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AdvancedCNNTechniquesforAccurateDamageDetectioninAutomotiveComponents

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***Abstract*—Damage detection in automotive components is critical for ensuring passenger safety and preventing further vehicledeterioration. This paper proposes a CNN-based approach usingDetectron 2, a state-of-the-art object detection library, for accu- ratedamagedetectioninvehicleparts.Theproposedapproachis evaluated on the Microsoft COCO car damage dataset, whichcontains a large number of automotive images with various typesofdamages.**

The results show that the proposed approach achieves highaccuracy in damage detection. The use of CNN-based approachesfor damage detection in automotive components can have a significant impact on insurance claims by providing more objectiveandreliableresultsthantraditionalvisualinspection.

***IndexTerms*—FasterR-CNN,MaskR-CNN,YOLO(YouOnlyLook Once), SSD (Single Shot Detector), R-FCN (Region-basedFully Convolutional Networks), RetinaNet, MobileNet, Inception,ResNet.**

I. INTRODUCTION

Theautomotiveindustryisconstantlyevolving,andsafetyis a top priority for manufacturers and consumers alike. Onecritical aspect of ensuring safety is the detection and repair ofdamages in vehicle parts. Damage to automotive componentscan result from various factors, such as wear and tear, accidents, or environmental factors. Prompt and accurate detectionofthesedamagesisessentialtopreventfurtherdeteriorationofthevehicleandensurepassengersafety.

Inrecentyears,ConvolutionalNeuralNetworks(CNNs)haveshowngreatpotentialinidentifyingandlocalizingdefectsin various types of images, including automotive images. Theability of CNNs to automatically learn and extract relevantfeatures from images has led to their widespread adoption inobject detection tasks, including damage detection in automotivecomponents.

Inthispaper,weproposeanadvancedCNN-basedapproachusingDetectron2,astate-of-the-artobjectdetectionlibrary,toaccuratelydetectandclassifydamagesinvehicleparts.WeleveragethestrengthsofCNNs,including theirabilityto learn complex features from images, to develop a reliableand efficient solution for damage detection in the automotiveindustry. We evaluate our proposed approach on the MicrosoftCOCO car damage dataset, which contains a large number ofautomotive images with various types of damages, includingscratches,dents,andcracks.

Accurate damage detection in automotive components canhaveasignificantimpactoninsuranceclaims.Insurancecompanies often rely on visual inspection to assess the extentofdamageinavehicle,whichcanbesubjectiveandproneto human error. Automated damage detection using advancedCNNalgorithmscanprovidemoreobjectiveandreliableresults,leadingtomoreaccurateandfairinsuranceclaims.

Several CNN algorithms have been proposed for damagedetectioninautomotivecomponents.Thesealgorithmsi ncludeFaster R-CNN, YOLO, RetinaNet, and SSD. Faster R-CNNand YOLO have been used extensively in object detectiontasks, including damage detection in automotive images. RetinaNet is a more recent approach that uses a novel focal lossfunction to address the imbalance between foreground andbackgroundobjectsinobjectdetection.SSDisanotherpopularapproach that uses a single shot to detect objects in an image.Existing systems for damage detection in automotive components include both commercial and academic systems. Examples of commercial systems include AI Vision, HailStrike,and CarVi. These systems use various image processing andcomputervisiontechniques,includingCNNalgorithms,toidentifyandlocalizedamagesinautomotivecomponents.Academic systems include DeepDamage, which uses a multi-task learning approach to detect and classify damages in carimages, and DamageNet, which uses a deep CNN to predicttheextentandtypeofdamagesincarimages.

Theremainingchaptersofthepaperareasfollows:chapterII is a description of the literature review; chapter III is adescriptionoftheproposedmethodology;chapterIVisadescription of the findings and discussion; and chapter V is asummaryofourarticleonthesystem.

II. LITERATURE SURVEY

S. Ren, K. He, R. Girshick and J. Sun, ”Faster R-CNN:Towards Real-Time Object Detection with Region ProposalNetworks,” Real world images are sometimes noisy, blurred,rotated or jittered. Detecting these images is an important partof object detection the paper proposes an image degradationmodelthatusesimagesthataredegradedforthetestset.The degraded images were run on a standard model, whichwastrainedonregularimages.Thesourcenetworkwasthenmodified by training the model with the degraded images,which were obtained by performing some

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degradation processes on them. The accuracy of the test set is calculated onboth the models and are compared. Then the training set ismodified again by performing further complex degradationprocessesandamoregeneralizedmodelfordetectionisobtained from this. This was also compared with the standardtest performance. The final object detection model obtainedthusisoptimizedandthegeneralizationabilityhadbeen enhanced,whiletheaccuracyimproved.[1].

