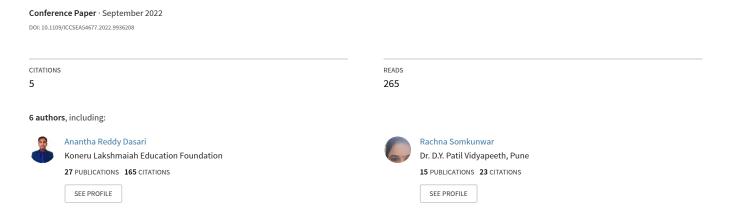
Automatic Vehicle Damage Detection Classification framework using Fast and Mask Deep learning



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Dasari Anantha Reddy* Computer Science and Engineering KLEF, Aziznagar Hyderabad, India anantha.d@klh.edu.in

Saroj Shambharkar Department of Information Technology K.I.T.S.Ramtek Nagpur, India sarojshambharkar123@gmail.com

Kandi Jyothsna Computer Science and Engineering MLRIT, Dundigal Hyderabad, India jyothsnak.josh@gmail.com

V Manoj Kumar Computer Science and Artificial Intelligence Electronics Engineering Department Department of Computer Engineering SR University, Ananthsagar Warngal, India manoj02526@gmail.com

Chandrashekhar N Bhoyar Nagpur,India cbhoyar@gmail.com

Rachna K. Somkunwar Priyadarshini College of Engineering Dr. D. Y. Patil College of Technology Pimpri, Pune, India rachna.somkunwar12@gmail.com

Abstract—Now a day's road accidents occurred very frequently in every part of the world. Damage investigation and detection after every accident becomes a very challenging and primary job for vehicle insurance department personnel and vehicle maintenance and rental industries. There is a necessity for some Automatic Vehicle Damage Detection System with the capability of detecting the minor and major damages that are occurred in a vehicle after any type of accident so that an appropriate appraisal can be made and a suitable amount paid to a guilty customer. There is an extensive growth in technology, which leads to the extensive development in Computer System Vision techniques. A tremendous amount of Computer Vision technology has been applied to various real-world life problems. There is a need for an effective automatic vehicle damage system to reduce the vast need for manual manpower required for this damage detection work after the occurrence of an accident. In most of the existing research work, the major problem faced by the researchers is there exist very few datasets to train the system which can be used to classify the damage. And the major challenge is the accuracy of those classifiers to classify the vehicle images into their appropriate damage classes. As the number of vehicles on the roadside goes on increasing, there is a need for automatic systems to ease the post-accident or damage processing goes on increasing. In our research work, we have proposed a Deep Learning-based Vehicle Damage detection assessment algorithm. The algorithm is based on image classification and objection detection methodology capable of automatically determining the actual damage position in a vehicle, degree, and type of damage from the various images received from the guilty user or from any person which will help them to provide a suitable maintenance amount, the calculation done by the insurance company. The proposed work provides a brief idea about the damages occurred during accident and also about the appropriate appraisal. The proposed system focused on fast response to the user, the user don't have to wait. The user will get the information just by providing the image of the damaged portion of a vehicle after an accident occurred with greater accuracy.

Index Terms-Accident, classification, Damage detection, Machine learning, object detection,

I. INTRODUCTION

A recent study reveals that over more than 50000 road accidents occurred yearly in the whole world. In most road accidents, the owner or driver of the vehicle, or vehicle insurance policyholder has to waste lots of time to receive the estimated amount for damage caused due to an accident occurred. Also, it is considered that most of the accidents occurred due to very fewer speed differences e.g. less than 15km/hr, this type of accident is known as a low-speed accident. The demand for damage estimation for such types of accidents is growing very rapidly and the most insurance company not give any damage appraisal for these types of accidents [1]. Even though there are various types of advanced technologies available which provide help to the drivers for detecting their vehicle damage position still every method has some pros and cons. Different researchers and vehicle insurance companies are developing various solutions for generating data from an accidental spot that has an automatic answering machine with application software that will raise questions to the guilty user and provides the answer to the user stored in its database known as chatbots and as per the answers and question, these chatbots will prepare claim settlement and generate an estimated cost for repairing of damage caused with the help of image received from the customer [2]. Some already existing systems and some on-board diagnostic(OBD) interface software is connected through customer vehicle to transfer data when the accident happens to insurance companies or vehicle management industries [3]. In previous days whenever accidents occurred and damage is caused to the vehicle, the customer has to contact the insurance companies, and also they have to wait for the arrival of an insurance agent to the actual accident spot for the inspection of the vehicle damage position and type. After the arrival of a responsible insurance agent, the traditional procedure has to follow for the detection of damaged caused by an accident,

