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# Practical Animal Detection and Collision Avoidance System using Computer Vision Technique

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**ABSTRACT:** Oneseriousproblemthatallthedevelopednationsarefacingtodayisdeathandinjuriesdueto roadaccidents.Thecollisionofananimalwiththevehicleonthehighwayisonesuchbigissue,whichleads to such road accidents. In this paper, a simple and a low-cost approach for automatic animal detection on highwaysforpreventinganimal-vehiclecollisionusingcomputervisiontechniquesareproposed.Amethod forfindingthedistanceoftheanimalinreal-worldunitsfromthecameramountedvehicleisalsoproposed. Theproposedsystemistrainedonmorethan2200imagesconsistingofpositiveandnegativesimagesand testedonvariousvideoclipsofanimalsonhighwayswithvaryingvehiclespeed.Asperthetwo-secondrule, ourproposedmethodcanalertthedriverwhenthevehiclespeedisupto35km/h.Beyondthisspeed,though the animal gets detected correctly, the driver does not get enough time to prevent a collision. An overall accuracy of almost 82.5% is achieved regarding detection using our proposed method.

**INDEXTERMS**Cascadeclassifier,computervision,histogramoforientedgradient,haar,imageprocessing, intelligent vehicle system, OpenCV, road injuries.

## I. INTRODUCTION

Today'sautomobiledesignprimarilydependsonsafetymea- sures, security tools and comfort mechanism. The approach hasfacilitatedthedevelopmentofseveralintelligentvehicles that rely on modern tools and technology for their perfor- mance. The safety of an automobile is the highest priority according to a recent report [1]. The report commissioned by World Health Organization in its Global Status Study on Road Safety 2013, revealed that the leading cause of death for young people (15-29 age) globally is due to road traffic collisions. Even though various countries have initiated and takenstepstoreduceroadtrafficcollisionsandaccidents,the totalnumberofcrashesandtrafficaccidentsremainashighas 1.24millionperyear[2].Roadtrafficaccidentsandinjuries are expected to rise by almost 65% by the end of 2020 [3]. Duetoroadaccidents,everyyear1outof20,000personslose theirlifeand12outof70,000individualsfaceseriousinjuries inIndia[4].Indiaisalsoknownforthemaximumnumberof road accidents in the world [5]. According to the data given by National Crime Records Bureau (NCRB), India, there was almost 118,239 people who lost their life due to road accidents in the year 2008 [6]. A major percentage of these road crashes and accidents involved car and other vehicles.

Roadaccidentsareincreasingduetotheincreaseinanum- berofvehiclesdaybydayandalsotheduetotheabsenceof anyintelligenthighwaysafetyandalertsystem.Accordingto datagiveninastudy[7],thenumberofpeoplewholosttheir lives in India due to road accidents was almost 0.11 million deaths in 2006, which was approximately 10% of the total road accident deaths in the world.

Accordingtotheaccidentresearchstudyconductedby JP Research India Pvt. Ltd. for the Ahmedabad-Gandhinagar region (cities of India), for the duration February 2014 to January2015,total206roadtrafficaccidentswererecorded and these were influenced by three main factors i.e. human, vehicle, infrastructure or a combination of them [8].

Thenumberinfigure1isapercentageofthetotalnumber ofaccidentssurveyed.Accordingtotherecord,humanfactor influenceonroadtrafficaccidentswas92%,vehicle9%and infrastructure 45%. Out of total 45% (91 accidents) infras- tructureinfluencedtrafficaccidents,6%(12accidents)were due to animals on the road whereas out of total 92% (171) humanfactorinfluencedtrafficaccidents,14%(24)weredue to driver inattention and absence of any timely alert system for preventing the collision . Similar types of surveys were conductedfortheMumbai-Puneexpressway,andCoimbatore

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**FIGURE1.**Influencesonroadtrafficaccidents[8].

byJPResearchIndiaPvt.Ltd.andtheconclusionshintedat asignificantpercentageofroadaccidentsresultingduetoan object(animal)ontheroad,driverinattention,andabsenceof an intelligent highway safety alert system.

## II. EVIDENCES OFANANIMAL-VEHICLECOLLISION

According to the report given by the Society for Prevention of Cruelty to Animals (SPCA), around 270 cattle had been broughttotheirhospital-cum-animal-shelterintheyear2013, mostofwhomwereaccidentvictims[27].Belowaresomeof the snapshot of the images with the sources which suggest that there are many challenges that the drivers are facing because of animals on the road.

## III. LITERATURESURVEY

Applications built on detection of animals play a very vital role in providing solutions to various real-life problems [9]. The base for most of the applications is the detection of animals in the video or image.

Arecentstudy[10]shownthathumanbeingshavetotake thefinalcallwhiledrivingwhethertheycancontroltheircar to prevent collision with a response time of 150ms or no. The issue with the above approach is that human eyes get exhausted quickly and need rest, which is why this method is not that effective. Some scientific researchers [11] have proposed a method that requires the animals to take a pose towardsthecameraforthetrigger,includingfacedetection. Theproblemwiththistechniqueisthatfacedetectionrequires animals to see into the camera which is, not necessarily captured by the road travel video. Animals can arrive fromascenefromvariousdirectionsandindifferentsizes,poses, and color.

Animals can be detected using the knowledge of their motion. The fundamental assumption here [12] is that the defaultlocationisstaticandcansimplybesubtracted. All blobs, which stay after the operation are measured asthe region of interest. Although this technique performswell in controlled areas, e.g. underwater videos, it does not work universally, especially road or highway side videos. Researchers [13] used threshold segmentation approach for getting the targeted animal’s details from the background. Recent researches [14] also revealed that it ’s hard todecidethethresholdvalueasthebackgroundchangesoften. A method applicable to moving backgrounds (e.g., due to cameramotion)ispresentedinsubsequentstudies[15],[16]. Theauthorsalsostatethatothermovingobjectsapart from the object of interest may be falsely detected as an animal.