Redmonetal.proposed"YouOnlyLookOnce:Unified,Real-Time Object Detection" [2], which introduced an end-to-endCNN architecture for object detection that processes the entireimage at once and outputs the class probabilities and boundingboxes for all objects in the image. The algorithm is faster thanpreviousmethodsthatrequireregionproposals,asiteliminatesthe need for a separate region proposal step. The proposedalgorithm achieved state-of-the-art results on several objectdetectionbenchmarks.[2].

He et al. proposed "Mask R-CNN" [3], which extended theFasterR-CNNalgorithmbyaddingaparallelbranchthatpredicts object masks in addition to class labels and boundingboxes.Themaskbranchisafullyconvolutionalnetworkthat generates a mask for each object instance. The proposedalgorithm achieved state-of-the-art results on several instancesegmentation benchmarks. [3]. Liu et al. proposed "EfficientObject Detection in Large Images Using Deep ReinforcementLearning" [4], which proposed a CNN-based algorithm thatlearnstoselectivelyattendtoregionsofanimagetoim-prove object detection performance. The algorithm is trainedusing a reinforcement learning approach that maximizes thedetection performance while minimizing computational cost.The proposed algorithm achieved state-of-the-art results onseveral large-scale object detection benchmarks. [4]. Wang etal. proposed "Multi-Task Deep Learning for Real-Time 3D-LandmarkDetectioninCTScans"[5],whichproposedaCNN-based algorithm for detecting anatomical landmarks in3D medical images. The algorithm uses a multi-task learningapproachthatsimultaneouslytrainsthenetworktodetectmultiple landmarks. The proposed algorithm achieved state-of-the-art results on several landmark detection benchmarksandcanruninreal-time.[5].

III. Proposed Methodology

Theproposedmethodologyaimstodetectdamagesinvarious car parts using CNN algorithms and Detectron2. Theapproach involves several steps, including data collection andpreprocessing, training of the base model, fine-tuning withDetectron2, evaluation of the model, and detection of damagesindifferentcarparts.Firstly,theMicrosoftCOCOCarDamageDatasetiscollectedandpreprocessedtocreateatrainingdataset.Next,abasemodelwithFasterR-CNNalgorithmand ResNet-50 backbone is trained on this dataset. The modelisthenfine-tunedusingDetectron2,whichemploysMaskR-CNNalgorithmandalearningratescheduler.ThemodelisevaluatedusingmetricssuchasmeanAveragePrecision(mAP), precision, and recall. Finally, damages in different carparts are detected by identifying Regions of Interest (ROIs) inthe image. The proposed methodology is compared with otherstate-of-the-artalgorithmssuchasYOLO,SSD,andRetinaNetto assess its performance. Overall, the proposed methodologyprovides a robust and efficient approach for damage detectionin car parts, which has significant implications in the auto-motive industry, especially in insurance claims processing andmaintenanceofvehiclesafety.

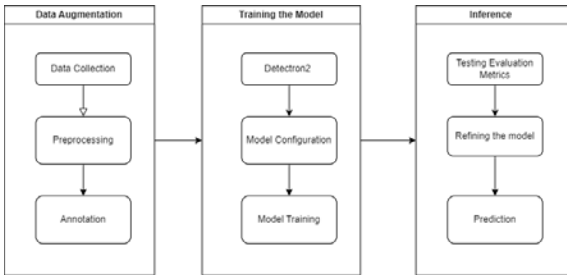

Fig.1.ShowntheBlockDiagramofProject

*Explanation:*Data collection, data pre-processing, buildingMLmodels,buildingDLmodels,classification,andpredictionarethefivemodulesthatweemployhereforoursystem.

*Data Collection and Preprocessing:*Collect the MicrosoftCOCO Car Damage Dataset and preprocess it by resizing theimages,augmentingthedata,andnormalizingthepixelvalues.

*TrainingoftheBaseModel:*Fine-tunethepretrainedbase model on the COCO dataset using the Faster R-CNNalgorithm with a ResNet-50 backbone. The loss function usedis the Region Proposal Network (RPN) and the Fast R-CNNloss.