and then the appraisal was calculated. It may happen that fundraiser appraisal calculated by insurance agents may not be calculated perfectly or accurately as we all know that machine calculations are more accurate than a human being. There is a need an implementation of an automatic system that is capable of making accurate cost estimation for vehicle damage caused by any major or minor accident instantly, accurately with the help of data provided by the user(insurance holder or vehicle driver) without a physical inspection done by the insurance company agent [4]. In this paper, we are focusing on the implementation of such a type of automatic system based on a machine learning algorithm(R-CNN) recurrent convolution neural network which will support the instant calculation of vehicle damage part estimation caused by accident immediately data provided by the user.

II. RELATED WORK

Examination of computerized reasoning has significantly improved the execution of both assembling and administration frameworks. One of the most related applications to perceive the vehicle mishap harm utilizes deep learning, artificial intelligence, machine learning, etc. The related work is based upon the incorporation of open source programming, gives an easy to use and value assessment, and backs numerous pictures preparing at that point for the estimation of damage made after the crash or accident. In [5] the time series data analysis is used by the researchers to detect and predict the damage portion of the vehicle. In this technique, the damage is considerably small due to low-speed accidents or crashes. The approach is initialized with preprocessing, and exploration followed by feature extraction. The feature extraction is then followed by the individual feature selection of different parts of a vehicle. The feature selection processes in this experiment are automatic and manual one-to-one feature selection is also considered using recursive feature elimination with crossvalidation is used. Finally, the Random Forest Classifier has been implemented for the classification of damaged parts and non-damage parts. The damaged parts are further then classified into the severity of damage for the assessment of the damage. This process is optimized using hyper-parameter optimization. In [6] authors present the automation process of car insurance claim settlement of damaged car images using deep learning. The automatic classifier [10] has been built using a multilayer Convolution neural network (S-CNN) consisting of 10 layers. The CNN architecture is used to classify the damaged images. To improve the accuracy of the CNN model, dataset augmentation has been done. The results have been evaluated and tested on both the dataset without augmentation and with augmentation. The results obtained from the augmented dataset are much better than without the augmented dataset. The results of the CNN classifier would be further improved by the inclusion of transfer learning and ensemble learning and finally fine-tuned making the accuracy of the classifier up to 90%. In [7] the automatic machine learning-based approach is used to identify the impact point and the damage made after the low-impact vehicle crash or

accident. The approach uses the time series vehicle data to recognize the point of impact of the low-intensity crash. In this, the Time series decision tree classifier was designed and implemented over time series in-vehicle data to make automatic identification [16] and the probabilistic prediction of the point of impact after the low-intensity crash. The prediction accuracy of the developed decision tree classifier is around 90% as experimented with results presented by the author.In [8] presented pattern recognition-based damage detection mechanism, it is a signal processing-based model, that comprises signal detection, noise removal, feature extraction, building and training a classifier, and finally predicting the damage that appears in the vehicle. In this, the signal detection is done using the displacement or vibration sensor. The wavelet transform [11] is used to remove noise. Principal component analysis [12] for feature extraction and reduction. The classifier is built known as a feed-forward multilayer perceptron neural network ensemble classifier. The build classifier can identify single as well as multiple damages to a structure based on acoustics signals collected from the vehicle. This scheme can also be used as preventive maintenance for a vehicle.

TABLE I: Comparison of existing work

| Methodology | Advantages | Challenges | |
|-----------------------|--------------------------|-------------------------|--|
| Deep Learning | High performance, | Need GPU to attend to | |
| | low latency inference, | high accuracy | |
| | and high accuracy | | |
| Linear Support Vector | Sensitivity and speci- | Not suitable for multi- | |
| Machine | ficity is more than | class classification | |
| | 90% | | |
| | | | |
| Principle Component | able to classify retinal | Not able to classify | |
| Analysis and Machine | vasculature | the retinal data into | |
| Learning Methods | | severity class | |
| Image Processing | Classifier accuracy | Complex data struc- | |
| | more than 90% | ture | |