Researchersin[17]triedtodiscoverananimal’spresence in the scene (image) affecting the power spectrum of the picture. This method of animal detection was also consid- erednotappropriatesincequickerresultswiththisapproach wouldinvolvemassiveamountofimageprocessinginashort period [18]. Researchers in [19] also used the face detector technique initiated by Viola and Jones for a particular ani- mal type. After the animal face is identified, the researchers track it over time. The problem with this technique is that face detection requires animals to see into the camera not necessarily captured by the road travel video. Animals can arrive from a scene from various directions and in different sizes,poses,andcolors.Anothermethodforanimaldetection and tracking that uses texture descriptor based on SIFT and matching it against a predefined library of animal texturesisproposedin[20].Theproblemwiththismethodisthat it is restricted to videos having single animal only and very minimal background clutter.

In Saudi Arabia, the number of collisions between the camelandavehiclewasestimatedtoreachmorethanahun- dred each year [21]. Authors in [21] implemented a deploy- able Camel-Vehicle Accident Avoidance System (CVAAS) andexploitedtwotechnologiesGPSandGPRStodetectthe

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camelpositionandthentransmitthatpositiontotheCVAAS server consequently. The CVAAS server checks the camel positionanddecidestowarnthedriversthroughactivatingthe warning system if the camel is in the danger zone. Authors in [21] do mention that cost of deploying such CVAAS ona great scale is too much. Also, the system suffers from many false negatives due to dependency on many parame- ters like a width of the dangerous zone, variation in camel speedanddelayinreceivingSMSmessage.Authorsin[22] designedasystem,whichuseswebcameraswhichareplaced in the detecting areas from where the animal can cross their boundary.Thevideosaresenttotheprocessingunitandthen usesimageminingalgorithm,whichidentifiesthechangein set reference background. If there is a change in the newly acquired image, then authors are applying content-based retrieval algorithm (CBIR) to identify the animal. The pro- posedmethodin[22]basedonCBIRalgorithmsuffersfrom manyissueslikeunsatisfactoryqueryingperformance-CBIR systems use distance functions to calculate the dissimilarity between a search image and database images, low-quality recovery results. This approach is very slow and response times in the range of minutes may take place if the database is enormous.

To find the accurate location of fishes in the marine, researchers[23]aimedatechniqueusingLIDAR(lightdetec- tionandranging).Someoftheabove-specifiedmethodshave been discussed in [24] and [25] also.

## IV. RESEARCHGAPANDCHALLENGES

- Though various practical solutions for automatic lane detection and pedestrian detection on highways are availablestillresearchrelatedtoautomaticanimaldetec- tion on highways is going on.
- Animaldetectioninwildlife(forest)videosorunderwa- tervideos(controlledareas)havebeentriedinpastbut the challenges are much more when detecting animals onhighways(uncontrolledareas)asbothanimalaswell asacameramountedvehicleismovingapartfromother obstaclesontheroadwhicharealsomovingorstation- ary.Thereisnoissueofspeed(vehiclespeedaswellas animalspeed)anddetectingdistanceofanimalfromthe vehicleinwildlifevideoswhichiscrucialandcriticalin animal detection on highways.
- The biggest challenge in detecting animals comparedto pedestrians or other objects is that animals come in varioussize,shape,pose,colorandtheirbehaviorisalso notentirelypredictable.Thoughthebasicshapeandsize of a human being are pretty average and standard, the same is not true for animals.
- Although various methods and approaches have been usedandarestillinprogresstodetect,solveandreduce the number of animal-vehicle collisions, the absenceof any practical systems related to an animal-vehicle collisiononhighwayshasdelayedanysubstantialdevel- opment in the scenario [24].

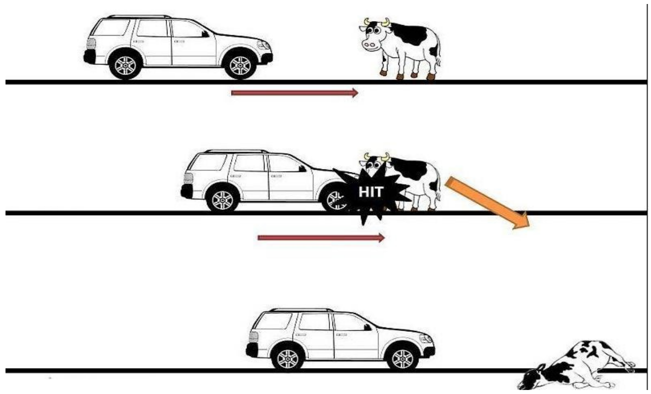


**FIGURE2.**Case1scenario[26].

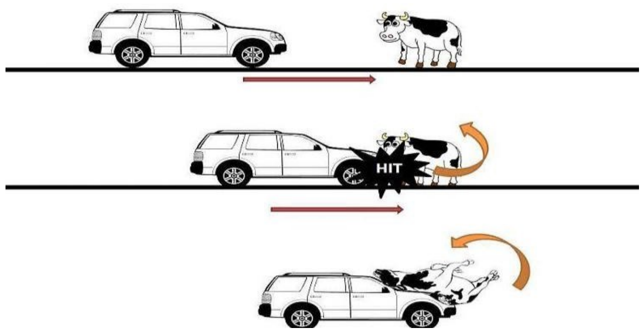


**FIGURE3.**Case2scenario[26].

## V. DIFFERENT SCENARIOS AND CONSEQUENCES OF ANIMAL-VEHICLE COLLISION ON HIGHWAY

Animal-vehiclecollisioncanbeclassifiedusingtwo ways[26]:

1) Directcollision
2) Indirectcollision

Direct collision: It happens when the vehicle directly hits theanimal.Followingcasesandoutcomemayoccurdepend- ingonthespeedofthevehicleandthespeedoftheincoming or outgoing animal.

