External Damage Detection of Cars using Deep Learning

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Abstract— This paper's focus is to detect external damages in cars with the help of Deep Learning. There is a primary role of cars in today's world. And, automatically detecting exterior damages in cars can prove to be a notable interest to the customers and the industries of car insurance. Also, customers want their car back on the road quickly if the car was damaged due to any reason. The companies of car insurance need to accord with the inspections of cars on a daily basis. Those type of inspections are a lengthy and extensive process. Despite the fact that the alternate of such manual examination cycles may be far away, creating a system to help, speed up or upgrade the interaction may be conceivable with the present innovation. Therefore, we aspire to develop a functioning model of a system that will be able to detect if an uploaded image is a car or not. Then, further it can detect that the car is damaged or not. Also, it will tell us the location (front, rear and side) and severity (minor, moderate and severe) of damage in the cars. We used transfer learning with VGG16 architecture (a convolutional neural network model), logistic regression to get the classifier for the images and Django framework for the frontend part. We got 89.94% accuracy for damage detection, 70% for damage localization and 67% for damage severity.

Keywords: VGG16 architecture, transfer learning, CNN, deep learning, Django framework

I. INTRODUCTION

Detecting damages in pictures containing cars is a task of image classification which assigns an image to a specific category. This comes under Computer Vision technique which is used to decipher and comprehend the visual world. Utilizing computerized pictures from cameras, machines can precisely distinguish objects and afterwards respond to it. In any case, having the option to naturally distinguish damage in cars is a topic of research that has numerous conceivable real-world applications. Car insurance agencies and Car rentals need to manage car damages consistently. It regularly happens that cars must be investigated for harms, frequently in conditions that are badly arranged for clients, and expensive to the actual organizations. It is consequently imperative to have the option to robotize vehicle's harm recognition, making it both more advantageous and less expensive. The technique utilized all through this task comprises of adjusting arrangements that are known to work in an assortment of picture grouping issues, to the specific issue of outwardly distinguishing damages in cars and afterward assessing their presentation moderately to other existing arrangements. On the off chance that the vehicle for which the protection was purchased must be investigated by an Insurance agency, the entire motivation behind selling protection through the Internet would be crushed. The client would at this point don't have the comfort of rapidly purchasing a protection, since he would need to trust that the review will be performed before the viability of the protection was allowed. Then again, the insurance agency would presently don't have the advantage of diminished expenses in selling its items through these channels, on the grounds that a specialist would need to drive down to the protected vehicle area, potentially a distant area, to play out the examination. Both these burdens would be moderated if the customer transferred some photographs of the vehicle to be consequently reviewed by a system that could declare if the vehicle has damages or not. So, we'll develop such a system where user can detect damage in car very quickly.

II. RELATED WORKS

In [1], the authors considered the issue of classifying car damages. They investigated about deep learning based procedures for this reason. At first, they attempted straightforwardly training a CNN. At last, they tried to experiment with ensemble learning and transfer learning. Test results showed that transfer learning works better compared to fine-tuning of specific domain. They accomplished exactness of 89.5% with a mix of ensemble and transfer learning.

In [2], the authors proposed that once the picture is transferred, the system will handle the picture and distinguish the gouge, scratches, broken glasses, and so forth. Then, it is grouped into the different severity classes by considering the highlights of the vehicle like the model and the time of assembling. Eventually, the client gets to know about a degree of harm severity and a normal expense from which the harm can be recuperated. They applied the idea of picture examination, which is utilized to acquire precise damage consequence of any outside part of the vehicle.

In [3], the authors tried to experiment with the pictures of car damage for pre-preparing and uses Labelme to make labels of dataset, which are separated into training sets and test sets. Feature extraction is done with Feature Pyramid Network and ResNet is optimized. The results showed that the improved Mask RCNN has better detection accuracy, masking accuracy and Average Precision value. It improves the effectiveness of taking care of auto collision pay issues.

In [4], the authors proposed a system that can characterize the damaged vehicle and anticipate how the damage occurred. CNN is used for recognizing different classes of harm in the minor and significant parts of vehicle. The harms are like scratches, glass break and broken head light. CNN is utilized for object acknowledgment task. It is applied in the particular context of vehicle harm acknowledgment.

