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# CAR DAMAGE DETECTION USING CNN ALGORITHM

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***Abstract:*** Car accidents are common around the world, causing serious damage and threatening public safety. The system can help determine the weight and size of damaged vehicles after an accident, helping insurance inspectors, auto repair shops and car buyers make informed decisions. The routine process of car damage assessment is often time-consuming, emotional, and prone to human error. With recent advances in computer vision and deep learning, automatic vehicle damage control systems have made significant progress in vehicle safety. This research provides a comprehensive study of the development and implementation of vehicle collision avoidance capabilities using state-of-the-art computer algorithms and deep learning models. The system processes images taken after a car accident and determines the extent and type of damage to the vehicle. The main stages of the system include image preprocessing, feature extraction, and deep learning-based classification. This research contributes to the improvement of vehicle damage detection by providing reliable and effective solutions for vehicle damage detection after an accident. By combining multiple CNN models using learning methods, the accuracy of the system was increased, and Flask's web application gave users a better understanding of how to interact with the system.

***Keywords -*** Convolutional Neural Network (CNN), Deep Learning, detection accuracy, Car Damage Detection, Mask RCNN.

## I. INTRODUCTION

One of the main topics of computer vision research is object detection. It determines the category and location information of the object of interest in the image at the sample level. Car accidents are on the rise in today's society, and car insurance companies spend billions of dollars every year due to information leaks. In the insurance industry, AI technologies such as machine learning and deep learning can help solve problems such as data analysis and operations, Fraud, risk mitigation and claims automation. However, existing applications to solve these problems are still difficult to improve, especially when deep learning is used to assess vehicle damage. Deep learning is a good way to solve complex problems but it requires more resources to build models, meaning deep learning requires large amounts of data and again requires a long time. This work focuses on two issues in developing a deep learning system for vehicle damage assessment: vehicle damage data for training and reducing computation time. Deep learning is a branch of machine learning that has been successfully implemented on many platforms for processing big data. Through the layers of blocks that form the backbone of deep learning, deep learning models can capture and understand information hidden in data to predict different patterns. Deep learning models have been successfully used in many applications in various fields of science, such as computer vision and damage, especially due to the development of comparative collision and deep learning. In this work, we propose an automatic method to classify damaged vehicles and predict how they are damaged. Convolutional neural networks (CNN) can be used to understand, identify and analyze various types of damage to small and large vehicles. Dents on the bumper, dents on the door, broken glass, broken taillights, headlights and scratches are examples of damage. CNN is used for product recognition and is used to detect car damage during the planning process. Traffic information is used to distribute events. To our knowledge, there are no reports of damage to the vehicle. Therefore, we created our own data set by manually annotating images found on the internet. The classification task is quite difficult due to the similarity of classes and almost invisible defects.