*Case1:*Vehiclehitstheanimalandanimalgetsthrownto theside.Thisscenariomaybelesscritical,butdamageswill be there. Figure 2 shows the case 1 scenario.

*Case 2:* Vehicle hits the animal, and the animal jumps/ getsraisedintheairandagaingetsbackorfallsbackonthe windshield.Thisisquitecriticalanddangerousscenarioand can cause the death of the animal or even the driver of the vehicle. Figure 3 shows the case 2 scenarios.

*Case3:*Vehiclehitstheanimalandrunsovertheanimal. Inthiscase,aparticularinjurywilloccurtotheanimal. Itmayalsohappenthatbecauseoftheimpactofacollision, the vehicle may get overturn which can cause injury to the driver. Figure 4 shows the case 3 scenarios.

Indirectcollision:Inthiscase,anaccidentoccursbecause ofanimalonlybutnotdirectly.Thedriverofonevehiclefinds ananimalonthehighwayandtriestochangethedirectionor

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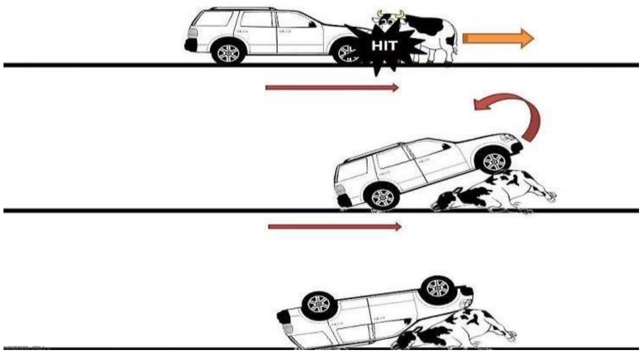


**FIGURE4.**Case3scenario[26].

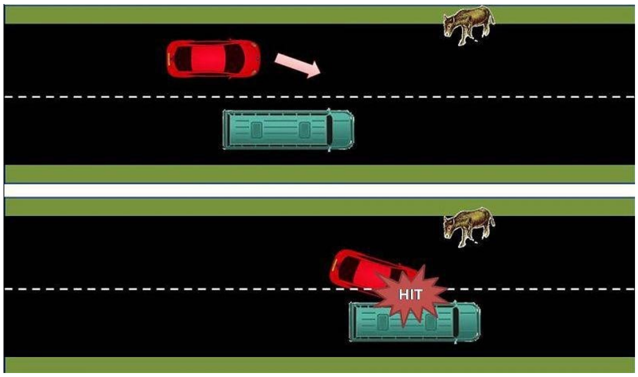


**FIGURE5.**Indirectcollisionscenario[26].

thelaneandcollideswiththevehiclewhichisrunning on the other lane. Figure 5 shows the indirect collision scenario.

In all the cases as discussed above, if the driver has some automatic animal detection system in the vehicle, then it is possible to some extent to prevent injuries and collisions between vehicle and animal.

## VI. OBJECTIVESANDSCOPEOFWORK

Intelligent highway safety and driver assistance systems are very helpful to reduce the number of accidents that are hap-peningduetovehicle-animalcollisions.OnIndianroads,two typesofanimals–thecowandthedogarefoundmoreoften than other animals on the road. The primary focus of the proposedworkisfordetectionofanimalsonroadswhichcan havethepotentialapplicationofpreventingananimal-vehicle collision on highways. Specific objectives of the research work are:

- To develop a low-cost automatic animal detection system in context to Indian roads.
- Finding the approximate distance of animal from the vehicle in which camera is mounted.
- Todevelopanalertsystemoncetheanimalgetsdetected ontheroadwhichmayhelpthedriverinapplyingbrakes or taking other necessary action for avoiding collision between vehicle and animal.

## VII. SPECIFICREASONSFORANIMAL(COW)DETECTION

AccordingtothesurveysandreportgivenbytheSocietyfor PreventionofCrueltytoAnimals(SPCA)*and*[27]–[31],the number of accidents on Indian roads has increased due to increase in a number of vehicles day by day and also due to thepresenceofanimalsontheroad(mainlytwoanimal'sdog andcow).Thecollisionofananimalwiththevehicleonthe highwayisonesuchbigissueapartfromotherproblemssuch asoverspeed,abruptlanechange,anddrunk-driveandothers whichleadtosuchroadaccidentsandinjuries.Theassociated number of fatalities and injuries are substantial too.

Specific reasons behind developing automatic cow detection system in place of any other animal are:

- Indiaismainlyanagriculturebasedcountrywhere70% of people depend on agriculture, and 98% of them depend on cow based agriculture.
- The cow is a sacred animal in India and nobody wants to hit a cow.
- Cowmilkisthemostusefulandcompatiblewithhuman mother's milk than any other animal or so.
- According to some surveys, cow's milk and cow dung have many medicinal benefits.
- Cows, as well as dogs, are found quite often than other animals on the Indian roads.
- As cow is a large (heavy) sized animal, the collision between a cow and vehicle will be very much severe. Thecollisionbetweenasmall(lessweight)sizedanimal like dog and car won't be that much severe.

