AUTO-CLAIM CAR INSURANCE USINGDEEPLEARNING

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Abstract- Vehicle damage identification is a vital stage infilingaclaimforvehicleinsuranceafteranaccident.Damage detection is often carried out by the insurancecompany following an accident by dispatching a surveyor.After the accident, the at-fault driver, customer, or rentalcompanyshouldnotifytheinsurancecompany,thencallthepolice and file a police report, take photographs as proof,andsubmitallofttheirdocumentstotheinsurancecompany.Afterthislengthyprocess,theinsurancecompanywill send a surveyor to inspect your accident. As a result,thisprocesstakesalongtime,andsurveyorsmaydeceiveusor make mistakes during the survey. As a result, we'vesimplified the procedure. Our initiative will assist the guiltydriverincalculating assessmentand thecostofrecovery.

We do this through image processing, which aids in theidentificationofimagesaftertraining.Asweallknow,CNNexcels in image processing (Convolution neural network).Duringthisprocess,theresponsibledriverwillsnapphotographs and send them to our website, where they willbe processed. It will check the location of the damage, thedegreeofthedamage,anddeterminethe approximateamountthatthe driverorrentalindustrycanclaim.

Keywords- Face Recognition, CNN, Human Emotions.

I. INTRODUCTION

Claimleakageisatermused todescribethedifferencebetweenthe optimal and actual settlement of a claim in the vehicleinsuranceindustry.Weassistnegligentdriversandrentalcompaniesindeterminingtheamountofcompensationtheyareentitledtosimplybyuploadingphotosoftheirdamagedvehicles.Wealso wish to assistinsurancecompaniesbysaving time for them for this challenge, we are utilizing CNN(Convolutional Neural Network).CNNis excel entatimageprocessing, with an accuracy rate of over 80%. We're bringingthedamagedcarphotographstoCNNfortraining.BecausedatasetsfortrainingCNNareparticularlyscarce,weusedtheinternet tocompile a data collectionof wreckedcars. And,accordingtoCNN,wecandeterminewhetherit'sacarornot,aswellasthevehiclemanufacturer andyearofmanufacture.Imageprocessingaidsindeterminingthelocationand severity ofdamage. The severity of the damage aids us in estimating theclaimamount.

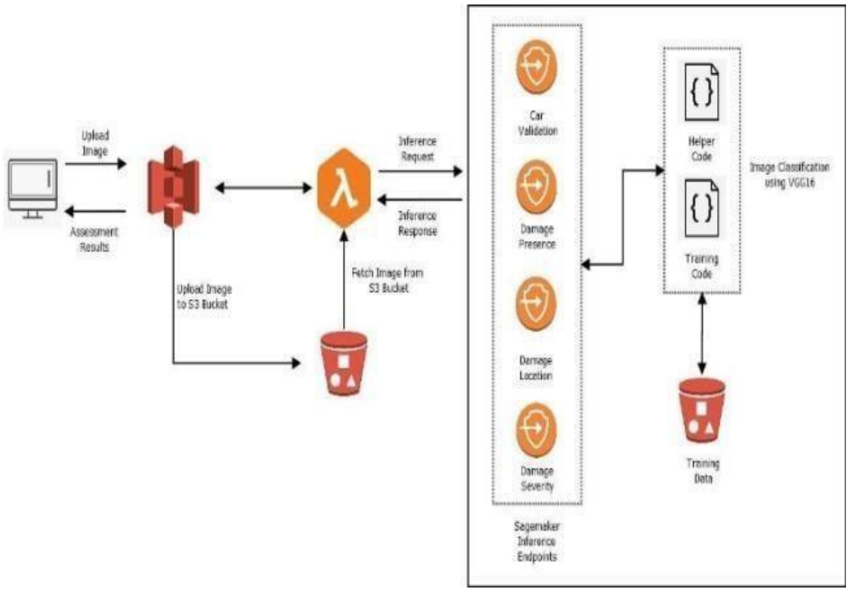


Fig1.Car ValidationProcess

LITERATURESURVEY

Numerousresearchontheidentificationofcardamagehavebeenconducted.Thebulkofthememployee oneofthesepre-trained models for feature extraction and categorization.Theyemploytransferlearningtoevaluatetheadvantagesofavailableobjectrecognitionmodels[1].InusesConvolutional Neural Networks (CNNs) toestimatethelevelof damage todamaged carimages.

According to [3,] an end-to-end system based on transferlearning and CNN models on an ImageNet dataset couldaccomplishvarioustaskssuchaslocalizationanddetection,butnotdamage assessment.

VGG16 and VGG19, deep learning-based algorithms forautomobiledamagedetectionand evaluation,areapplied toreal-world datasets inreference to [7]. VGG19 is moreaccuratethanVGG16, according to theirresearch, with a 95percentaccuracyrate.