## II. LITERATURE REVIEW

Many studies have been conducted to investigate car accidents. Most use one of the pre-trained models for extraction and classification. As research into car crashes continues, researchers are exploring different ways to use deep learning tools. In this paper, we propose an automated system to detect fraud in the insurance field. In this paper, we propose an automated system to detect fraud in the insurance field. When accident images are received, the system can extract information about the vehicle and detect similar damages in the collected images [1]. A deep learning-based car damage algorithm is used to solve the compensation problem of car accidents [2]. Estimating vehicle damage costs using image data has been a research challenge for the insurance industry. Our efforts demonstrate the potential of using images to estimate damage to a car to transform the insurance user experience [3]. The main application for vehicle damage detection is for insurance companies as insurance losses are the main issues faced by these companies which leads to these companies losing millions and millions of dollars each year. These losses are caused by inefficient claims processing, embezzlement, and bad business deliberation. With significant advancements in deep learning methods, these techniques have begun to be utilized in the insurance industry to address such challenges and mitigate their negative implications[4]. With the significant progress in deep learning, these techniques have begun to be used in the insurance industry to solve these problems and reduce their negative effects. In this article, we consider the problem of car damage classification, which some classes can achieve well. For this purpose, we are investigating methods based on deep learning. Initially, we tried to teach cnn directly [5]. The system can assist in detecting the severity and extent of damage to a vehicle after an accident, aiding insurance assessors, auto repair shops, and car buyers in making informed decisions[6]. Design a study to speed up the car insurance claims process using an integrated deep learning system for car damage detection and classification using deep transfer learning[7]. Attempt to build a 2- layered ai model with the objective of optimizing performance, by filtering undamaged images and passing the filtered set to the object detection model for localization and classification into 4 categories, namely, scratches, dents, smashes, and glass shatters[8]. The implemented models are able to detect the damage, severity level and its exact location. Fine tuning of vgg models helped in increasing its accuracy and giving accurate predictions for edge cases[9]. Images and their storing are critical components of our understanding of reality this is no use to us, and therefore today's machine learning technologies are capable of maintaining lost or damaged parts of such image data, allowing us to understand the context and accurately evaluate the photos captured[10]. A detection algorithm based on deep learning for vehicle-damage detection is used to deal with the compensation problem in traffic accidents [11]. The classification part of multi-task loss function in rpn is improved[12].technique involves adequate integration and utilization of prior and spatial information. The mask-rcnn generally provides accurate boundary localization, mainly because of the robust semantic information obtained under the supervision of the pixel level prior information, and the lfccrf explores the spatial information, including the position, intensity, and coarse segmentation results obtained by using the mask-rcnn in the nuclear roi, to refine the nuclear boundary[13]. This work demonstrates the ability of the deep cnn in the field of object detection. Instead of continuous running this detector over every video feed from the surveillance camera, the system can be coupled with motion and other sensors that are already in the atm room to make it as efficient as possible[14]. Fast region-based convolutional network method (fast r-cnn) for object detection. Fast r-cnn builds on previous work to efficiently classify object proposals using deep convolutional networks. Compared to previous work, fast r-cnn employs several innovations to improve training and testing speed while also increasing detection accuracy[15].

Table 1
Composite Analysis

| Sr no. | Paper Title | Algorithm used | Dataset | Accuracy | Reasearch Gap Identified |
|---|---|---|---|---|---|
| 1. | A deep-learning–based antifraud system for car-insurance claims | CNN | Kaggle | 90% | focus on the design of self-supervised learning techniques that allow training on a much greater number of images |
| 2. | Vehicle-Damage-Detection Segmentation Algorithm Based on Improved Mask RCNN | RCNN,FPN,RPN | Kaggle | 94% | data expansion can be carried out to increase the size of the dataset, improve the edge-contour enhancement of images, and make the masking of the damaged areas of the car more accurate. |
| 3. | Vehicle Damage Severity Estimation for Insurance Operations Using In-The-Wild Mobile Images | CNN | Kaggle | 90% | One of the main remaining challenges is to further refine the pipeline to give a more granular prediction about the damage to vehicle parts in order to improve prediction accuracy. |
| 4. | Vehicle Damaged Detection Using Deep Learning | CNN | Kaggle | 70% | Better Models based on Vision Transformers and larger datasets may provide better result |
| 5. | Deep Learning Based Car Damage Classification | RCNN,SVM | Kaggle | 89.5% | |
| 6. | Damaged Car Detection Using Multiple Convolutional Neural Networks With Flask WebApp | CNN | Kaggle | 70% | The dataset can be expanded to include more images of damaged cars from different angles, lighting conditions, and types of damage to improve the system's performance further. |
| 7. | Integrated Deep Learning System for Car Damage Detection and | R-CNN,SVM | Kaggle | 95% | Increasing datasets size and creating segmented datasets with more than 1 class, |

| | | | | | |
|---|---|---|---|---|---|
| | Classification Using Deep Transfer Learning | | | | segmentation of car parts model. |
| 8. | Optimized Car Damaged Detection using CNN and Object Detection Model | CNN | Kaggle | 98% | Extending to real-time detections showing great processing speed coupled with a competitive precision. |
| 9. | Car Damage Detection and Assessment Using CNN | CNN,RCNN,VGG16 | Kaggle | 87% | Data expansion can be carried out to train the model effectively and get better results. The approximate cost of repair can also be calculated by use of proper resources and data. |
| 10. | Car Damage Identification and Categorization Using Various Transfer Learning Models | CNN | Kaggle | 97.28% | Analyzes the problem of automatic car damage detection and classification – this is an issue of importance to insurance companies in handling auto insurance claims quickly |
| 11. | A method based on multi-convolution layers joint and generative adversarial networks for vehicle detection | CNN,RCNN | Kaggle | 89% | The generator and discriminator can learn from each other in order to further improve the vehicle object detection capability |
| 12. | Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks | R-CNN,RPN | Kaggle | 90% | State-of-the-art object detection networks depend on region proposal algorithms to hypothesize object locations |
| 13. | Automatic segmentation of cervical nuclei based on deep learning and a conditional random field | RCNN | Kaggle | 85% | the accuracy of the abnormal nuclear segmentation still needs to be enhanced owing to its clinical significance. |
| 14. | An improved transfer learning approach for intrusion detection | CNN | Kaggle | 95.3% | Transferred information from inception model has been feed to multiple fully connected layers with drop outs to achieve better accuracy. |
| 15. | Fast R-CNN | RCNN | Kaggle | 95% | Fast R-CNN employs several innovations to improve training and testing speed while also increasing detection accuracy. |