The speed with which the vehicle is coming and hitting the animalalsoplaysacriticalroleindecidingtheimpactofthe collision.

## VIII. BRIEFOVERVIEWANDADVANTAGES OFHOGANDCASCADECLASSIFIER

Ahistogramoforientedgradients(HOG)isusedincom-putervisionapplicationsfordetectingobjectsinavideo or image, which by definition is a feature descriptor [32]. Figure 6(a) and 6(b) shows the block diagram and block normalization scheme of HOG.

As shown in figure 6(a), first the input image is given to color normalization block. Color normalization is used for object recognition on color images when it is important to removeallintensityvaluesfromthepicturewhilepreserving color values. After color normalization, the second step of calculation is the computation of the gradient values. The most common method is to apply the 1D centered point discrete derivative mask in both the horizontal and vertical directions.Specifically,thismethodrequiresfilteringthegrey scale image with the following filter kernels:

$$D_X=[-1\ 0\ 1] \quad \text{and} \quad D_Y=\begin{bmatrix}1\\0\\-1\end{bmatrix}$$

So,givenanimageI,weobtainthexandyderivativesusing a convolution operation: $I_X= I*D_X$ and $I_Y= I*D_Y$.

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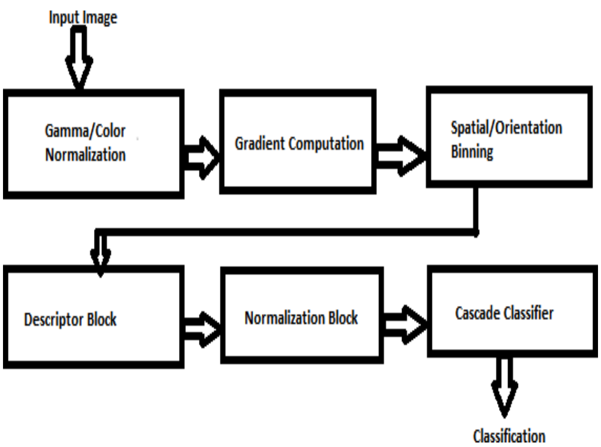
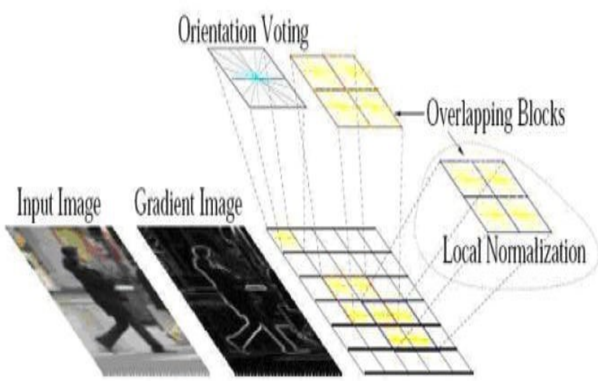



(a)

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(b)

The magnitude of the gradient is given by $|G| = \sqrt{I_X^2 + I_Y^2}$,

and orientation of the gradient is given by $\theta = \arctan(I_Y/I_X)$.

The next step of calculation involves creating the cell histograms. Each pixel within the cell casts a weighted vote for an orientation-based histogram channel based on the values found in the gradient computation. The cells themselves are rectangular, and the histogram channels are evenly spread over 0 to 180 degrees or 0 to 360 degrees, depending on whether the gradient is ‘‘unsigned’’ or ‘‘signed’’. As for the vote weight, pixel contribution can be the gradient magnitude itself, or the square root or square of the gradient magnitude. To account for changes in illumination and contrast, the gradient strengths must be locally normalized, which requires grouping the cells together into larger, spatially-connected blocks which are the next step. The HOG descriptor is then the vector of the components of the normalized cell histograms from all of the block regions. These blocks typically overlap, meaning that each cell contributes more than once to the final descriptor.

Two main block geometries exist: rectangular R-HOG blocks and circular C-HOG blocks. R-HOG blocks are square

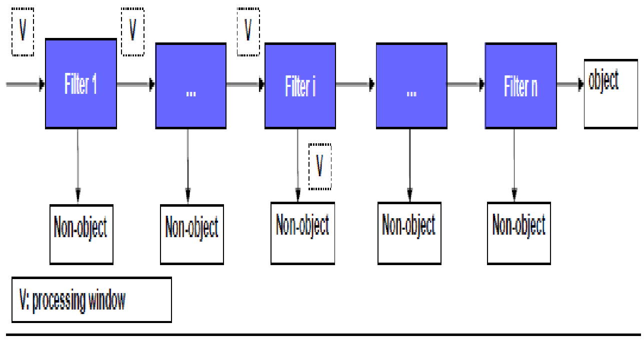


**FIGURE 7.** Boosted cascade classifier [33].

grids, represented by three parameters: the number of cells per block, the number of pixels per cell, and the number of channels per cell histogram. There are different methods for block normalization. Let $v$ be the non-normalized vector containing all histograms in a given block, $\|v_k\|$ be its k-norm for $k=1,2$ and $e$ be some small constant (whose value will not influence the results). Then the normalization factor can be one of the following:

$$\text{L2-norm: } f = \frac{v}{\sqrt{\|v\|_2^2 + e^2}}$$

$$\text{L1-norm: } f = \frac{v}{\|v\|_1 + e}$$

$$\text{L1-sqrt: } f = \sqrt{\frac{v}{\|v\|_1 + e}}$$

Finally, the image goes to cascade classifier for classification of the object. HOG descriptor is mainly suitable for animal detection in video or images due to some key advantages compared to other descriptors. First, it operates on local cells, so it is invariant to geometric and photometric transformations. Secondly, coarse (spatial) sampling, fine orientation sampling, and strong local photometric normalization allow different body movement of animals to be overlooked if they maintain a roughly upright position.

