AUTOMATED SEGMENTATION AND IDENTIFICATION OF WILDLIFE FOR PREVENTING ROADKILL IN HIGHWAYS

A PROJECT REPORT

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in partial fulfillment for the award of the degree

of

BACHELOR OF TECHNOLOGY

in

INFORMATION TECHNOLOGY

SRI VENKATESWARA COLLEGE OF ENGINEERING, PENNALUR

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MARCH 2019

BONAFIDE CERTIFICATE

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ACKNOWLEDGEMENT

We thank our Principal **Dr. S. Ganesh Vaidyanathan, Ph.D.,** Sri Venkateswara College of Engineering for being the source of inspiration throughout our study in this college.

We express our sincere thanks to **Dr. V. Vidhya, M.E, Ph.D.,** Head of the Department in charge, Information Technology for her permission and encouragement accorded to carry this project.

With profound respect, we express our deep sense of gratitude and sincere thanks to our supervisor **Ms. B.T.Shobana, M.E,** Assistant Professor, for her valuable guidance and suggestions throughout this project.

We are also thankful to **Ms. Kiruba Wesley, M.E., and Ms.A.Kala, M.E.,** Assistant Professor for their encouragement and valuable guidance to complete the project successfully.

We also express our thanks to all Faculty of Department of Information Technology, Sri Venkateswara College of Engineering, for rendering their support in completion of our project.

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ABSTRACT

Roadkill refers to animals that have been struck and killed by motor vehicles on highways. It is an alarming issue because of the animal suffering, loss of wild animals, road safety, and the economic impact on both drivers and road management. It is a global tragedy with ever-rising trend. Early roadkill mitigation techniques prioritize the hardening of the highway, an attempt to make it a safer place for animals and also make it easier for humans to identify the animals on highway without any difficulty. Our study is focused on this tragic activity.This study completely focuses on saving the wild animals from the high speed vehicles in highways, that cost their lives. The model proposed employs the technique of image processing to detect all kind of animals . The device is attached to the road and when a detection of an animal crossing the road is made, a warning signal is given out. This is a beacon for the drivers who can take the necessary steps to slow down their vehicle well in advance thus saving the wildlife.

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CHAPTER 1

INTRODUCTION

1.1 ROADKILL

While a lot of research has been performed on the visual analysis of human beings and human related events, the automated analysis of animal has been widely neglected in the past. An alarming problem that all the developed nations are facing today is death and injuries due to road accidents. The human-animal conflict is one such big issue, which is predominant in the highway regions near the forest region. Roadkill is an act that takes a toll on the lives of humans or animals that happen to collide with the moving vehicle on the road. It is a global tragedy with an ever-rising trend.

Even though various countries have initiated and taken steps to reduce road traffic and accidents, the total number of crashes and traffic accidents remain as high as 1.24 million per year. It is predicted that they are expected to rise by almost 65% by the end of 2020. The statistics in India is ceaselessly alarming. In 2017, whopping 1.47 lakh people died in road deaths. To put the death toll due to road accidents in perspective – in the last one decade, the average annual road death crashes stand at 1.3 lakh per year - a figure that surpasses the population of many small Indian cities. This has an adverse effect on the economy, as India loses 3% of its GDP in road accidents which were highly preventable.

It is known that roads fragment habitat, disrupt migration corridors, and expose sensitive species to a deadly array of hazards. And now, rather than the simple road kill accounts that dominated the literature from the 1920s to 1970s, ecologists are recognizing road kill as part of a larger threat to wildlife. For rare or isolated populations, vehicle collisions can be a matter of life or death—not just at the individual level but also for entire species. Road ecologists are now confirming what many road engineers likely knew all along: that not all roads are equal. In fact, even individual segments of the same road can vary dramatically in how animals perceive, use, or cross them. Some stretches of road are simply more important and more deadly than others. The reason behind this is the higher vehicle speeds, heavier traffic, and wider roads definitely make crossings more treacherous. But another critical factor is where human highways cross wildlife highways. More often than not, road kill peaks where wildlife corridors such as riparian zones or strips of forest intersect with roads. The increased ecological understanding of roads has led, in a growing number of places, to elegantly simple solutions. Tapping the insights of engineers and biologists alike, highway planners can use common highway structures such as bridges and culverts to help wildlife cross to safety.

The major reason behind the surge of road accidents are due to the increase in the number of vehicles day by day and also due to the absence of any intelligent highway safety and alert system. These mishaps are influenced by three main factors i.e. human, vehicle, infrastructure or a combination of them. The best way forward is to develop an intelligent alert system to prevent these fatalities.

