Intelligent Emergency Response System with Automated Vehicle Damage Classification

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***Abstract*—Road safety is still a top priority, thus developing cutting-edge solutions for effective damage and accident detection is essential. In this paper, a unique automated approach for identifying and classifying cars involved in collisions is presented. The suggested solution examines real-time imagery from traffic cameras and sensors using cutting-edge computer vision and machine learning techniques to quickly identify events. The algorithm uses a multi-step procedure, classifying the cars according to the degree of damage after first identifying possible collisions. The classification takes into account several factors, such as the kind of vehicle, possible safety hazards, and the extent of the damage. Authorities can improve overall road safety and accelerate emergency response times by integrating such a system into the current traffic management infrastructure. This study makes a valuable contribution to the developing field of intelligent transportation systems by providing a quick and efficient way to identify and categorize the involved automobiles in an accident.**

***Findings*– USB, Dataset, YOLOv8, Damage Detection, CNN**

I. Introduction

Our research's goal is to create a safe transport management system that will allow both the perpetrator and the victim to be identified and placed under authority right away. We also aim to identify the likelihood of a fatality.

In our daily lives, there are many tragic and pitiful incidents that happen on the roads. Most crucially, when harm is done, the victims are abandoned where the perpetrator attempts to flee; in the majority of these cases, the perpetrator manages to escape, and the victim is not provided with prompt assistance by the legal or medical systems. This is the rationale for our desire to create a system that would enable us to quickly apprehend the culprit each time an incidence happens.

Our goal is to acquire a method for identifying a car that may have been involved in an accident or may have caused one. Here, we'll use a model to identify the car using the USB (Universal-Scale Object Detection Benchmark) process, aiming over the car. We'll also categorize the damage scale, try to determine the likelihood of casualties or fatalities, and classify it. Moreover, we'll attempt to manage the hospitalized treatments immediately, taking into account the likelihood of casualties and damages. Additionally, we'll work to guarantee an instant automated system for law enforcement or medical support management.

II. Motivation

We want to generate a system where any kind of accident spotted on the road would be classified automatically and the initiative (Medical Support/ Ambulance/ Law Enforcement Support) will be taken according the risky factor of the classified damages of the respective vehicle as soon as possible. It will be a very efficient system where nobody will suffer by the lack of immediate support system and can be treated very earlier so that the chances of occurring fatality because of the delay of medical treatment will be reduced with a strong manner.

III. LITERATURE REVIEW

[1] In this paper, **Xinkuang Wang et al.** identifies the damage and classified along 6 catergorized so that one can easily access the insurance facilities for a valid damages. Salient object detection (SOD) is one of the key procedure of this paper. CNN-based models to identify the damage category. And for the object detection and instance segmentation task, YOLO [2], and Mask R-CNN [3] are referenced.

Dataset : CarDD contains 4,000 high-resolution car damage images with over 9,000 well annotated instances of six damage categories. [GitHub Dataset] Following a similar manner in the COCO dataset, the objects in the CarDD dataset are also classified into three scales, where the “small,” “medium,” and “large” instances are with areas under 128^2 , over 128^2 but under 256^2 , and over 256^2. And the results of the small, medium, and large instances in CarDD are 38.6%, 32.6%, and 28.8%, respectively.

In this paper **Van Ruitenbeek et al.** [4] describes their research and examines the effectiveness and assessment of a vehicle damage detection model. It assesses the model's performance against experts in the field and determines how useful it is in real-world scenarios. The annotation procedure and the dataset used for training are also covered in the document. To maximize the performance of the model, a number of experiments and approaches are provided. Using one hundred photos from the Damage Dossiers dataset, the model's performance is compared with domain experts. The experts and the model are given identical photos, and the outcomes are compared. The model's performance is assessed in a light street that has been specifically constructed, in addition to employee manual examination. The training dataset, which consists of photos taken from Google image search, is described in the text. To maximize the model's performance, various tests and techniques—such as transfer learning and fine-tuning—are carried out. Models used include CNNs, YOLO v3 with Darknet-53, and FSSD with Darknet-53. Dataset: The Damage Dossiers and Damage Web datasets were the two used in the study. There are 2499 Damage Dossiers in the Damage Dossiers collection, and each dossier has several pictures of vehicles that have been damaged. After preprocessing, the dataset's size was lowered from 19,907 photos to 3513. About 2500 photos from the internet were gathered for the Damage Web collection by means of web scraping. After preprocessing, there are 1338 photos in the final dataset.