Cascading is a concatenation of various classifiers (group based learning). The technique involves taking all the data collected from the output of the first classifier as a supple- mentary data for the next classifier in the group [33]. The key advantages of boosted cascade classifiers over mono- lithic classifiers are that it is a fast learner and requires low computation time. Cascading also eliminates candidates (false positives) early on, so later stages don’t bother about them.

As shown in figure 7, each filter rejects non-object win- dows and let object windows pass to the next layer of the cascade. A window is considered as an object if and only if all layers of the cascade classifies it as object [33]. The filter i of the cascade is designed to

- Reject the possibly large number of non-object windows
- To allow possible large number of object windows for quick evaluation

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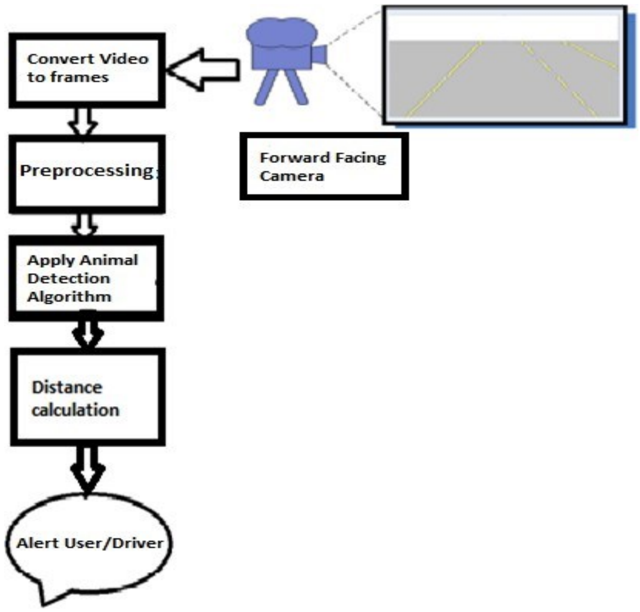


**FIGURE8.**Architectureofanimaldetectionandcollisionavoidance system.

(a)

(b)

**FIGURE9.**(a)Positivesamples.(b)Negativesamples.

## IX. RESEARCHMETHODOLOGY

Asshowninfigure8,thevideoistakenfromaforward-facing opticalsensor(camera)inwhichamovinganimalispresent apart from other stationary and non-stationary objects. This video is stored in the computer and converted into different frames. Then we are doing pre-processing steps to enhance theimage.Forfeatureextractionandlearningofthesystem, we are using a combination of HOG and boosted cascade classifier for animal detection. All the image processing techniques are implemented in OpenCV software. Once the animalgetsdetectedinthevideo,thenextstepistofindthe distanceoftheanimalfromthetestingvehicleandthenalert thedriversothathecanapplythebrakesorperformanyother necessaryactionwhichisdisplayedoncommandpromptas amessage.Dependingonthedistanceoftheanimalfromthe cameramountedvehicle,threekindsofmessages(indication) aregiventothedriveri.e.animalverynear,ifanimalisvery neartothevehicle,animallittlefar,iftheanimalislittlefar fromthevehicleandveryfar,iftheanimalisveryfarandat a safe distance from the vehicle.

## X. PROCEDUREFORTRAININGANDTESTING

India has more than 20 varieties of cow found in different states of India such as Gir, Sahiwal, Red Sindhi, Sahiwal, Kankrej,Dandi,andothers.Wehavecollectedandaddedall thevarietiesofacowinthedatabasefortrainingthesystem. Followingistheproposedprocedurefortrainingandtesting of the data for animal detection:

- Collectallpositiveandnegativeimagesinthedatafolder (figure 9(a) and 9(b))
- GenerateAnnotation
- Createsamplei.e.generate.vecfile
- TraindataandgeneratingXMLfile.Table1showsthe parameters used /set during training of the system
- Testing

The average time it took to generate a cascade on Intel(R) Core(TM)i5-2430MCPU2.40GHz,4GBRAMwasalmost 14 hours.

**TABLE1.**Parameterssetupduringtrainingofthesystem.

| Parameters | Value/Type |
|---|---|
| numPos (number of positive samples) | 700 |
| numNeg (number of negative samples) | 1500 |
| numStages (number of stages in cascade) | 20 |
| stageType (type of stage in cascade) | BOOST |
| featureType (feature type for extraction) | HOG |
| sampleWidth (width) | 70 pixels |
| sampleHeight (height) | 40 pixels |
| boostType (type of boosting) | GAB (Gentle AdaBoost) |
| minHitRate (minimum hit rate of the classifier) | 0.995 |
| minFalseAlarmRate (minimum false alarm rate of the classifier) | 0.5 |

## XI. DISTANCECALCULATIONOFTHEDETECTEDANIMAL

Asshowninfigure10,thevideoistakenandconvertedinto frames(imageofsize640∗480).Followingistheprocedure for calculating the distance of the detected animal from the camera-mounted vehicle:

- Imageresolutionis640×480
- Xrangeis0to640
- Yrangeis0to480

Lettherightbottomcoordinateofthedetectedcowbe(x,y). Thenthedistanceofcowfromtheloweredge(car/camera)is 480 – y.