In [5], the authors trained the data into a R-CNN Mask which gives appropriate results when compared to the traditional Neural Networks. The model is layered over more than 3 arrangements of distinguishing the car and inspecting whether the damage is high or low. The classifier is projected with the flask framework to make the functioning experience simpler. It runs on a localhost. The gather time doesn't surpass 5 seconds independent of the picture quality. Exploratory outcomes showed that Mask R-CNN works better compared to convolutional R-CNN.

In [6], the authors proposed a procedure for the detection of various damages based on Mask R-CNN. The construction of Mask R-CNN is optimized for different damage identification. The advanced Mask R-CNN is prepared with 765 pictures. The trained Mask R-CNN is assessed with 25 actual test pictures.

In [7], the authors assessed for the recently evolved bus monitoring system. They also assessed for the affectability of the characteristic deflection, which is an indicator utilized by the bus observing system, in damage identification. Affectability of characteristic deflection is checked by bringing artificial damage into an extension that is awaiting removal and has ended its service life.

In [8], the authors portrayed about a road harm type recognition. Their solution depends on the deep learning techniques for a task of object detection. Their methodology uses an algorithm of object recognition to recognize different kinds of road damages by preparing the detector on various pictures sorted into a bunch of damages. They assessed their methodology using various adaptations of trained models. Their tests showed that their methodology accomplished an F1 score up to 0.62.

In [9], the authors determined the vehicles mishap scene through image detection. The user of vehicle can transfer a few photos of the harmed vehicle taken from a gadget and naturally assess the harmed vehicle and do the processing by guaranteeing for protection. This system may incorporate a gadget, for example, scanner that produces information delegate to the vehicle damage region. They introduced a 3D pose assessment strategy utilizing image gradient data of the photo and furthermore the 3D model projection.

In [10], the authors used a Deep on Edge model which is a deep convolutional neural network that detects damaged portions from pictures. To assess the system, they compared the accuracies of DoE damage detection with other baseline techniques. Their results showed that DoE performs better than the previous strategies. Then, they investigated whether their system is able to detect the line damage on a running vehicle. With this exhibit, they showed that their system would be practically helpful.

In [11], the authors proposed an approach for a fraud behaviour feature engineering in order to improve the prediction models overall performance. The conduct being evaluated depends on the RFM model alongside an extra conduct investigation identified with policy lapse. Besides, modelling and ensemble feature selections are utilized to manage the high dimensionality issues that the feature engineering methodology carries alongside it, just like class imbalance issues.

In [12], the authors applied algorithms of deep learning like VGG16 and VGG19, for vehicle harm identification and appraisal in the datasets. The methods identify the harmed part of a car and evaluates its severity. They found the impact of pre-prepared CNN models, which are prepared on the ImageNet dataset. They used transfer learning in VGG model and utilized a few methods to improve the precision of their system. In the wake of examining and carrying out their models, they tracked down that the consequences of utilizing transfer learning and regularization can perform better compared to those of fine-tuning.

In [13], the authors presented the functioning of the damage evaluation system. Furthermore, it examines the acknowledgment of each useful module in detail. Based on the interest of accident protection claims, canny transportation and progressed machine vision calculation, a damage detection system of Vehicle Insurance and Artificial Intelligence were built by the authors.

In [14], the authors showed a vehicle damage appraisal system in vehicle protection field dependent on the procedures of artificial intelligence. They used recordings rather than photographs to associate with clients to make the entire methodology as basic as possible. They adopted video detection and division methods in computer vision. The system uploads recordings of videos captured by mobiles, perceives car damage on the cloud non-concurrently and afterward returns damaged parts and fix expenses to the clients.

In [15], the authors investigated about the various avenues with respect to transfer learning and outfit learning. Preliminary outcomes showed that the transfer learning works accurately. They achieved the accuracy of 89.5 percent with a mix of transfer and ensemble learning. They performed the data augmentation on the dataset images which comprises of guard, gouge, scratch, glass break, Imprint, broken head light, broken tail light, crush and Entryway.