III. VEHICLE DAMAGE CLAIM AND ESTIMATION

The vehicle damage is defined as deformation in any part of the complete body of a vehicle. Deformation consists of 'dents' which means various depressions in the vehicle body surface and 'dings' mean different deformations in the surface of the vehicular body. Vehicle damage is rapidly increasing as the usage of vehicles is increasing very rapidly even in rural areas also. It should be noted that there is a standard and global classification [5]. Some basic classifications for vehicle damages are discussed below in Figure 1

A. Minor damage

This type of damage classification includes tiny scratches or dings on the surface of the vehicular body. Example of minor damage includes tiny scratches or dents on the surface, side mirror, or headlights of a vehicle, as shown in Figure 2a

B. Moderate Damage

This category includes some big dent in vehicular body surface like the door of the vehicle are blocked and can't be moved(open and closed), or seat belt airbags seat stands,

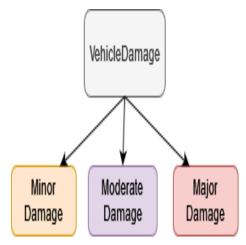


Fig. 1: Classification of Vehicle Damage

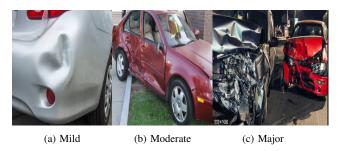


Fig. 2: Damage of vehicle with respect to Mild, Moderate and Major

upper luggage stands of the vehicle, headlights are partially damaged, as shown in Figure 2b

C. Major Damage

In this category, the vehicle body surface is completely damaged, like it's mangled with another vehicle. Frames, a glass of the door, side mirror, headlights, and all vehicle body are damaged, as shown in Figure 2c

In fig. 1, the Vehicle damage categories minor, moderate and major are used for cost estimation then it is utilized for claiming the insurance amount of the vehicle from the insurance company. The categories in figure mild, moderate and major are also used to determine the reappearance of the vehicle on the road. Once the severity of the damage is identified and the category of the vehicle damage is determined on any of the above-classified categories. The classified category will define the exact physical condition of the damaged vehicle. For any automatic vehicle damage detection system, the determined classified category plays a key role in further data and system processing.

IV. PROPOSED METHODOLOGY

The proposed framework is capable of predicting the type of vehicle damage i.e. either its minor damage or major damage. The main objective behind the proposed research work is to design a framework for an automatic intelligent damage

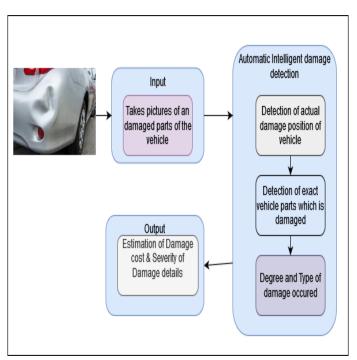


Fig. 3: Flow of Proposed System with input and ouput

detection algorithm for investigating damage caused by an accident in a vehicle that consists of three individual parts. The experimental result shows that our proposed algorithm achieved better accuracy than the existing approaches. The proposed system is based on the machine learning algorithm as it evolving technology in artificially intelligent systems. Our proposed work consists of three sub-parts as given below:

- Detection of actual damage position of the vehicle
- Detection of exact vehicle parts which is damaged
- · Degree and Type of damage occurred

Once the accident occurred on the road, the user will collect the actual 2-d images of a damaged surface of a vehicle. These 2D images will serve as an input for further processing of our proposed system. Figure 3 describes the processing block diagram of our proposed approach.

Input This block depicts the input to be fed to our proposed system. Here, input will be collected in the form of 2D images taken by the customer (Driver/insurance policyholder) immediately after the accident occurred and damage caused to the vehicle. The picture will contain different angles and degrees of the damaged part.

1) Detection of Exact damage position of vehicle: The major processing work in our proposed framework is to identify the actual position of damage caused due to the impact of the collision with another object. Here, we will consider damage as an object, and there are so many object detection techniques available for detecting objects in? Computer Technology can be applied to find the exact position of a damaged vehicle. A most commonly used object detection algorithm namely Recurrent Convolution Neural Network for object detection (R-CNN) which is based on a machine-learning algorithm

can be applied here to detect the damage position(object). Mainly it makes use of the Focal Loss technique to put back-crossed data loss to resolve the problems and also for generating limitation boxes. The obtained results show that the R-CNN is capable of detecting exact damages in the picture, the disadvantage of this detection technique is it can determine only one damage as a multiple damages as depicted in the Figure 4 As shown in Figure 4, the damaged





Fig. 4: Exact Damage Position of Vehicle

position in real has two damaged but when it is detected using an object detection algorithm it will give output as one damaged position, hence we have to apply the algorithm in a back-forward manner. Hence, the recursive—convolution neural network is the best suitable algorithm to detect the exact position of a damaged part of a vehicle.