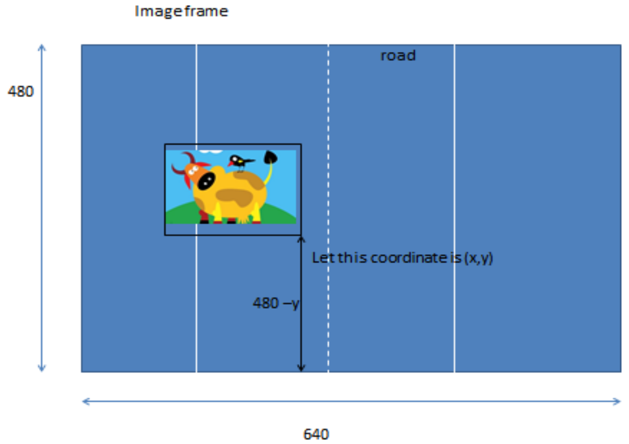


**FIGURE10.**Distancecalculation.

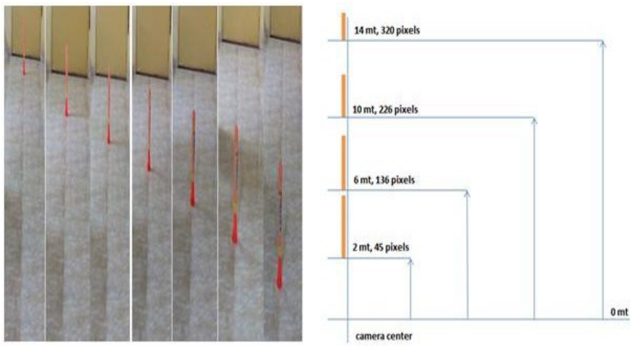


**FIGURE11.**Thesameobjectkeptatdifferentpositions(depth)fromthe cameracentre.

Note:Theabovemethodofdistancecalculationworkswell withtheflatgroundsurface.Suffersabitifthegroundsurface is not perfectly flat.

## XII. CONVERSIONFROMPIXELSTOMETERS

Thereissomerelationshipbetweenthedepthoftheobjectin pixelanddepthinrealworldunits(meters)fromthecamera mountedvehicleoncetheobject(animal)getsdetectedinthe frame. As the depth of the object in meters from the camera mountedvehicleincreases(sizeoftheobjectdecreases),the depthinpixelsalsoincreasesandviceversa[34].Thishinted us to find a relationship between the depth of the object in pixels and meters. Once the camera position in the car and height of the camera from the ground was fixed (camera calibrationdone),wetookdifferentimagesofthesameobject kept at various depths from the camera centre (figure 11). Thedepthoftheobjectfromthecameracentreinmeterswas known to us.

We then noted the corresponding depth of the object in pixels. Table 2 represents the relation between pixels and meters. Graph of depth in meters versus depth in pixels was plottedinExcel(figure12)andthebestfittingsecondorder polynomial equation is

$$y=0.0323x^2+22.208x+1.3132 \quad (1)$$

whereyisthedepthinpixelsandxisdepthinmeters.

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**TABLE2.**Relationshipbetweenpixelsandmeters.

| Depth (mt) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Depth (pixel) | 23 | 45 | 69 | 91 | 114 | 136 | 159 | 180 | 206 | 226 | 245 | 274 | 295 | 320 |

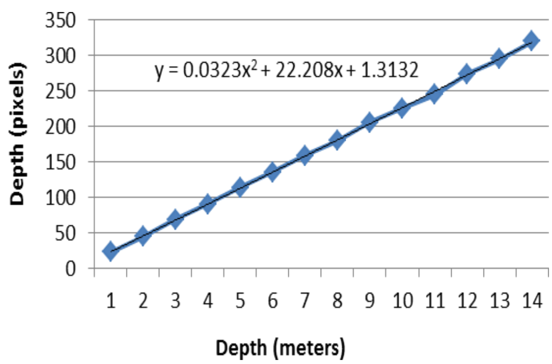


**FIGURE12.**Graphofdepth(meters)versusdepth(pixels).

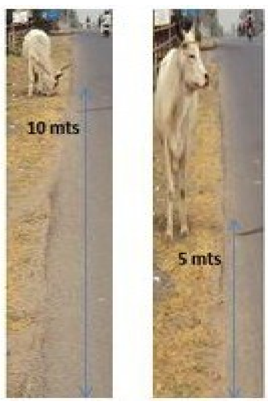


**FIGURE13.**Testingimages(depthinmeterswasalreadyknown).

## XIII. TESTING OF ACTUAL DISTANCE VERSUS CALCULATEDDISTANCE

Asshowninfigure13,wetooktwoimagesofacowin which we knew the depth of the cow in meters from the camera-mountedvehicle.Wethencalculatedthedepthusing thetechniqueasmentionedearlier.Table3showstheresults of actual depth and calculated depth. The error is very less (less than 2 percent).

## XIV. EXPERIMENTSANDRESULTANALYSIS

WeareusingHOGdescriptorswhicharefeaturedescriptors andareusedincomputervisionandimageprocessingforthe purposeofobjectdetection[32].Forobjectclassification,we are using boosted cascade classifiers. A good source for the animalimagesistheKTHdataset[35]andNECdataset[36] thatincludedpicturesofcowsandotheranimals.Somemore animal images have been clicked (during different weather conditionsi.e.morning,afternoonandevening)forcreating

**TABLE3.**Actualdepthversuscalculateddepth.

| Parameters | Observation 1 | Observation 2 |
|---|---|---|
| Actual depth (meters) | 10 | 5 |
| Calculated depth (meters) after converting from pixels to meters | 9.85 | 4.95 |
| Error in Percentage (%) | 1.5 | 1 |

a robust database of almost 2200 images consisting of pos- itive images in which the target animal is present and neg- ative images in which there is no target animal for feature extractionandfortrainingtheclassifier.Aftertheclassifieris trained andthe detection system isbuilt, we tested thesame on various videos.