1.2 IMAGE PROCESSING

Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image or characteristics/features associated with that image. Nowadays, image processing is among rapidly growing technologies. It forms core research area within engineering and computer science disciplines too.

Digital image processing (DIP), as a computer-based technology, carries out automatic processing, manipulation and interpretation of visual information, and it plays an increasingly important role in many aspects of our daily life, as well as in a wide variety of disciplines in science and technology. Digital image processing deals with manipulation of digital images through a digital computer. It is a subfield of signals and systems but focus particularly on images. DIP focuses on developing a computer system that is able to perform processing on an image. The input of that system is a digital image and the system process that image using efficient algorithms, and gives an image as an output. The most common example is Adobe Photoshop. It is one of the widely used application for processing digital images.

Image processing basically includes the following three steps:

- Importing the image via image acquisition tools.
- Analysing and manipulating the image.
- Output in which result can be altered image or report that is based on image analysis.

There are two types of methods used for image processing namely, analogue and digital image processing. Analogue image processing can be used for the hard copies like printouts and photographs. Image analysts use various fundamentals of interpretation while using these visual techniques. Digital image processing techniques help in manipulation of the digital images by using computers. The three general phases that all types of data have to undergo while using digital technique are pre-processing, enhancement and display, information extraction.

1.3 MACHINE LEARNING

Machine learning is a branch of science that deals with programming the systems in such a way that they automatically learn and improve with experience. Here, learning means recognizing and understanding the input data and making wise decisions based on the supplied data.

It is very difficult to cater to all the decisions based on all possible inputs. To tackle this problem, algorithms are developed. These algorithms build knowledge from specific data and past experience with the principles of statistics, probability theory, logic, combinatorial optimization, search, reinforcement learning, and control theory. Work in machine learning is now converging from several sources. These different traditions each bring different methods and different vocabulary which are now being assimilated into a more unified discipline.

1.3.1 SUPERVISED LEARNING

Supervised learning deals with learning a function from available training data. A supervised learning algorithm analyzes the training data and produces an inferred function, which can be used for mapping new examples. Classification, also known as categorization, is a machine learning technique that uses known data to determine how the new data should be classified into a set of existing categories. Classification is a form of supervised learning. For example, supervised machine learning is used to detect which emails can be marked as spam and not spam. An email spam filter will be fed with thousands, possibly millions of emails. Each of these emails will already have a label - ‘spam’ or ‘not spam’. The supervised machine learning algorithm will then figure out which type of emails are being marked as spam. Next time an email is about to hit the inbox, the spam filter will use statistical analysis to figure out how likely it is that the email is spam. If the probability is high, it will label it as spam and the email won’t hit the inbox.

1.3.2 UNSUPERVISED LEARNING

Unsupervised learning is an extremely powerful tool for analyzing available data and look for patterns and trends. It is most commonly used for clustering similar input into logical groups. The most common unsupervised learning method is cluster analysis, which is used for exploratory data analysis to find hidden patterns or grouping in data. The goal in unsupervised learning is generally to cluster the data into characteristically different groups. Unsupervised machine learning is more challenging than supervised learning due to the absence of labels.

Some widely known application of unsupervised learning is in market segmentation for targeting appropriate customers, anomaly/fraud detection in banking sector, image segmentation, gene clustering for grouping gene with similar expression levels, deriving climate indices based on clustering of earth science data, document clustering based on content etc.

CHAPTER 2

LITERATURE SURVEY

The design of identification system to detect wildlife has been studied by various researchers around the world. Some of the methods proposed are as follows.

2.1 STUDY OF RELATED WORK

i. **Automated detection of elephants in wildlife video** by Matthias Zeppelzauer

Biologists often have to investigate large amounts of video in behavioral studies of animals. These videos are usually not sufficiently indexed which makes the finding of objects of interest a time-consuming task. A fully automated method is proposed for the detection and tracking of elephants in wildlife video which has been collected by biologists in the field. The method dynamically learns a color model of elephants from a few training images. Based on the color model, elephants are localized in video sequences with different backgrounds and lighting conditions. Temporal clues from the video is also exploited to improve the robustness of the approach and to obtain spatial and temporal consistent detections.

The proposed method detects elephants (and groups of elephants) of different sizes and poses performing different activities. The method is robust to occlusions (e.g., by vegetation) and correctly handles camera motion and different lighting conditions. Both near- and far-distant elephants can also be detected and tracked reliably. The proposed method enables biologists efficient and direct access to their video collections which facilitates further behavioral and ecological studies. The method does not make hard constraints on the species of elephants themselves and is thus easily adaptable to other animal species.

Advantage:

- Able to detect and track elephants of different sizes and poses in their natural habitat. The approach robustly handles occlusions and detects elephants even if most of their bodies are hidden, e.g., behind vegetation.
- Provides the spatial location and complete tracking information for each detection.