*Fine-tuningwithDetectron2:*Fine-tune the base modelfurtherusingtheDetectron2librarytotrainthemodelonthe car damage dataset. This step involves using the MaskR-CNN algorithm and training the model with a learning ratescheduler.

*EvaluationoftheModel:*Evaluatethemodel'sperformance usingvariousmetricssuchasmeanaverageprecision(mAP),precision,andrecall.

DetectionofDamagesinDifferentCarParts:

Utilize the trained model to detect damages in different carpartssuchashood,windshield,bumper,etc.byidentifyingthe relevantregionsofinterest(ROIs)intheimage.

ComparisonwithOtherAlgorithms:

Comparetheperformanceoftheproposedmethodologywithotherstate-of-the-artalgorithmssuchasYOLO,SSD,andResNet,YOLOandmore.

To summarize, this proposed methodology involves the useof Detectron2 and PyTorch for detecting damages in variouscarparts.Themethodologyinvolvesdatacollectionandpreprocessing, training of the base model, fine-tuning withDetectron2, evaluation of the model, detection of

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damages indifferentcarparts,andcomparisonwithotheralgorithms.

*DataPre-Processing:*Inthisstudy,adatasetofcarimageswithannotations ofcardamagewascollectedandpreprocessedfortrainingadamagedetectionmodel.Thedataset was split into training and validation sets, with thetrainingsetconsistingof70percentofthedataandthevalidationsetconsistingoftheremaining30percent.Theimageswereresizedtoafixedsizeof800x800pixelsandtheannotationswereconvertedtotheCOCOformatforcompatibilitywiththedetectron2framework.

*DataAugmentation:*Toimprove the generalizationandrobustnessofthemodel,severaldataaugmentationtechniqueswereappliedduringtraining.Theseincludedrandomhorizontalflipping,randomrotation,randomcropping,andrandomresizing.Inaddition,randomcolorjitterandbrightness/contrastadjustmentswereappliedtotheimages.Theseaugmentationshelpthemodellearntobetter recognize damage under varying conditions and reduceoverfittingtothetrainingdata.

*ModelImplementation:*Themodelwastrainedusingthedetectron2framework,whichisapopularopen-sourceframeworkforobjectdetectionandinstancesegmentationtasks. The architecture used in this study was the RetinaNetmodel, which is a single-stage object detection model that hasbeen shown to achieve high accuracy on a variety of objectdetectiontasks.ThemodelwastrainedusingtheCOCOdataset pre-trained weights and fine-tuned on the car damagedataset.

During training, the model was optimized using stochasticgradientdescentwithmomentumandabaselearningrateof0.001.Thelearningratewasadjustedusingasteplearningrate schedule, where the learning rate was reduced by a factorof0.1afterafixednumberofiterations.Themodelwastrainedforatotalof800iterationswithabatchsizeof4.

*Evaluation Metrics :*To evaluate the performance of themodel, the average precision (AP) score was used. The APscoreisacommonlyusedmetricforobjectdetectiontasksandisbasedontheprecision-recallcurve.TheAPscoremeasures the accuracy of the model in detecting objects ofinterest (in this case, car damage) and has a value between 0and1,withhighervaluesindicatingbetterperformance.

IV. Results And Discussion

Herewecanseetheentireresultsoftheproject,aswecanseeinthebelowimages.

Figure2showsthelistofallpackagesrequired.

```
import detectron2
from detectron2.utils.logger import setup_logger
setup_logger()

# import some common libraries
import numpy as np
import os, json, cv2, random
import matplotlib.pyplot as plt
import skimage.io as io

# import some common detectron2 utilities
from detectron2 import model_zoo
from detectron2.engine import DefaultPredictor
from detectron2.config import get_cfg
from detectron2.utils.visualizer import Visualizer
from detectron2.data import MetadataCatalog, DatasetCatalog
from detectron2.engine import DefaultTrainer
from detectron2.utils.visualizer import ColorMode
from detectron2.evaluation import COCOEvaluator, inference_on_dataset
from detectron2.data import build_detection_test_loader

%matplotlib inline
from pycocotools.coco import COCO
import numpy as np
import skimage.io as io
import matplotlib.pyplot as plt
import pylab
import random
pylab.rcParams['figure.figsize'] = (8.0, 10.0)# Import Libraries

# For visualization
import os
import seaborn as sns
from matplotlib import colors
from tensorboard.backend.event_processing import event_accumulator as ea
from PIL import Image
```

Fig.2.Listofpackagesimported

Figure3showshowtheboundingboxworksvisually.