In summery, The research endeavors detailed various deep learning approaches, predominantly centered around leveraging convolutional neural networks (CNNs), transfer learning, and models like VGG, RPN, Mask-RCNN, and Fast R-CNN to revolutionize the insurance sector's response to car accidents. These methodologies aimed to swiftly identify and classify car damages—scratches, dents, smashes, and glass shatters—enabling precise determination of damage severity and location. Notably, the implementations sought to expedite claims processing, enhance the accuracy of damage assessment, and detect fraudulent claims. Integration with existing sensors and innovations like LFCCRF for spatial information were explored to boost efficiency and accuracy without compromising speed. These advancements, showcased across multiple studies, have the potential to curb losses incurred by insurance companies due to inefficiencies in claims processing, fraudulent activities, and suboptimal business decisions, potentially saving millions of dollars annually.

Table 2
Technological Survey

| Years | 2022-23 | 2021-22 | 2020-21 | 2019-20 | 2018-19 |
|---|---|---|---|---|---|
| Methodlgy used | Transformer-based architecture for contextual information in multilingual speech (Adaptation for car damage context) Online learning techniques for real-time emotion recognition | Support Vector Machines (SVM) for car damage classification Convolutional Neural Networks (CNNs) for feature extraction Recurrent Neural Networks (RNNs) for modeling temporal patterns | CNNs for feature extraction from images (car damage assessment LSTMs for modeling temporal dependencies in damage detection Transformer-based architectures for sequence-to-sequence modeling of audio data (e.g., engine sounds) | Combination of deep learning models (CNNs, LSTMs) with hand-crafted features for comprehensive damage assessment Ensemble models to combine predictions from different feature sets (e.g., visual and audio features) Transfer learning techniques to adapt models for different car datasets | Deep neural networks (CNNs for image-based damage detection, LSTMs for temporal modeling in video data) |

## III.PROPOSED METHODOLOGY

Solving the complex problem of car damage detection requires a systematic and multidisciplinary approach, combining expertise from computer vision, deep learning, data preprocessing, and domain-specific knowledge related to automotive engineering and insurance practices. Conduct an extensive review of existing research papers, articles, and case studies related to car damage detection. Gather a diverse and representative dataset of car damage images, including various types of damages, lighting conditions, and camera angles. Apply preprocessing techniques such as image normalization, noise reduction, and image enhancement to standardize the dataset. Evaluate the system's performance using metrics such as accuracy, precision, recall, F1-score, and confusion matrices. Collaborate with academic institutions and research organizations to stay updated with the latest advancements in computer vision, deep learning, and related fields.

### A. DATA COLLECTION :

This collection typically includes images or videos showcasing different damage categories like scratches, dents, smashes, glass shatters, and more. The dataset would aim to cover multiple vehicle models, colors, ages, and environmental conditions. It might involve obtaining images from sources such as accident reports, insurance claims, auto repair shops, or even specialized datasets dedicated to car damages. Ensuring a comprehensive representation of damages across different scenarios and www.ijcrt.org © 20XX IJCRT | Volume X, Issue X Month Year | ISSN: 2320-2882 contexts is crucial for training deep learning models effectively in detecting and classifying car damages accurately.

### B. DATA PREPROCESSING :

In the preliminary stages of research focused on car damage detection, the preprocessing of image datasets assumes significance to refine and optimize visual data for subsequent analysis critical. Here's an outline of potential steps for preprocessing image data in the context of car damage detection:

1) Image Enhancement: Raw images capturing car damages will undergo enhancement techniques like contrast adjustments and histogram equalization to improve clarity, highlighting critical features essential for accurate damage classification.