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III. DATASET DESCRIPTION

We collected dataset manually from the internet where there are 920 images of damaged cars and 920 images of undamaged cars. We randomly split the dataset into 80%-20% where we used 80% for training and 20% for testing purpose. Table 1 describes the dataset images description.

Classes	Training size	Test Size
Damaged cars	920	230
Undamaged cars	920	230
Front	419	73
Rear	228	50
Side	272	48
Minor	278	48
Moderate	315	55
Severe	386	68

Table 1. Dataset Description

IV.PROPOSED WORK

After collecting the dataset, we did the implementation for the 4 checks that is Car Recognition, Car Damage Detection, Damage Localization and Damage Severity. Deep learning is associated with neural networks which we will use for predictions in the input image.

A. Car Recognition

We imported modules like Keras and json. Keras is used to evaluate deep learning models whereas json will be used for transmission of data. We uploaded VGG16 where weights are taken from ImageNet database and saved the model with .h5 format. **VGG16,** proposed by A. Zisserman and K. Simonyan is a convolutional neural network (ConvNet) model. This model has achieved test accuracy of 92.7 percent in ImageNet dataset that has over 14 million images which belongs to 1000 classes.

VGG16 is a CNN model which classify the input into certain category after processing it. There are 13 convolution layers and 3 fully connected layers in VGG16. We have passed the input through the convolution layers with certain filters to extract the features from input and get the feature map. We'll also pass it through max pooling to diminish the number of parameters if an image is too enormous. Lastly, we passed it through one fully connected layer after flattening the output and ReLu to present non-linearity in the ConvNet and classify the object finally. So, we used VGG16 model for training purpose and prepared the image whose target size will be of 224 x 224. We collected top 5 predictions using VGG16 for the given image and sorted the images based on classes. We prepared all the 920 images of dataset, got the common 27 category list and saved the category counter file as a pickle file which contains the classification of images based on their categories. For an uploaded image, it checks if predictions made for it are there in the category list or not. If it's there, that is a car else it's not a car.

B. Damage Detection

TensorFlow is used in the backend which is used for data pre-processing, building, training and estimating the model. We loaded the base VGG16 model with weights and then excluded the top dense layer. We only used one fully connected layer and 13 convolution layers from VGG16. Got the labels after pre-processing and training the images contained in the dataset. The labels contain an array of 0 and 1 for damaged and not damaged cars respectively based on the images. We also got the features with respect to the cars and transferred the learning. Hence, used the concept of Transfer Learning. It's a famous technique in deep learning where the models which are pre-trained are utilized as the beginning stage for another task. We fit the Logistic Regression model to categorize the image into damaged or not damaged cars and got the classifier file. With the help of classifier, we got the predictions on test data. For damage detection, the accuracy we got is 89.94 percent.

C. Damage Localization and Severity

The process of using VGG16 model with 13 convolution layers and one fully connected layer and getting the labels, features for the trained images are same. But now, the labels contain an array of 0,1 and 2 for front, rear and side damaged cars respectively based on the images. For severity detection, the labels contain 0,1 and 2 for minor, moderate and severely damaged cars respectively based on the images. For both tasks, again we used transfer learning and fit the Logistic Regression to get the location and severity of damage in cars. With the help of classifier, we checked the results by uploading the image. For damage localization, the accuracy we got is 70 percent. For damage severity, the accuracy we got is 67 percent.

D. Integration of all the Checks

We integrated all the checks and collected classifier file for all the above three checks. Then, we made the predictions for the images. First check is done to classify if it's a car or not. If it's a car, message given is "Car check passed". If it's not a car, message given is "Are you sure this is a picture of your car? Please submit another picture of your car" and further checks are not done. If the car is damaged, it gives the message as "Car damaged" and proceeds to location and severity detection. If a car is not damaged, message given is "Are you sure that your car is damaged? Please submit another picture of the damage. Hint: Try zooming in/out, using a different angle or different lighting" and next checks are not done".

E. Integration with Django Framework

We have used Django framework that is based on Python language to connect the deep learning application with the frontend part and make an efficient web app. We added Html and CSS in this application to display the content on website and design the web app. JavaScript is used for interactivity purpose and Bootstrap to add responsiveness to the website. Ajax is used which permits website pages to be refreshed asynchronously by exchanging some data with the server which happens behind the scenes. So, part of a web page is updated without reloading the entire web page.