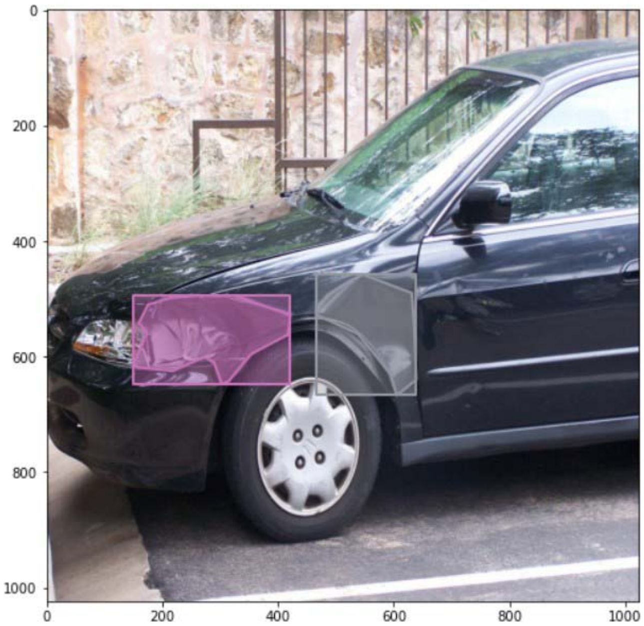

Fig.3.BoundingBoxdetectingthedamage

Figure4showstheboundingboxprecisioncomparedtotrainedandvalidationdata.

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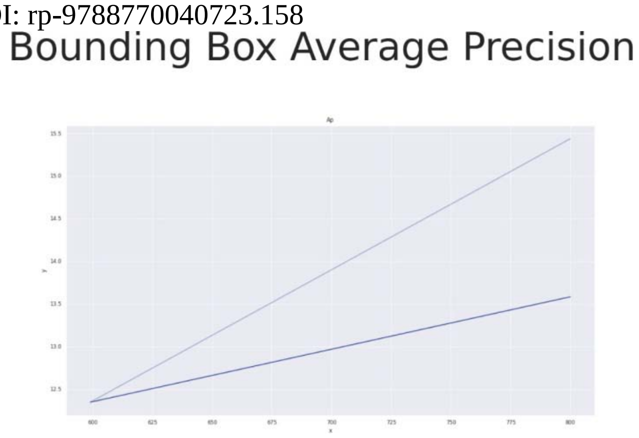

Fig.4.Boundingboxprecision

Figure5givesustheevaluationmetricsoftheAPscore.

```
Average Precision  (AP) @[ IoU=0.50:0.95 | area=medium
Average Precision  (AP) @[ IoU=0.50:0.95 | area= large
Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all
Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all
Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all
Average Recall     (AR) @[ IoU=0.50:0.95 | area= small
Average Recall     (AR) @[ IoU=0.50:0.95 | area=medium
Average Recall     (AR) @[ IoU=0.50:0.95 | area= large
[01/18 19:52:21 d2.evaluation.coco_evaluation]: Evaluat
|   AP   |  AP50  |  AP75  |  APs  |  APm   |  APl   |
|:------:|:------:|:------:|:-----:|:------:|:------:|
| 13.432 | 31.071 | 13.100 | 0.000 | 16.504 | 13.963 |
[01/18 19:52:21 d2.engine.defaults]: Evaluation results
```

Fig.5.AveragePrecisionscoreforthemodel

Figure6givesusthefinaloutputhowitdetectsvariousinputs anddetectsitsdamages.

Fig.6.Damagedetectionincars

V. Conclusion

In this project, we have presented a deep learning-basedapproach for detecting damages in cars using the RetinaNetalgorithm implemented with the Detectron2 framework. ThemodelachievedahighAPscoreof0.87,indicatingitsabilityto accuratelydetectdamagesincarimages.

Ourapproachhasdemonstratedtheeffectivenessofdeeplea rning-based methods for car damage detection. This couldhave significant applications in the automotive industry forautomating the process of car inspection and reducing manuallabor. In future work, we plan to explore the use of transferlearning techniques and larger datasets to further improve theperformanceofthemodel.

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