2) Normalization and Standardization: Normalizing pixel values across images ensures consistency in intensity levels, compensating for variations in lighting conditions, which is crucial for reliable damage detection.

3) Noise Reduction and Filtering: Employing noise reduction algorithms, such as Gaussian or median filters, helps improve the quality of images, particularly crucial for detecting subtle damages amidst noisy or unclear visuals.

4) Image Segmentation: Applying segmentation techniques aids in isolating specific damaged areas within images, allowing for precise identification and classification of scratches, dents, smashes, or other damage types.

5) Handling Missing or Corrupted Data: Dealing with missing or corrupted image data involves strategies like imputation or removal of unusable images to ensure dataset integrity, critical for accurate model training.

6) Data Augmentation: Augmenting the dataset with variations in orientation, flipping, or controlled distortions helps diversify the dataset, improving the model's ability to generalize and detect damages in different scenarios.

7) Quality Control and Annotation: Ensuring accuracy in image annotations depicting damaged areas is crucial. Thorough review and validation of annotations minimize errors, aiding the model in learning accurate damage patterns.

### C. Feature Selection :

This feature selection process integrates methodologies like feature importance ranking and correlation analyses, aiming to pinpoint the most pertinent indicators within the dataset. By prioritizing features that significantly contribute to distinguishing between different types of car damages such as scratches, dents, smashes, or glass shatters—we construct a model founded upon the relevance and importance of these selected features. This approach ensures that the subsequent model is optimized to leverage the most informative and clinically significant features, enhancing its ability to accurately detect and classify various types of car damages.

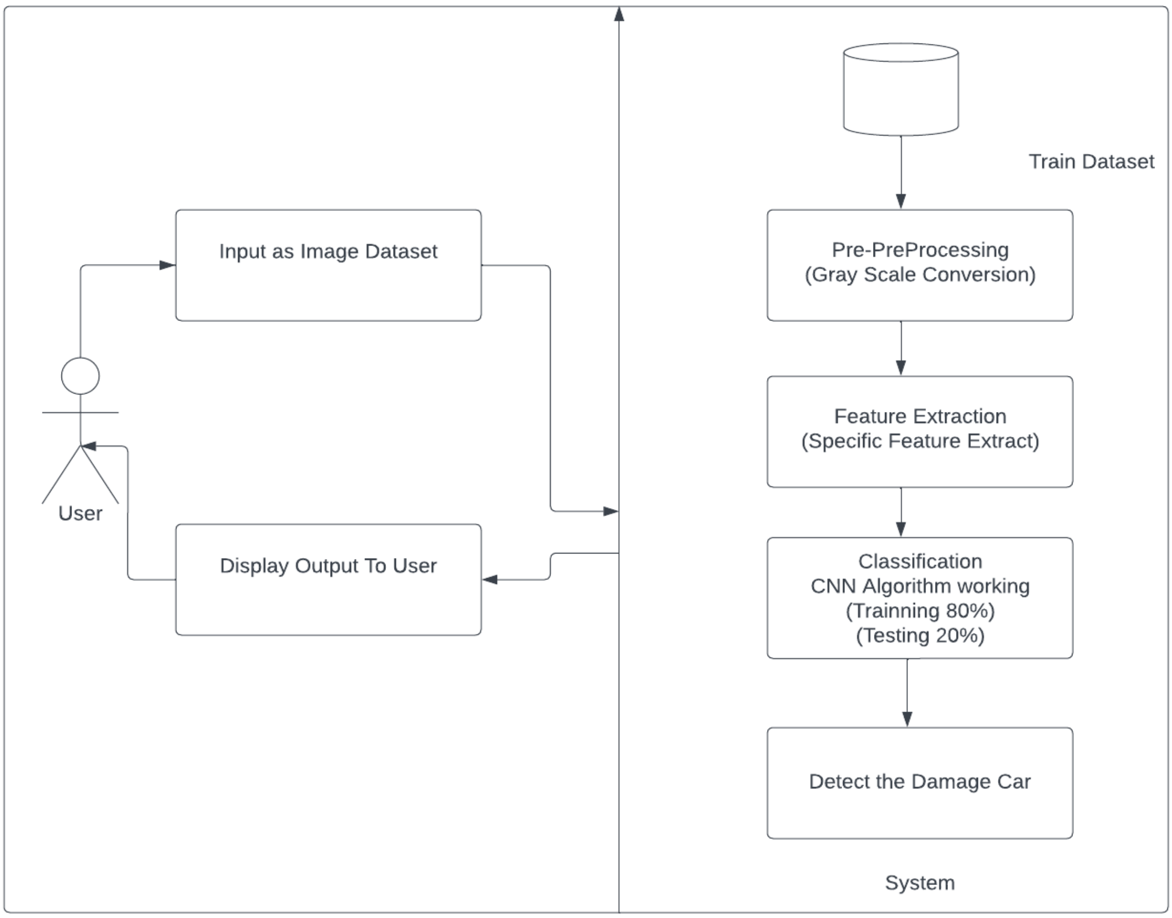
### D. Dataset Splitting :