2) Detection of Exact Vehicle Damaged Part: The estimation of the repair cost of the damaged vehicle is fixed by recognizing the type of exact damage of the vehicle, degree of damage, and total no. of damaged parts of the vehicle. It should be noted that damaged occurred in various parts of the vehicle gives various repairing difficulty, hence this part of our proposed work plays a very important role. To identify the damages that occurred in the vehicle through various images given by the customer the image segmentation is to be performed on the received image. For the image segmentation process, we have proposed an M-RCNN algorithm. Mask-RCNN has all features to give the best solution for any image segmentation. This algorithm makes use of an advanced ROI alignment technique for replacing the ROI buffering in Fastest-RCNN, & resolves each pixel-level segmentation of an image in MASK -PREDICTION. In the ROI-Buffering process, a different appropriate revolving process is used, which is having a very small effect on any sort of classification problems but has an excellent effect on the processing of pixel-based segmentation. The mask-prediction uses a faster convolution neural network (FCNN) for predicting every ROI-Buffering and generates the corresponded MASK. The MASK-RCNN algorithm has been used to train the already selected dataset and tested on that dataset. After testing, the result obtained shows that it perfectly fulfilled our needs and provides an excellent accuracy level. Mask R-CNN algorithm is used to train the dataset and tested it. It is found that Mask R-CNN can perfectly meet our needs and achieve high accuracy. Details are shown in the section of the experiment.







Fig. 5: Damage Marking

3) Degree and Type of damage occurred: To estimate accurate cost estimation of a vehicle part, it is important to correctly predict the degree and type of damage parts of a vehicle. To improve the anticipating precision of initiation in our dataset, explained data in pictures in the dataset is broken down. It is discovered that the way that the equivalent damage can have a place with various types of damage types may lead to the diminishing exhibition of Inception, which appeared in Figure 5

$$P_c = \frac{e^v}{\sum_{k}^{c} e^v} \tag{1}$$

In 1, P_c represented the probability of classification, v is the neuron value. Because of the attributes of Convolution softmax function 2, at the point when the likelihood that the characterization result has a place with a specific class is especially enormous, the likelihood of having a place with different classifications is very small.

$$S_{max}(v) = \frac{1}{1 + e^{-x}} \tag{2}$$

A. Proposed Algorithm

The deep learning-based methodology is adopted to make the accurate prediction and classification of the image into its appropriate class. The proposed algorithm is based on the Mask R-CNN algorithm which shows better experimental performance rather than the R-CNN. The Mask R-CNN has multiple Convolution layers along with the combination of supervised max-pooling and hidden layers. The final integration of the algorithm is done by the activation function. In the subsequent section, the experimental results of the proposed methodology to classify the image based on the degree and the type of damage are discussed.

B. Dataset

Since there are very few openly accessible data sets for vehicle damage characterization, we have used the Kaggle data set size with 300MB https://www.kaggle.com/anujms/car-damage-detection comprising of 1100 pictures(damage and whole) having a place with various sorts of vehicle damages. We consider seven regularly watched sorts of harms, for example, guard imprint, entryway mark, glass break, the headlight was broken, tail light broke, scratch and crash. Moreover, we additionally gather pictures that have a place with no damage class. The pictures were gathered from the web and were physically explained shown in Figure 6.

TABLE II: Features and challenges of the the existing skin diseases classification frameworks

Algorithm: FMR-CNN **Dataset preprocessing:** Scaling, Channel extraction, and equalization. **Normalization:** Min-Max Normalization

Feature Selection and Extraction: Principal Component Analysis(PCA)

Fast MR-CNN Model: a stack of Convolution, Max-pooling, and Dropout layers, which helps to improve the prediction accuracy.

Convolution Layer: Convolution matrix and filter (3x3 or 5x5 low pass)

Gaussian filter and convolution matrix (16x16 to 128x128)) **Pooling Layer:** MAX-Operation with 2x2 or 4x4 of the input image. **Dropout Layer:** Preventing the structure from Overfitting makes Im-

provement in Performance. **Hidden Layers and Feature Pooling:** Optimization and Rearrangement after Dropout.