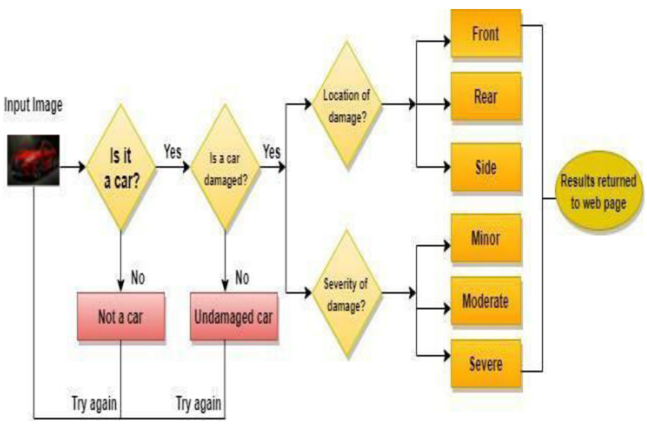

Fig.1. Flowchart for developing Car Damage Detection Toolkit

V. EXPERIMENTAL SETUP

We installed Anaconda Navigator and created a virtual environment in Anaconda prompt with Python 3.7.1. Then, we installed some dependencies like Keras, TensorFlow, pickle, Django and launched the Jupyter Notebook for implementation purpose.

Firstly, we did the implementation of car recognition. For this, VGG16 was used for training the images which were prepared with a size of 224 x 224. If the predictions made for an image are there in the category list, it's a car else it's not a car. Some of the category lists were 'minivan', 'sports_car', 'convertible', 'beach_wagon' and 'pickup'.

Next, we did the implementation of damage detection. We created a dictionary that contains train path, test path, features path, labels path, classifier path, model path and test size as 20%. We trained the images using VGG16 by passing them through various convolution layers with ReLu and one fully connected layer. Five Max pooling layers will be used which has stride 2 (number of pixels to be shifted over the input matrix) and is performed over a window of 2×2 pixel. Input layer is of size 224 x 224 x 3. First and second convolution layer is 224 x 224 x 64. Then, max pooling is performed which is 112 x 112 x 64. Third and fourth convolution layers is 112 x 112 x 128. Again, max pooling is performed which is 56 x 56 x 128. Fifth, sixth and seventh convolution layers is of 56 x 56 x 256. Then, max pooling is performed which is 28 x 28 x 256. Eighth, ninth and tenth convolution layers is of 28 x 28 x 512. Then, max pooling is performed which is 14 x 14 x 512. Eleventh, twelfth and thirteenth convolution layers is of 14 x 14 x 512. Max pooling is performed which is 7 x 7 x 512. Fully connected layer 1 has 4096 channels with ReLu. Feature's shape is (1840, 4096), Label's shape is (1840,), Train data is (1472, 4096), Test data is (368, 4096), Train labels: (1472,) and Test labels is (368,). We used the features and labels saved previously, then split the training and testing data. We fit the Logistic Regression, saved the classifier file and evaluated the model on test data. Then, we loaded the classifier to predict if the car is damaged or not.

The procedure of damage localization and severity is same as damage detection. First, training the VGG16 model on the images, transfer the learning, using the Logistic Regression model and using the classifier to make predictions on the input image. For damage localization and damage severity, Feature's shape is (979, 4096), Label's shape is (979,), Train data is (783, 4096), Test data is (196, 4096), Train labels: (783,) and Test labels is (196,). Following the above processes, we could finally upload an image and see if the car is damaged on the rear, front or at the side. For severity, we can see if the car is damaged minorly, moderately or severely. Then, we integrated all the checks and used the classifier files with Django framework to make a full-fledged web application. For implementation of frontend part with Django, Atom IDE is used. Table 2 describes the dependencies versions.