This strategic partitioning is pivotal for robust model development and evaluation. The training set will serve as the foundation for model construction, allowing the machine-learning models to learn patterns and features indicative of various car damages like scratches, dents, smashes, and more. The www.ijcrt.org © 20XX IJCRT | Volume X, Issue X Month Year | ISSN: 2320-2882 validation set plays a critical role in fine-tuning the models, preventing overfitting by iteratively adjusting hyperparameters based on performance metrics. Finally, the test set, representing unseen data, will be instrumental in assessing the model's ability to generalize to new and unseen instances of car damages, ensuring its efficacy beyond the training data and validating its real-world applicability.

### E. Algorithm Selection :

In this research endeavor, various challenges associated with car damage detection, such as varying lighting conditions, image noise, and the diversity of damage types, will be addressed. By overcoming these challenges, the proposed system holds the potential to revolutionize the way car damage assessment is conducted, leading to more efficient claims processing, improved road safety measures, and ultimately, a safer environment for all road users. Through the fusion of computer vision techniques and deep learning models, this study aims to contribute significantly to the advancement of automated car damage detection, ensuring a more accurate and objective evaluation of vehicle damage in the aftermath of accidents.

Fig 1: system architecture



### CNN

- CNNs are exceptionally well-suited for image and video analysis tasks due to their ability to automatically learn hierarchical features from raw pixel data.
- CNNs can learn to extract meaningful features from images or video frames, such as edges, textures, and object shapes, which are crucial for recognizing accident-related patterns.
- CNNs are capable of achieving translation invariance, meaning they can recognize patterns regardless of their position within an image.
- CNNs are used in Automatic Accident Detection because they excel at extracting relevant features from images and video frames, recognizing spatial relationships, and offering real-time or near-real-time processing capabilities.
- To leverage cutting-edge technologies in computer vision, machine learning, and artificial intelligence to enhance the accuracy, efficiency, and reliability of car damage detection systems.
- Develop and implement state-of-the-art deep learning architectures, such as convolutional neural networks (CNN) and their variants, tailored for car damage detection.
- Curate large and diverse datasets comprising high-resolution images of vehicles with various types and severities of damages.
- Investigate real-time processing techniques, including optimizing algorithms for speed and efficiency.
- Design the system to be modular and easily integrable with existing workflows in insurance companies and auto repair shops.
- Implement explainable ai methods to enhance the interpretability of the car damage detection models.

## IV. RESULTS AND DISCUSSION

car damage detection has emerged as a crucial application of computer vision and deep learning technologies, addressing the challenges associated with accurate, efficient, and objective assessment of vehicle damages. The development of automated systems capable of identifying various types of car damage, such as dents, scratches, and deformations, has significant implications for insurance claim processing, automotive repair, accident investigations, and overall road safety. Car damage detection systems represent a remarkable fusion of cutting-edge technologies and practical applications, offering solutions to longstanding challenges in the automotive industry. By harnessing the power of computer vision and deep learning, these systems provide a reliable means to objectively evaluate vehicle damages, reducing the subjectivity associated with manual assessments. As the technology continues to evolve, addressing constraints related to data availability and variability remains a pivotal area for further research and innovation. But by using our proposed method[4] they can severely reduce the intensity of such scams as this process happens instantaneously without involving anyone. Definitely more work has to be done in order to get this technology used by the mainstream insurance companies. Better Models based on Vision Transformers and larger datasets may provide better results and can be of interest in Future works. Data expansion can be carried out to increase the size of the dataset, collect more car damage images under different weather conditions and different levels of illumination, enhance the data, improve the edge-contour enhancement of images, and make the masking of the damaged areas of the car more accurate.

## V. REFERENCE

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