[5]In this paper by **R. Jaiswal et. al**, in order to detect auto damage, computer vision has become a potent technology that has an impact on fleet management, safety, insurance, and inspections. This study focuses on CNNs and transfer learning for damage assessment, examining the state-of-the-art methods, difficulties, and practical applications of this technology. VGG, Inception) and taking into account transfer learning and object identification models (YOLO, Faster R-CNN, SSD). Training and Testing Models: dividing up the data set, adjusting hyperparameters, and assessing performance indicators. The system's application for fraud detection in auto insurance claims is mentioned in the paper. It is important to talk about the moral ramifications of utilizing these kinds of technologies for insurance claims and damage assessment.

[6] **Convolutional neural networks (CNNs)** are rapid, scalable, and end-to-end training networks that have been widely used in computer vision research. This has made it possible to use deep transformational networks to identify damage to motor vehicles. By utilizing pre-trained CNN models and innovative processing approaches, we were able to achieve 96.39% accuracy, which is significantly better than previous findings on the same test set. In this research, we classify the types of motor vehicle injuries using the Convolutional Neural Network (CNN) method. Absence of a comparison Although other studies on automobile damage detection are mentioned in the study, a thorough comparison of their methodology with current techniques is not provided.

IV. Dataset Property

We used the ”Car Damage Severity Dataset” [7] which is authored by Prajwal Bhamere. We were able to obtain a limited pool of dataset that consist of different types of damaged cars, which were collected directly from the internet. The dataset used in this research included includes 2362 images and was categorized into three different categories: Minor, Moderate, and Severe. The dataset was split into two sections, one for Training and the other for Validation, in-which 80% of the data was used to Train our classifiers and 20% was used to Test our results from the training, with each of the three categories having their respective Training and Validation data. The dataset pre-processed before the training session. Also the dataset was found from a renowned benchmark platform kaggle.

	Minor	Moderate	Severe
Train	730	778	854
Validation	82	75	91
Total	812	853	945

TABLE I
Detailed Processed Dataset

V. Methodology

Our Methodology segmented parts are given followed to find the most effective and useful model for our datasets.

a) 1. ***Dataset Collection:****:* Collect a dataset from Kaggle consisting of vehicle images categorized into three classes: ”minor,” ”moderate,” and ”severe” damage. The dataset is organized into folders based on damage severity.

b) 2. ***Data Preprocessing:****:*

- Load images from the dataset folders.
- Resize and normalize the images to a consistent size (e.g., 64x64 pixels).
- Apply data augmentation techniques to enhance the diversity of the dataset.
- Shuffle the dataset to ensure randomness.

c) 3. ***Dataset Splitting:****:*

- Split the preprocessed dataset into training, validation, and test sets using a suitable ratio (e.g., 80% training, 10% validation, 10% test).
- Maintain the balance of classes in each split to ensure representative training and evaluation.

d) 4. ***Model Processing (CNN):***:

- Build a Convolutional Neural Network (CNN) model for vehicle damage categorization.
- Design the CNN architecture with convolutional layers, max-pooling layers, and fully connected layers.
- Compile the model with appropriate loss function, optimizer, and evaluation metrics.

e) 5. ***Model Processing (YOLOv8):***:

- Optionally, explore the application of YOLOv8, a powerful object detection algorithm, for vehicle damage categorization.
- Configure and train YOLOv8 to detect and categorize damaged areas within images.

f) 6. ***Compilation and Training:***:

- Compile the CNN model or YOLOv8 with the chosen parameters.
- Train the model using the training set, validating the performance on the validation set.
- Utilize techniques like ModelCheckpoint to save the best model during training.

g) 7. ***Evaluation Model:***: Evaluate the trained model on the validation set to assess its accuracy and identify potential overfitting.

h) 8. ***Test Model:***: Assess the model's performance on the test set, providing a reliable estimate of its generalization capability.

i) 9. ***Random Damaged Vehicle Image Prediction:***:

- Select random damaged vehicle images from the test set for prediction using the trained model.
- Utilize the model to predict damage severity and analyze the results.

j) 10. ***Result Analysis and Comparative Study:***:

- Conduct a comparative analysis between the CNN and YOLOv8 models in terms of accuracy, speed, and resource utilization.
- Comparison of loss and accuracy to evaluate the performance.
- Discuss the strengths and limitations of each model, addressing challenges and potential areas for improvement.
- Provide insights into the practical implications and potential applications of the proposed vehicle damage categorization system.

