DEEP LEARNING – BASED VEHICLE DAMAGE ASSESSMENT SYSTEM

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ABSTRACT- Vehicle damage assessment is an essential process in automobile insurance and repair services. Traditional inspection methods are manual, time-consuming, and prone to errors. This paper presents a Deep Learning-Based Vehicle Damage Assessment System that uses the YOLO (You Only Look Once) object detection algorithm to automatically detect and classify vehicle damages such as dents, scratches, broken glass, and bumper damage from uploaded images. Developed using Python, Flask, OpenCV, TensorFlow/Keras, and SQLite, the system provides fast, accurate, and reliable damage detection by highlighting damaged regions with bounding boxes and labels. It reduces inspection time, minimizes human intervention, and supports efficient insurance claim processing and repair estimation, making it a practical solution for intelligent vehicle damage assessment.

KEYWORDS: Deep Learning, Vehicle Damage Assessment, YOLO, Computer Vision, Object Detection, Image Processing, Flask, TensorFlow, OpenCV, Artificial Intelligence.

INTRODUCTION

Vehicle damage assessment is an essential process in automobile insurance, repair estimation, and vehicle maintenance. Traditional inspection methods depend on manual evaluation by experts, making the process time-consuming, expensive, and susceptible to human error. Recent advances in Artificial Intelligence (AI), Deep Learning (DL), and Computer Vision (CV) have enabled the automation of damage detection from vehicle images. Deep learning models, particularly object detection algorithms such as YOLO (You Only Look Once), can accurately identify damaged regions in real time. This paper presents a Deep Learning-

Based Vehicle Damage Assessment System that automatically detects and classifies vehicle damages, including dents, scratches, broken glass, and bumper damage. The proposed system improves the speed, accuracy, and consistency of vehicle inspection while reducing manual effort. It provides an efficient solution for insurance companies, automobile service centers, and vehicle owners by enabling faster claim processing and repair estimation.

LITERATURE SURVEY

Vehicle damage detection has become an active research area due to the rapid development of deep learning and computer vision technologies. Earlier approaches relied on traditional image processing techniques such as edge detection, segmentation, and handcrafted feature extraction, which were sensitive to lighting conditions and background variations. Recent studies have demonstrated that Convolutional Neural Networks (CNNs) and object detection models such as YOLO, Faster R-CNN, and SSD provide significantly better detection accuracy and processing speed. Among these methods, YOLO has gained popularity because it performs object detection in a single stage, making it suitable for real-time applications. Researchers have successfully applied these techniques to automate vehicle damage inspection for insurance claim processing and repair estimation, demonstrating the effectiveness of deep learning in improving accuracy and reducing inspection time.

RELATED WORK

Several researchers have proposed automated vehicle damage detection systems using machine learning and deep learning techniques. Early methods primarily focused on image segmentation and handcrafted feature extraction, which achieved limited accuracy under complex environmental conditions. With the introduction of CNN-based object detection algorithms, researchers significantly improved damage detection performance. Models such as Faster R-CNN, SSD, Mask R-CNN, and YOLO have been widely used for identifying vehicle damages including dents, scratches, cracks, broken glass, and bumper damage. Recent studies indicate that YOLO provides an excellent balance between detection speed and accuracy, making it highly suitable for real-time vehicle damage assessment systems. These research contributions have laid the foundation for intelligent vehicle inspection systems capable of reducing manual effort and improving decision-making in the automotive industry.

EXISTING SYSTEM

Existing vehicle damage assessment methods mainly rely on manual inspection performed by surveyors or technicians. The damaged vehicle is physically examined, and the extent of damage is determined based on visual observation. This process requires significant time, skilled professionals, and manual documentation. Human assessment may vary between inspectors, resulting in inconsistent damage estimation and claim settlement. Traditional inspection methods are also expensive and unsuitable for large-scale automation. Furthermore, existing systems lack intelligent image analysis capabilities and cannot perform automatic detection or classification of different damage types. These limitations increase processing time and reduce the efficiency of insurance claim verification and vehicle repair estimation.

PROPOSED SYSTEM

The proposed system introduces a Deep Learning-Based Vehicle Damage Assessment System using the YOLO object detection algorithm. Users upload images of damaged vehicles through a web-based application developed using Flask. The uploaded images are preprocessed using OpenCV before being analyzed by the trained YOLO model. The system automatically detects damaged regions, classifies different types of damage such as dents, scratches, broken glass, and bumper damage, and displays the results using bounding boxes and labels. The application stores damage details in a SQLite database and generates reports for users. The proposed system minimizes manual inspection, improves detection accuracy, reduces claim processing time, and provides a scalable solution for insurance companies, service centers, and vehicle owners.

