are used in this system to automatically analyze car damage images and extract key features such as dents, scratches, and structural deformities. The model includes convolutional, pooling, activation (ReLU), dropout, and fully connected layers to detect and classify damage severity.

Unlike traditional models, CNNs learn features directly from images without manual extraction, improving accuracy and scalability. Data augmentation techniques like rotation and flipping are applied to enhance model generalization. This enables reliable prediction of insurance amounts based on image-based damage analysis. Top of Form

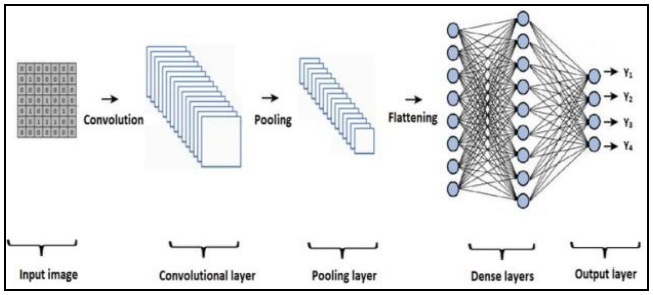

Fig 3: CNN Architecture

Flow Diagram

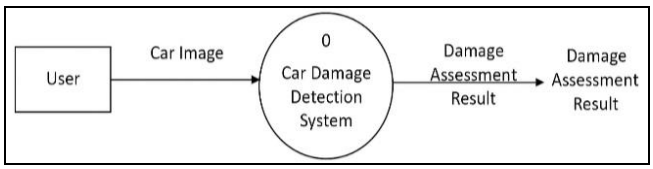

Fig 4: Block diagram

Sample Output

Fig 5: Input raw image

Image Preprocessing

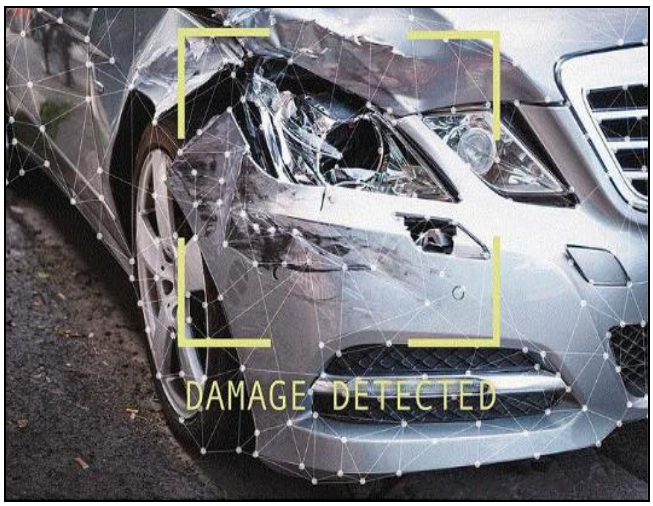

Fig 6: Image Pre-processing

Conclusion

The proposed system leverages Convolutional Neural Networks (CNNs) to accurately predict insurance claim amounts based on car damage images. By automating the damage assessment process, the system ensures faster, more transparent, and unbiased claim settlements compared to traditional manual evaluations. Preprocessing techniques such as noise removal, data augmentation, and feature extraction improve the model's ability to analyze various types of vehicle damage. The CNN model effectively identifies dent depth, scratch severity, and structural deformities, enabling a highly accurate insurance payout estimation. By integrating structured data such as car make, model, and accident history, the system enhances prediction reliability while reducing fraud risks. This AI-driven approach significantly improves the efficiency of insurance processing, minimizes disputes.

Future Enhancement

- **Real-time Mobile Application:** Develop a mobile or cloud-based application for real-time car damage detection and insurance estimation, improving accessibility and convenience for users and insurers.
- **Integration with Telematics and Vehicle Data:** Combine image data with vehicle telematics (speed, force of impact, location) to improve prediction accuracy and context.
- **Blockchain Integration:** Store damage assessments and insurance claims on a blockchain ledger to enhance transparency and prevent fraud.
- **Enhanced Dataset Diversity:** Expand the dataset to include various vehicle types, damage scenarios, and lighting conditions to improve model generalization and performance.
- **Explainable AI (XAI):** Implement explainable AI methods to make model predictions interpretable for users and insurance professionals, increasing trust and accountability.
- **Automated Severity Grading:** Improve classification to provide fine-grained damage severity grading and associated cost range, aiding in accurate claim estimation.

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