This formalized methodology architecture outlines the step-by-step process from dataset collection to result analysis, providing a structured approach for your paper on vehicle damage categorization.

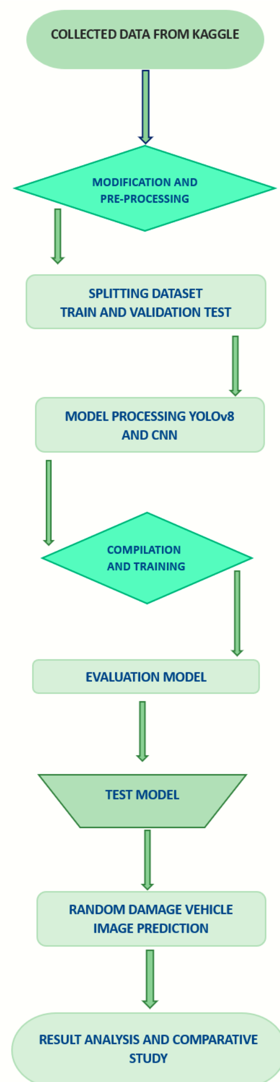

Fig. 1. Methodology Architecture

VI. Model (CNN) for Classifying Damage

In this paper, the focus is on leveraging Convolutional Neural Networks (CNNs) for the task of categorizing vehicle damage into minor, moderate, and severe categories. The CNN architecture includes convolutional layers to capture localized features associated with varying degrees of damage severity, and a 3x3 max-pooling layer for downsampling spatial dimensions. CNN shape was (2186, 64, 64, 3). The network likely concludes with fully connected layers for integrating extracted features and generating predictions. Training involves a labeled dataset, and evaluation metrics such as accuracy, precision, recall, and F1 score are employed to assess model performance. It's crucial to address challenges, such as ensuring a diverse dataset and optimizing network architecture and hyperparameters, to enhance the effectiveness of the proposed approach in predicting and categorizing vehicle damage.

VII. Model (YOLOv8) for classifying Damage

In this paper focused on categorizing vehicle damage by severity, the utilization of YOLOv8, a powerful object detection algorithm, introduces several key advantages. YOLOv8's exceptional object detection capabilities allow for not only categorization but also precise localization of damaged areas within images, offering a comprehensive understanding of the severity. The model's efficiency in training, real-time processing speed, and configurability make it well-suited for applications requiring quick assessments. However, the need for bounding box annotations in the dataset preparation stage and the model's computational intensity during training should be considered. Evaluating the model's performance using metrics such as mAP becomes crucial, and a comparative analysis with traditional CNN-based approaches is recommended to determine the optimal solution for the specific task. Thorough documentation of the methodology, along with discussions on advantages and challenges, will contribute to a comprehensive exploration of YOLOv8's effectiveness in the context of vehicle damage severity categorization. We have used here the specific yolov8n-cls.pt model to evaluate our dataset.

A. *Result Analysis*

Our selected model here are **YOLOv8 and CNN** which performs quite well over the accuracy and loss test also the prediction was very accurate.

Model Name	Accuracy	Loss
CNN	99.85%	1.73%
YOLOv8	68.1%	29.79%

TABLE II
ANALYTICAL COMPARATIVE RESULT

The train-loss reduced to around approx 0.0173 using CNN where as using YOLOv8 reduced to 0.2979. also the accuracy is 99.85% using CNN where as YOLOv8 is comparatively less than CNN which is about 68.1%. From the results we found the model works pretty fine as the accuracy is quite good also we conclude a decision that CNN is more likely doing excellent over training our dataset.