Activation Function: Non-Zero gradient rectifier Activation function as Output layer.



Fig. 6: Sample data set images

V. RESULT AND DISCUSSION

As shown in Figure 7, our proposed system will identify the exact damage position through the different pictures taken by the user. These different images captured will be fed as an input to the neural network which is used with backward –input position & then the output has been obtained as an actual damage position which has been depicted using as of rectangular mark shown yellow and green colored and fine dashed lines rectangular frames as shown in Figure 8.







Fig. 7: Exact Annotated Damage Position

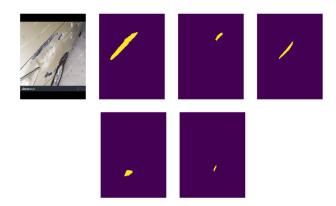


Fig. 8: Actual type of Damage

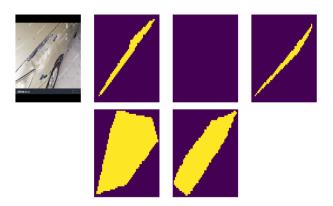


Fig. 9: Degree of damage

As we know the almost all vehicle parts have standard parts, they fall in at most 31 types such as front & rear bumper skin coat, rear and front bumper grilles, Rear & front fog lamps, vehicle network system, shell outer plate, rearview model, front view model, set of the mirror assembly, front and back types assembly, license plate assembly, front and rear bonnet, etc. Every damage type consists of deformations of parts, scrapes, cracks, scratches, and major damages. The damage degree has three types to display results major, minor and moderate damage degree. The result has been obtained using FRCNN (Fastest –Recurrent Neural Network) classifier where the segmented image has been fed as an input. Figures 7 and 8 depicts the various exact vehicle part and degrees of a damaged vehicular part after the accident occurred.

VI. CONCLUSION

The system of vehicle damage appraisal including the recognizable proof of vehicle parts, damage position, damage type, and degree characterization is proposed. The fundamental commitment is introduced a brief idea, related work, and a novel method for the classification of vehicle damage into different categories using digital data. It coordinates different calculations in computer vision and applies those to genuine and required issues of industry and society. Using proposed techniques is utilized for the recognizable proof of harmed parts, and the outcomes are handled with a disjoint set and

TABLE III: Degree and Type of damage occurred

| Damage Type | Severity | Recall | Precision | Accuracy |
|-------------|----------|--------|-----------|----------|
| Scratch | Mild | 79.8 | 79.5 | 82.1 |
| | Moderate | 86.5 | 81.5 | 88.6 |
| | Severe | 80.2 | 83.5 | 80.3 |
| Deformation | Mild | 79.9 | 80.6 | 81.7 |
| | Moderate | 83.9 | 72.1 | 89.8 |
| | Severe | 86.8 | 80.6 | 79.9 |
| Cracking | Mild | 82.4 | 81.6 | 83.9 |
| | Moderate | 83.5 | 80.4 | 88.4 |
| | Severe | 80.6 | 81.9 | 80.7 |
| Damage | Mild | 72.1 | 82.6 | 78.6 |
| | Moderate | 80.6 | 78.9 | 86.5 |
| | Severe | 81.6 | 79.6 | 80.5 |

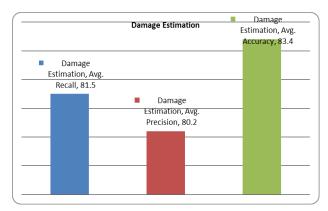


Fig. 10: Results of Classifier Evaluation parameters

the recognizable proof exactness is improved. Cover Fast MR-CNN is received for the distinguishing proof of vehicle parts, the damaged parts are dictated by the strategy for inspecting, and the time multifaceted nature is extraordinarily decreased. Moreover, Inception is applied for the grouping of harm types and the last layer is amended to be reasonable for multi-mark characterization. This paper mentioned the related issues and their probable solution. In the concluding remarks, highlighted the accuracy of the classifier to classify the image into the type and the degree of the damaged vehicle. In future work, it is attainable to join with the qualities of vehicle damage evaluation data and discover calculations reasonable for issues to arrive at higher exactness to improve prediction accuracy to the maximum level. The work can be extended for the automatic vehicles users in damage detection with addition of some new categories addition to mild ,moderate and major damage to improve the prediction accuracy.

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