Videoshavebeentakenusingacamerahavingaframerate of 30fps mounted on the testing vehicle. Hardware used in ourexperimentisASUSx53s,Intel(R)Core(TM)i5-2430M CPU2.40GHz,4GBRAM.SoftwareusedisMicrosoftVisual Studio10Professional,OpenCV2.4.3,64bitoperatingrun- ning under Windows 7.

Parameters which are necessary for checking the perfor- mance of the test/classifier are Sensitivity (True Positive Rate), Specificity (True Negative Rate) and Accuracy [37] which are given as

$$\text{Sensitivity}=TP/(TP+FN) \quad (2)$$
$$\text{Specificity}= TN/(TN + FP) \quad (3)$$
$$\text{Accuracy}= (TN+TP)/(TN+TP+FN+FP) \quad (4)$$

Hereinaboveequations,TNstandsfortruenegative; TP stands for true positive; FN stands for false negative,and FP stands for false positive. True positive (TP) and true negative (TN) are the most relevant and correct parameters of classification. False Positive indicates that the animal is detected in the frame (video) even though the animal is absent in that particular frame at that given location. False Negative (FN) indicates that there is no animal present in the frame (video) even though the animal is present in that particular frame.

In our implemented animal detection system, we took640framesinwhich105framesareshowinganimaldetected i.e.rectangularboxeventhoughthereisnoanimalpresentin thoseframeatthoseplaces.So,falsepositiveinthiscaseturns outtobe105andtruenegativeturnsouttobe535.Similarly outof640frames,125framesareshowingnoanimaldetected i.e.norectangularboxeventhoughanimalsarepresentinthat frame.Sofalsenegativeturnsouttobe125andtruepositive turns out to be 515. Substituting the above parameter values

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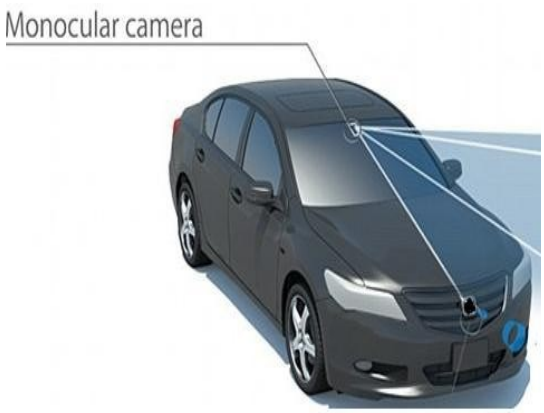


**FIGURE14.**Cameramountedvehicle.


**FIGURE15.**Truepositivecase.

**FIGURE16.**Falsepositivecase.

inequation(2),(3)and(4),wegetsensitivitycloseto80.4%, specificitycloseto83.5%andaccuracyoftheclassifierclose to 82.5%.

Figure14showstheon-boardcamerawiththeprocessing and display system inside the car on the dashboard side.We performed extensive experiments and spent so many hourstestingthesystemindifferentweatherconditionson


**FIGURE17.**Falsenegativecase.

**FIGURE18.**Animaldetection at0 kmphspeed (morningcondition).

theroad.Figure15showsthetruepositivescenariowherein inthevideo,animal(cow)ispresentandourproposedsystem correctly detects it and gives an indication (box). Similarly, figure 16 shows a false positive case wherein animal (cow) is detected in the video by the system even though it is absentinthatparticularframeatthatgivenlocation.Figure17 showsafalsenegativecasewhereinthoughtheanimal(cow) is present in the video; the system indicates absence (no box) of the animal. Figure 18 shows animal detected in the morning condition with the experimental camera mounted vehicle stationary i.e. at 0 kmph speed. Figure 19 shows animal detected in the afternoon condition with the vehicle speed at 40 kmph. Figure 20 shows animal detected in the evening state at a distance of 11 meters from the camera mounted testing vehicle with the vehicle moving at a speed of 60 kmph. Figure 21 shows multiple animals detected in oneofthetestingvideosatadistanceof17metersfrom

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**FIGURE19.**Animaldetectionat40kmph(afternoonstate).

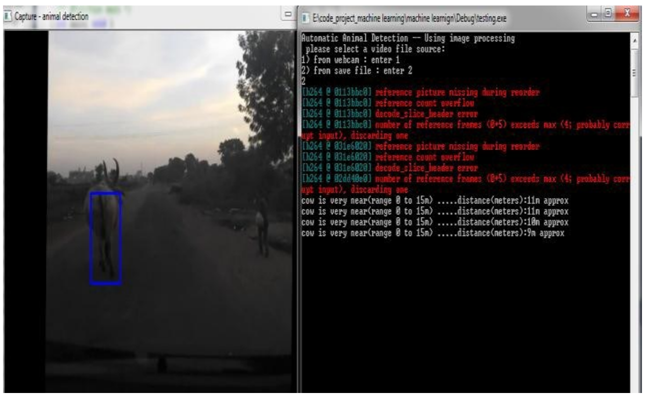

**FIGURE20.**Animaldetectedatadistanceofapproximately11meters fromthecameramountedvehiclewiththespeedof60kmphinevening time.

**FIGURE21.**Multipleanimalsdetectedinoneofthetestingvideo (detectingdistanceof17meters).

the camera mounted vehicle. Training and testing on large datasets will improve the detection rate and accuracy of the classifier.