Dependencies	Version
Python	3.7.1
Django	1.10
Keras	1.16.5
NumPy	1.16.5
scikit-learn	0.21.3
TensorFlow	1.14.0

Table 2. Versions of Dependencies

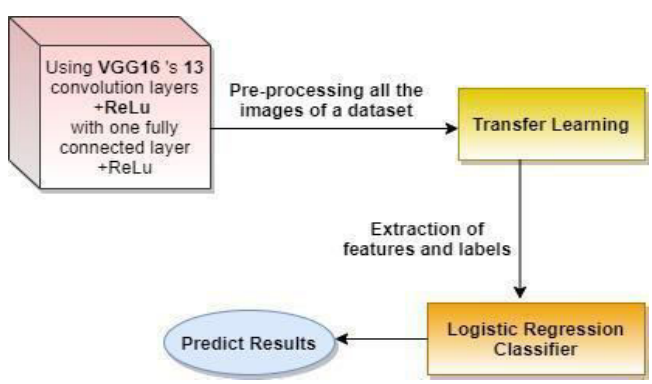

Fig. 2. Setup for Transfer Learning

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VI. RESULTS

VGG16 model is used and images are trained of the dataset successfully. Then, we transferred the learning and used the classifier to make predictions. We got the confusion matrices for damage detection, damage localization and damage severity. Hence, we found that accuracy of 89.94% is there in damage detection, 70% in damage localization and 67% in damage severity. Then, we used the Django framework to make a full-fledged web application and tested various images for prediction.