Model Name	Precision	Recall	F1 Score
CNN	0.98641	0.98630	0.98632

TABLE III
COMPARATIVE EFFECTIVENESS OF CNN

The comparative effectiveness analysis reveals compelling results for the CNN model, showcasing exceptional precision, recall, and F1 score values of 98.64%, 98.63%, and 98.63%, respectively. These metrics collectively highlight the model's remarkable accuracy in correctly predicting and capturing instances of vehicle damage across different severity classes. The high precision indicates a minimal rate of false positives, while the equally impressive recall emphasizes the model's proficiency in identifying the majority of actual positive cases. The F1 score, being a harmonic mean of precision and recall, further underscores the balanced and robust performance of the CNN model.

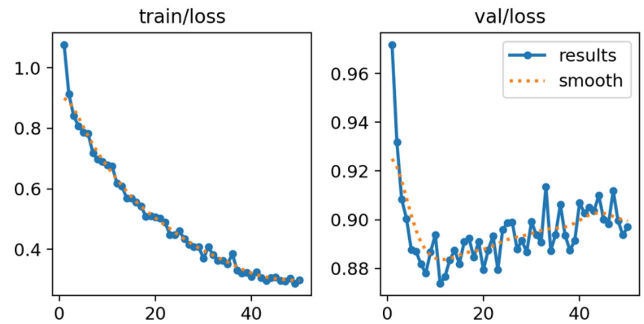

Fig. 2. Performance using YOLOv8

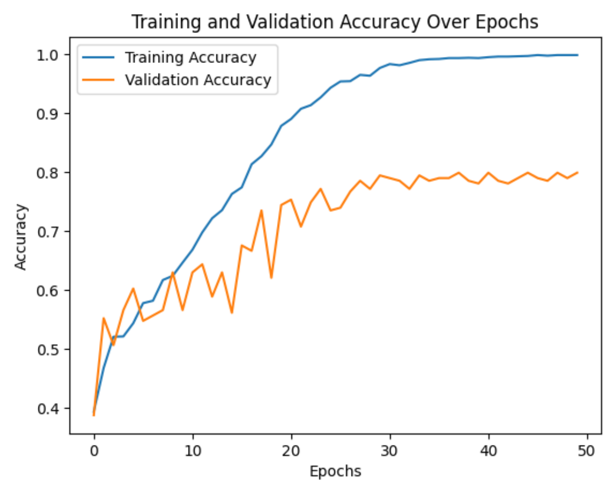

Fig. 3. Performance using CNN

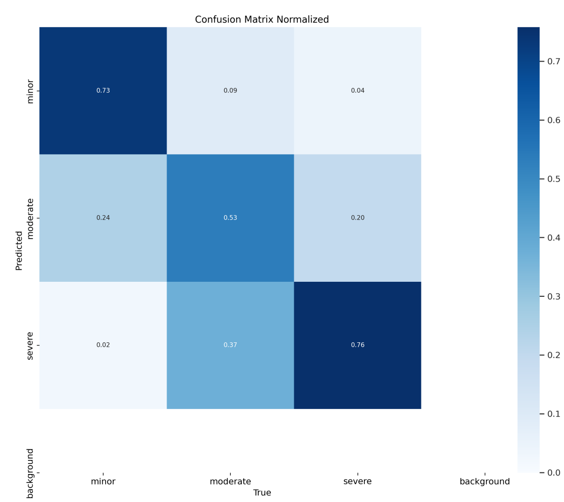

Fig. 4. Normalized CM using YOLOv8

VIII. Conclusion

In conclusion, we must say the Convolutional Neural Network (CNN) utilized in this study effectively categorizes vehicle damage into minor, moderate, and severe classes. The high-performing and validated model holds promise for real-world applications, particularly in automated emergency response systems.

Additionally, exploring the use of YOLOv8 for vehicle damage classification offers a potential avenue for future research, bringing real-time object detection capabilities to enhance efficiency in rapid response scenarios.

In essence, the developed vehicle damage classification system shows promise in improving emergency response by providing timely and accurate assessments of damage severity. Ongoing research and refinement of the model, coupled with exploration of emerging technologies, could further advance the Automate System and Damage Detection, contributing to the evolution of support systems for swift on-site response.

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