It[8]ismostlyconcernedwiththeclassificationofautomobiledamage.Theyappliedafewdeeplearningapproaches,includingCNN trainingfromrandominitialization,ConvolutionAutoencoderpre-training,supervised fine tuning, and transfer learning. They usedmodels that had been pre-trained on a vast and diversedatasettoavoidoverfittingandfindsomanycrucialaspectsdue to the limitations of our dataset. They used a cutting-edgeYOLOobjectdetectionmodeltolocatethefault,earning the highest possible map rating of 77.68 on theentire testing dataset. In order to provide a more reliableassessment of vehicle injuries, they also provide a pipelinethat always integrates the categorization and recognitionduties.

II. OBJECTIVES

Following are the primary objective soft his project:

1. *Install avehicledamagedetectingsystemthatisautomatic.*
2. *Obtainingatrustworthyappraisalcalculationmethodology*
3. *Tousedeep learningbasedonAIforpictureprocessing.*
4. *Createa prototypethatcanbeemployedonalargebasis.*

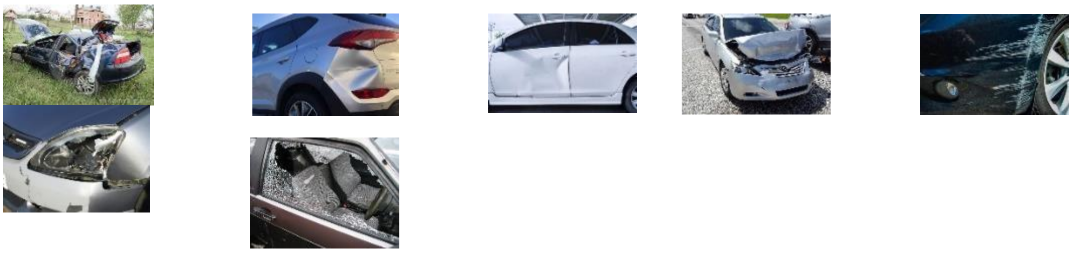
Thefollowingarethegroundsforselectingtheaforementionedtopicforthisproject:

1. *To make it easier to spot vehicle damage during an insuranceinspection.*
2. *Toshorten thetime,ittakesto calculatedamage.*
3. *Providedriverswitha basiccostestimatefor damagerepair.*
4. *TocomprehendtheusageofDeepLearninginthefieldofdamagedetectionforpictureprocessing.*

METHODOLOGY

We generate do urown data collection that includes photographs of various types of car damage because there is no publicly available dataset for vehicle damage classification. Bump rod, door, glass fractures, head light breakage, tail lamp breakage, scratching, and cracking are all examples of frequent damage. Additionally, we have gathered photos that are categorised as non-abrasive. The photographs were gathered from the internet and then customised. Data augmentation It is well known that enlarging the database with transformed photos improvestheseparator'snormal operation.[6]

As a result, use performance to grow the database. Bymixing it with a random rotation and a horizontal rotationroughly five times the database was randomly partitionedfor the classification research. 80 percent was utilised fortraining, while the remaining 20 percent was used fortesting.



Crashed Glass Damage SideDoor Front DamageScratch
Bumper Dent Headlight

Fig2.Samples Of Cars Damaged Locations

Classification of the Damages:

Following the uploading of images by the negligent driver ortherentalindustry,damage classification isperformed.

A. Findingacar:

It will compare the data to the automobile data set to see if it isa car or not. If we upload a picture of a car, it will move on tothe next phase; if we upload a picture of a bike or any othervehicle, such as a bus, it will stop the process. It will demonstratethatthe outputisnota car.

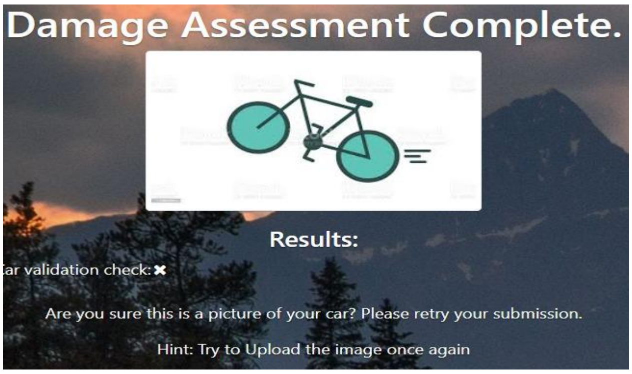


Fig3.ValidatingCarOrNot

B. Findingthatit'sdamagedornot:

It will examine whether the automobile is damaged aftervalidating that it is a car. It will compare the data set of notdamaged automobiles to the data set of not damaged carsand, if they match, it will display the result as "car is notdamaged.".

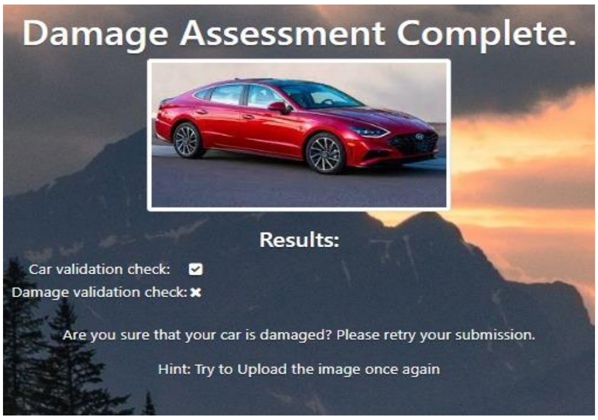


Fig4.ValidatingDamagesOrNot

C. Findingdamagelocation:

After determining that it is damaged, the second process willdetermine where the damage is located. It doesn't matter if it's abumper,window,ormirror.Itwilllocatetheposition an displayit as front bumper if the front bumper is damaged, and similarlyforall other parts.