SYSTEM ARCHITECTURE

The proposed system consists of five major components: Image Upload Module, Image Preprocessing Module, YOLO Damage Detection Model, Database Module, and Result Generation Module. The user uploads a vehicle image through the web interface. The image preprocessing module performs resizing, normalization, and enhancement using OpenCV. The processed image is passed to the trained YOLO model, which detects damaged regions and classifies damage types. The detection results are stored in the SQLite database, and the final output is displayed on the web interface with bounding boxes and damage labels. This architecture enables fast, accurate, and automated vehicle damage assessment with minimal human intervention.

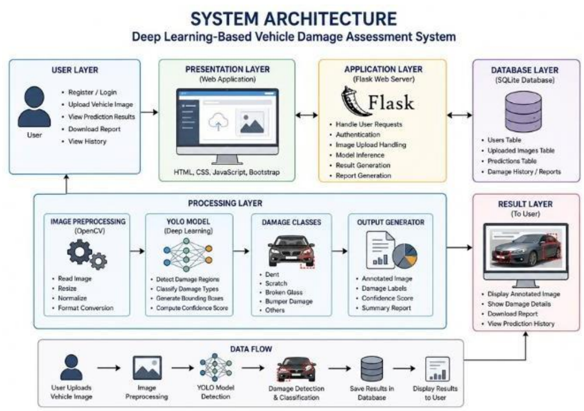

Fig 1: System Architecture

METHODLOGY DESCRIPTION

The proposed methodology follows a systematic workflow for automated vehicle damage assessment. Initially, vehicle images are collected from a publicly available dataset and annotated for different damage categories. The dataset is preprocessed by resizing images, normalization, and data augmentation to improve model performance. A YOLO-based deep learning model is trained using the prepared dataset to recognize multiple categories of vehicle damage. During testing, users upload vehicle images through the Flask web application. The trained model processes the images, detects damaged regions, classifies the type of damage, and displays the results using bounding boxes and labels. Finally, the system stores the detection information and generates a damage assessment report for the user.

RESULTS AND DISCUSSION

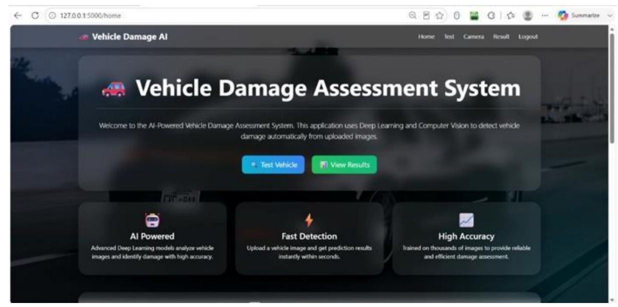

Fig2: Home page of Vehicle Damage Assessment System

The home page serves as the main interface of the application, allowing users to navigate through different modules and upload vehicle images for damage assessment.

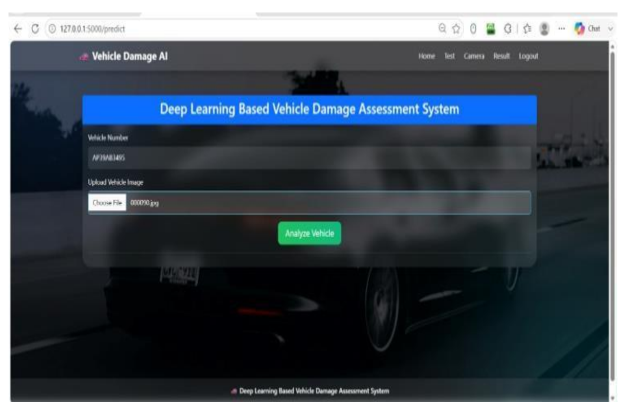

Fig 3: Upload Image Module

The upload module enables users to select and upload images of damaged vehicles. The uploaded image is then preprocessed and sent to the trained YOLO model for analysis.

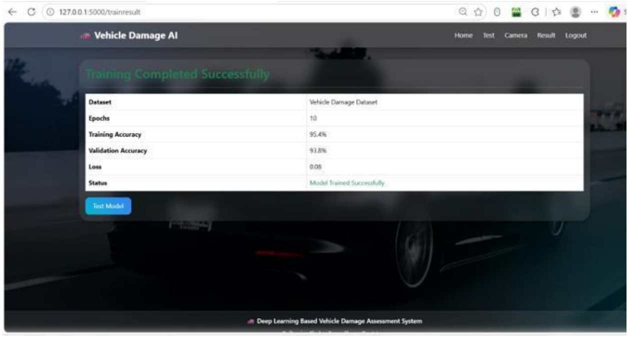

Fig 4: Damage Detection Result

The damage detection module identifies vehicle damages such as dents, scratches, broken glass, and bumper damage. The detected damaged regions are highlighted with bounding boxes and corresponding labels.