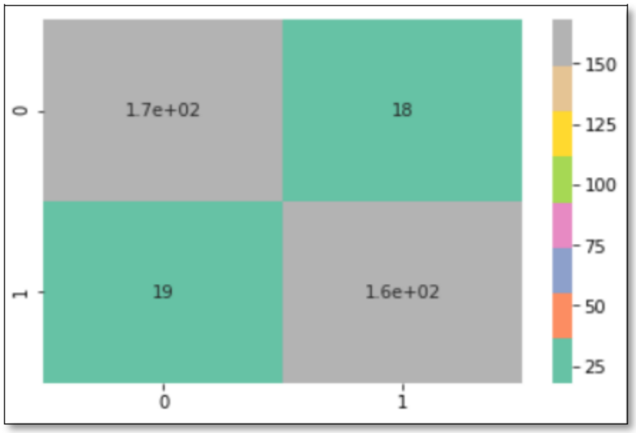

Fig.3. Confusion Matrix for Damage Detection

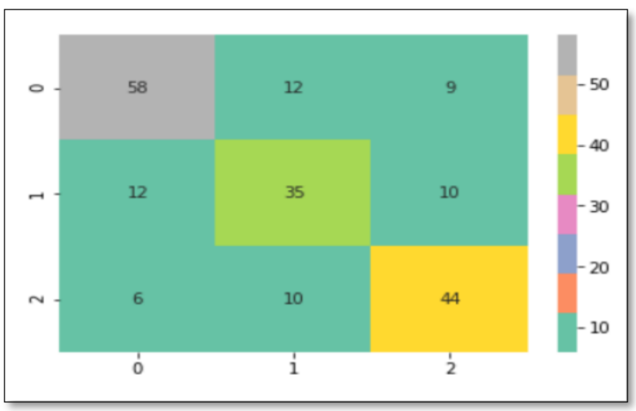

Fig.4. Confusion Matrix for Damage Localization

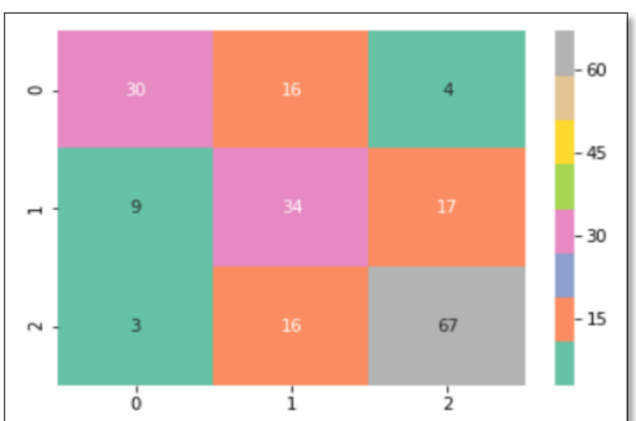

Fig.5. Confusion Matrix for Damage Severity

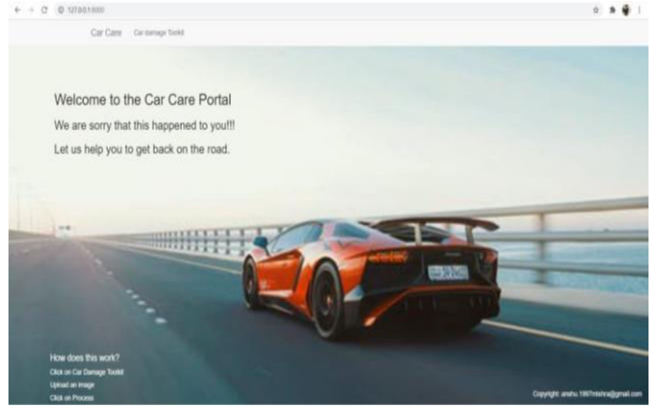

Fig.6. Home Page of the application

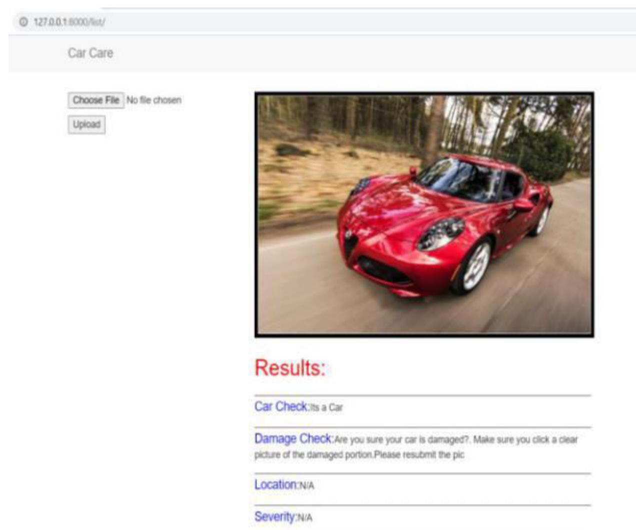

Fig.7. Image of an undamaged car

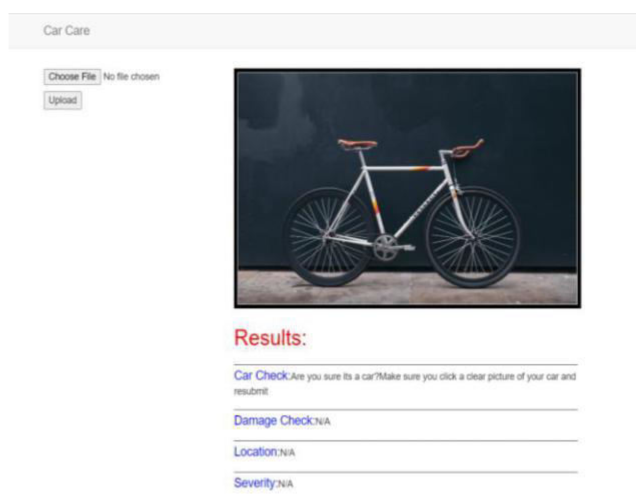

Fig.8. Image of not a car

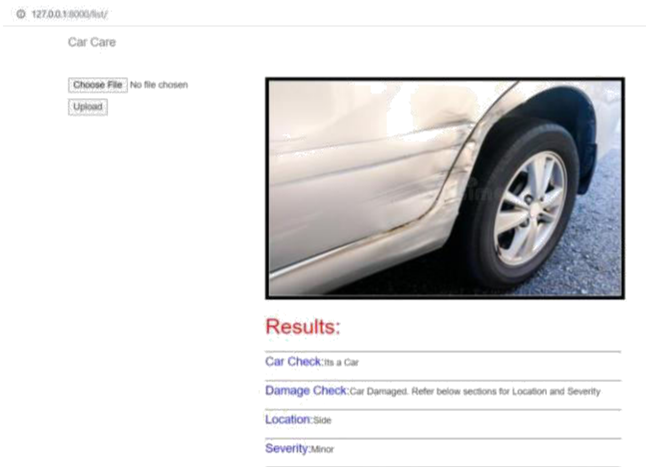

Fig.9. Car damaged with the location side and severity being minor.