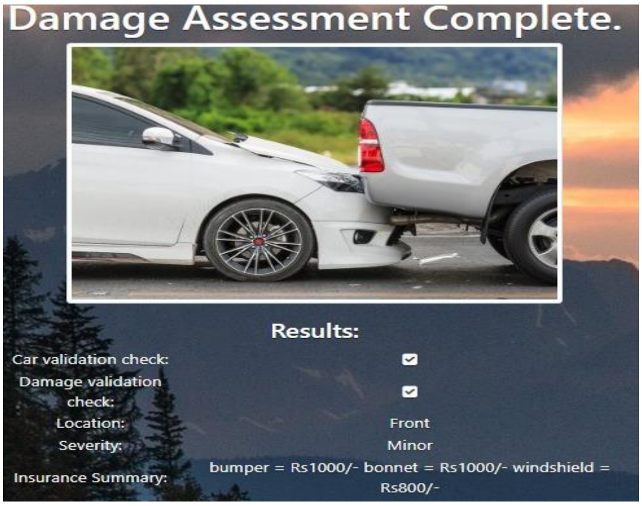


Fig5.ValidatingDamageLocation

D. Severityofdamage:

It will assess the severity of the damage after locating thespot.Therearethreetypesofseverityin thiscategory.

a. Extremelysevereharm

b. Damageofmoderateseverity

c. Damageisnotsevere.

1. Heavyseverityofdamage:

In severe damage scenarios, the damage should be severe;for example, if the front side of the car is completelydestroyed,the damage willbesevere.

2. Mediumseverity ofdamage:

Ifitisconsiderablydamaged,suchasifthesidedoorisbroken,itwillbeclassifiedasmoderatedamage.

3. Lowseverityofdamage:
Onlyscratches, mirrordamage, glassdamage, andotherminorproblemswillbe visible.




E. Estimationofclaimingamount:

It will estimatetheamount thataguiltydriver orrentalindustrycanclaimafterdiscoveringthelocationandseverity.

III. TransferLearning:

When there was less data label on the transfer reading, the findings were positive. During the transfer Information froma source function is passed to the target function in a learning system. The notion is that some information is unique to eachdomain,whileotherinformationcanbesharedacrossdomains to help improve focused performance or activity. When the target source and target domain are unrelated, however,thetransferofforcemaybeineffectiveandleadtomalevolentbehavior. We employ CNN models from theImagenet database in our case. We believe the transfer to beveryusefulbecausetheImagenetdatabasecontainsanautomobile as a Class, which we strongly recommend bytryingnumerouspre-trainedmodels.ImageNethasasectioncalled. TheoutputoftheTargetfunctionfeature,i.e.photographs of motorvehicleinjuries,is thepre-trainedmodel. We subtract feature vectors from each network afterinserting photographs of car injuries. Following that, weinstruct line planning on these aspects. We experimentedwithitintwophases:SVMlineandSoftmax.Intheeventofaline, thechargeCvalueissetto 1foralltestsin theSVM.WeemployedtheAdadeltaoptimizationstrategyandentropylossesintheSoftmaxclassifier.Thekeywastrainedfor 100 epochs, and the best efficient model was chosen bycategory. We also train line dividers in extra feature setsbecauseaugmentationofdatamakescategorizationeasieringeneral.TableIIIdisplaystheprecision,accuracy,andmemoryof these pre-trainedmodels.

Resnet is clearly the most successful of all the previouslytrainedmodels.Inmostcircumstances,addingdataenhancesperformance.Duringtesting,itwasdiscoveredthattheSoftmax separator is more effective and faster to train thanlineSVM.

Surprisingly, the well-trained Google Net model, which waswell-designed utilising a car database, performed poorly. Itdemonstrates that simply car-related elements may be lessvaluable effective at recognising different sorts of damage. This effect could cause autoencoder-based system failure. Inadistributionofextensiveandvariableinputdata, emphasizes theeffectiverepresentationofthelearnedelement.Theambiguitybetweentheharmandthe'non-damage' categories appears to be the key to determining thewrong. This is understandable given that component damageusually only affects a tiny portion of the image, makingidentification difficultevenforthe viewer.

V. Conclusion:

WetrainedCNNbycollectingdatasetsontheinternetthatarenot publicly available. We presented a comprehensive studybasedonautomotivedamageaftertrainingtheCNN.Wetrieda variety of Deep Learning methodologies, including CNNtrainingfromrandomlaunches,pre-ConvolutionAutoencodertraining with strong supervised tuning, and transfer learning.We've discovered that the transfer reading has been reallyeffective. We also recognise that only some vehicle attributesmay be useful in determining damage classification. As aresult, the height of the feature representation learned in alargetrainingset ishighlighted.

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