The average processing (computation) time with our pro- posed image processing method is 100ms (10 frames per second)whichcanbestillbeshortenedusingNvidia'sCUDA processor. According to the article [39], the term response timeorbrainreactiontimeofthedriversintrafficengineering literatureiscomposedofmentalprocessingtime,movement

**TABLE4.**Speed-distancerelation.

| Vehicle speed (kmph) | Approximate distance of detection from the camera mounted vehicle (meters) | Approximate time available for the response (sec) |
|---|---|---|
| 0 (stationary) | 20 | Enough time to avoid collision as maximum speed of Indian cows is 3 to 3.5 kmph [38] |
| 20 | 18 | 3.24 |
| 30 | 17 | 2.04 |
| 35 | 17 | 2.04 |
| 40 | 15 | 1.35 |
| 50 | 14 | 1.00 |
| 60 | 11 | 0.66 |

**TABLE5.**Setoftestsbycascadeclassifier.

| Feature descriptor | TP | FP | TN | FN | Sensitivity | Specificity | Accuracy | Average processing time |
|---|---|---|---|---|---|---|---|---|
| HOG | 515 | 105 | 535 | 125 | 80.4% | 83.5% | 82.5% | 100ms |
| HAAR | 502 | 142 | 498 | 138 | 78.4% | 77.8% | 78.1% | 150ms |

timeandmechanicalresponsetime.Asperthe''two-second rule''whichisusuallyaruleofthumbsuggeststhatadriver shouldideallystayatleasttwosecondsbehindanyobjectthat isinfrontofthedriver'svehicle[40].Thetwo-secondruleis usefulasitcanbeappliedtoanyspeedandprovidesasimple andcommon-sensewayofimprovingroadsafety.Soifwego with''two-secondrule'',clearlyfromTable4(speed-distance relation as well as actual time (onboard) available for the driver to responds), it indicates that when the speed of the vehicleisbetween30to35kmph,thedrivergetssometime toapplybrakesandcanavoidacollision.Anythingabovethis speed,thoughthealertsignalisavailablethedriverwon'tbe able to avoid a collision.

## XV. COMPARISONOFHOGANDHAAR

Comparison of HOG with another popular feature descrip- tor (HAAR) is shown in Table 5. ROC (receiver operating characteristic) curve, which is a graphical plot that illus- trates the performance of a classifier system as its dis- criminationthresholdisvaried,isshowninfigure22for the hog-cascade classifier, haar-cascade classifier. The curve is created by plotting the true positive rate (TPR) againstthefalsepositiverate(FPR)atvariousthresh- old settings. Apparently, our method based on hog-cascade classifier gives good results compared to haar-cascade classifier.

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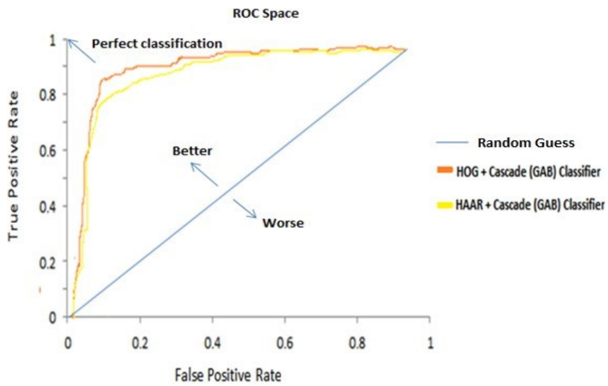


**FIGURE22.**ROCcurve.

## XVI. ACHIEVEMENTSWITHRESPECTTOOBJECTIVES

- Algorithm developed is working properly and able to detect an animal in different conditions on roads and highways.
- Estimationofanimaldistancefromthetestingvehicleis done. Maximum detecting distance of the animal from thecameramountedvehiclewasfoundtobe20meters.
- Speedanalysis(differentspeedslike20,30,35,40,50, 60 kmph) is implemented and tested.
- Alertsignaltothedriverisavailable.

## XVII. CONCLUSION

Anefficientautomaticanimaldetectionandawarningsystem can help drivers in reducing the number of collisions occur- ring between the animal and the vehicle on roads and high- ways.Inthispaper,wediscussedthenecessityofautomatic animaldetectionsystemandouralgorithmforanimaldetec- tion based on HOG and cascade classifier. The algorithm can detect an animal in different conditions on highways. Theproposedsystemachievesanaccuracyofalmost82.5% regarding animal (cow) detection. Estimation of approximate animaldistancefromthetestingvehicleisalsodone.Though the proposed work has been focused on automatic animal detectionincontexttoIndianhighways,itwillworkinother countriesalso.Theproposedmethodcaneasilybeextended for detection of other animals too after proper training and testing. The proposed system can be used with other avail- able, efficient pedestrian and vehicle detection systems and canbeofferedasacompletesolution(package)forpreventing collisions and loss of human life on highways.

## XVIII. LIMITATIONSANDFUTURESCOPE

Though our proposed system can detect the animals (cow) on roads and highways as well as gives alert to the driver,it has some limitations too. The proposed system can detect animaluptoadistanceof20metersonlywhenavehicle is stationary. The system can prevent collision of the vehi- clewiththeanimalwhendrivingataspeedinbetween 30 to 35 kmph. Beyond this speed, though animal gets detected time is not sufficient to prevent animal-vehicle collision.

Somemeansormethodofincreasingthedetectingdistance of the animal from the camera mounted vehicle needs to be done so that driver gets sufficient time for applying brakes or take any other action for preventing the collision which may be solved using high-end resolution cameras or radar. No effort has been made to detect animals during the night, whichisexpectedtobedoneinourfuturescopeofstudyand research

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