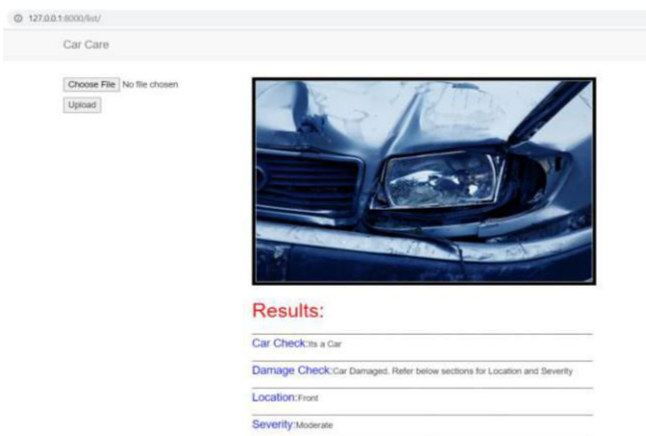

Fig.10. Car damaged with the location front and severity being moderate.

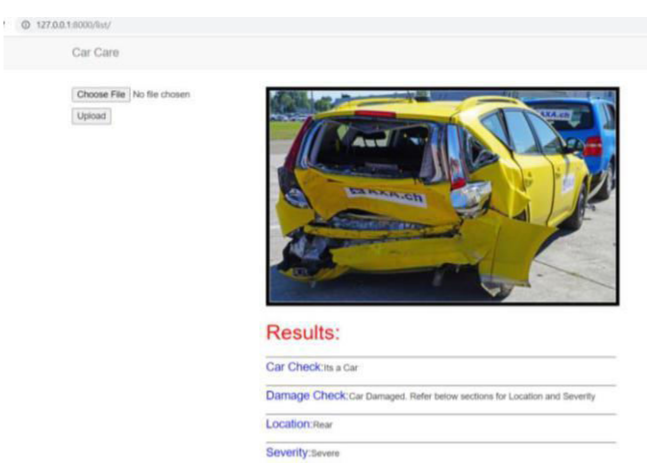

Fig.11. Car damaged with the location rear and severity being severe.

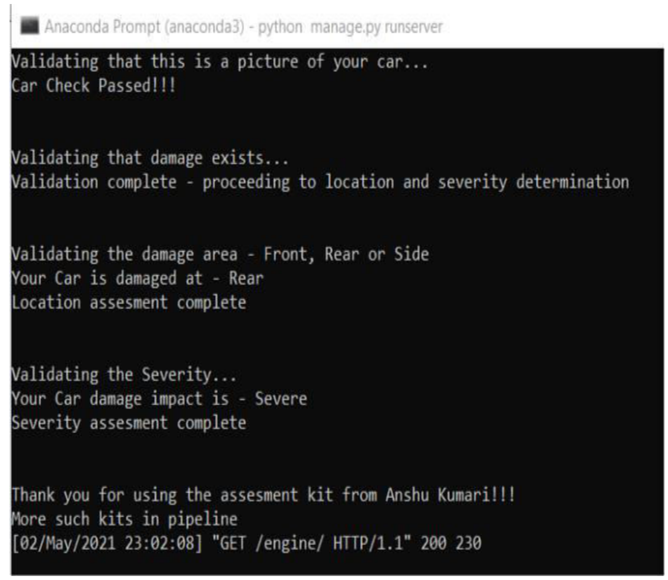

Fig.12. Output in a conda environment of a Car damaged with the location rear and severity being severe.

VII. CONCLUSION

In this paper, we used VGG16 to classify images. We used 13 convolution layers with ReLu and one fully connected layer. There are 5 max pooling layers. Then, we pre-processed and trained all the images of a dataset. We extracted the features and labels. Used transfer learning and fit the Logistic Regression to get the classifier. Using the classifier which is a pickle file, we could finally predict the results. Lastly, we integrated all the checks with Django framework to make a full-fledged web application. First check is to recognize if it's a car or not. Second check is to see if the car is damaged or not. Third check is performed to check the location of damage that is front, rear or side. Fourth check is performed to check for the severity of a damage.

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