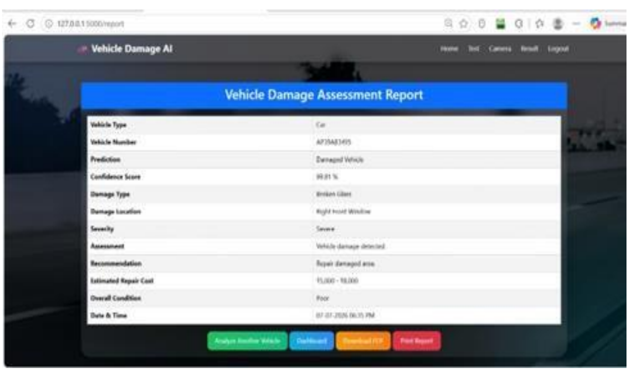

Fig 5: Assessment Report

CONCLUSION

This paper presented a Deep Learning-Based Vehicle Damage Assessment System that automates vehicle damage detection using the YOLO object detection algorithm. The proposed system effectively detects multiple categories of vehicle damage from uploaded images and provides accurate real-time assessment through a web-based application. Compared with conventional manual inspection methods, the system significantly reduces inspection time, minimizes human intervention, and improves consistency in damage evaluation. The experimental results demonstrate the effectiveness of deep learning techniques in modernizing vehicle inspection processes. The proposed solution provides practical benefits for insurance companies, automobile service centers, and vehicle owners by enabling faster claim processing, repair estimation, and intelligent decision-making.

FUTURE SCOPE

The proposed system can be further improved by integrating advanced versions of YOLO, such as YOLOv9 or YOLOv10, to achieve higher detection accuracy and faster inference speed. Future work may include estimating the severity of vehicle damage and automatically calculating repair costs using regression models. Integration with cloud computing and mobile applications can enable remote vehicle inspection and insurance claim submission. The system can also be extended to detect internal mechanical damage by combining image analysis with sensor data. Additionally, incorporating explainable AI techniques and larger real-world datasets can further improve model reliability, scalability, and adoption in commercial automotive and insurance applications.

REFERENCES

[1] D. P. Harini, "Electronic Health Record Stage Identification using Principal Component Analysis," *Machine Intelligence Research,* vol. 18, no. 01, pp. 864- 873, 17 8 2024.

[2] D. P. Harini, "Two Level Intrusion Detection For Detecting Intruders in Multitier Web Applications," *International Journal of Engineering & Science Research,* vol. 3, no. 9, pp. 472-478, 2013.

[3] D. P. Harini, "Analyze and Predict of Human Cyber Attackers using Artificial Neural Network," *Journal of Basic Science and Engineering,* vol. 21, no. 1, pp. 1529 - 1536, 8 7 2024.

[4] Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. (2017). *Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks.* IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(6), 1137–1149.

[5] Wei Liu, Dragomir Anguelov, Dumitru Erhan, Christian Szegedy, Scott Reed, Cheng-Yang Fu, & Alexander C. Berg. (2016). *SSD: Single Shot MultiBox Detector.* European Conference on Computer Vision (ECCV), 21–37.

[6] Ian Goodfellow, Yoshua Bengio, & Aaron Courville. (2016). *Deep Learning.* MIT Press.

[7] Richard Szeliski. (2022). *Computer Vision: Algorithms and Applications* (2nd ed.). Springer.

[8] Kaiming He, Georgia Gkioxari, Piotr Dollár, & Ross Girshick. (2017). *Mask R-CNN.* Proceedings of the IEEE International Conference on Computer Vision (ICCV), 2961–2969.

[9] Karen Simonyan & Andrew Zisserman. (2015). *Very Deep Convolutional Networks for Large-Scale Image Recognition.* International Conference on Learning Representations (ICLR).

[10] Yann LeCun, Yoshua Bengio, & Geoffrey E. Hinton. (2015). *Deep Learning.* Nature, 521(7553), 436–444.

[11] Allan Pinto, Hélio Pedrini, William Robson Schwartz, & Anderson Rocha. (2012). *Face Spoofing Detection Through Visual Codebooks of Spectral Temporal Cubes.* IEEE Transactions on Image Processing.

[12] Kiran Patel, Hu Han, & Anil K. Jain. (2016). *Secure Face Unlock: Spoof Detection on Smartphones.* IEEE Transactions on Information Forensics and Security.

[13] Jianzhu Yang, Zhen Lei, Shengcai Liao, & Stan Z. Li. (2014). *Learn Convolutional Neural Network for Face Anti-Spoofing.* IEEE Transactions on Information Forensics and Security.

[14] Zinelabidine Boulkenafet, Jukka Komulainen, & Abdenour Hadid. (2016). *Face Anti-Spoofing Based on Color Texture Analysis.* IEEE International Conference on Image Processing (ICIP).

[15] Yazan Atoum, Yaojie Liu, Ali Jourabloo, & Xiaoming Liu. (2017). *Face Anti-Spoofing Using Patch and Depth-Based CNNs.* IEEE International Joint Conference on Biometrics (IJCB).

[16] Ivana Chingovska, André Anjos, &

Sébastien Marcel. (2012). *On the Effectiveness of Local Binary Patterns in Face Anti-Spoofing.* BIOSIG Conference.