Disadvantage:

- Reach the limits of the approach by the detection of far-distant elephants. While the detection rate in this case is still high, the sensitivity to false positives grows.
- Indexing of unconstrained wildlife video is difficult.

ii. **Visual informatics tools for supporting large-scale collaborative wildlife monitoring with citizen scientists** by Zhihai He, Roland Kays, Zhi Zhang, Guanghan Ning, Chen Huang, Tony X. Han, Josh Millspaugh, Tavis Forrester, and William McShea

Collaborative wildlife monitoring and tracking at large scales will help us understand the complex dynamics of wildlife systems, evaluate the impact of human actions and environmental changes on wildlife species, and answer many important ecological and evolutionary research questions. To support collaborative wildlife monitoring and research, we need to develop integrated camera-sensor networking systems, deploy them at large scales, and develop advanced computational and informatics tools to analyze and manage the massive wildlife monitoring data. In this the following are covered: various aspects of the design of such systems, including (1) long-lived integrated camera sensor system design, (2) image processing and computer vision algorithms for animal detection, segmentation, tracking, species classification, and biometric feature extraction, (3) cloud-based data management, (4) crowd sourcing based image annotation with citizen scientists, and (5) applications to wildlife and ecological research.

Disadvantage:

- Need to develop integrated camera-sensor networking systems, deploy them at large scales, and develop advanced computational and informatics tools to analyze and manage the massive wildlife monitoring data.

iii. Automated identification of animal species in camera trap images

by Xiaoyuan Yu, Jiangping Wang, Roland Kays, Patrick A Jansen, Tianjiang Wang and Thomas Huang

Image sensors are increasingly being used in biodiversity monitoring, with each study generating many thousands or millions of pictures. Efficiently identifying the species captured by each image is a critical challenge for the advancement of this field. An automated species identification method is presented for wildlife pictures captured by remote camera traps. The process starts with images that are cropped out of the background, then using improved sparse coding spatial pyramid matching (ScSPM), which extracts dense SIFT descriptor and cell-structured LBP (cLBP) as the local features, that generates global feature via weighted sparse coding and max pooling using multi-scale pyramid kernel, and classifies the images by a linear support vector machine algorithm. Weighted sparse coding is used to enforce both sparsity and locality of encoding in feature space. The method is tested on a dataset with over 7,000 camera trap images of 18 species from two different field cites, and achieved an average classification accuracy of 82%. The analysis demonstrates that the combination of SIFT and cLBP can serve as a useful technique for animal species recognition in real, complex scenarios.

Advantage:

- The combination of SIFT and cLBP as descriptors of local images features significantly improved the recognition performance.

Disadvantage:

- Biometric features species analysis need to be included in the local features, such as color, spots, and size of the body.

iv. **From Tiger to Panda: Animal Head Detection** by Weiwei Zhang, Jian Sun, and Xiaoou Tang, Fellow, IEEE

Robust object detection has many important applications in real-world online photo processing. For example, both Google image search and MSN live image search have integrated human face detector to retrieve face or portrait photos. In this the focus is on popular online photo category—animal, which is one of the top five categories in the MSN live image search query log. The problem of animal head detection of a set of relatively large land animals is done, such as cat, tiger, panda, fox, and cheetah. First, a new set of gradient oriented feature , Haar of Oriented Gradients (HOOG) is used, to effectively capture the shape and texture features on animal head. Then, two detection algorithms, namely Bruteforce detection and Deformable detection is used to effectively exploit the shape feature and texture feature simultaneously.. Additionally, an animal head detector is applied to improve the image search result through text based online photo search result filtering.

Advantage:

- Achieved much improved results by decomposing texture and shape features
- Improved the detection results through joint detection based on the shape and texture features
- The texture and shape detectors are improved by a set of new oriented gradient features.

Disadvantage:

- Less animals are used for detection.
- Accuracy of the detection method is less.

v. **Animal–Vehicle Collision Mitigation System for Automated Vehicles** by Abdelhamid Mammeri, Depu Zhou, and Azzedine Boukerche

Detecting large animals on roadways using automated systems such as robots or vehicles is a vital task. This can be achieved using conventional tools such as ultrasonic sensors, or with innovative technology based on smart cameras. Following steps were performed: a comparative study between three detectors: 1) Haar-AdaBoost; 2) histogram of oriented gradient (HOG)-AdaBoost; and 3) local binary pattern (LBP) AdaBoost, which were initially developed to detect humans and their faces. These detectors are implemented, evaluated, and compared to each other in terms of accuracy and processing time. Based on the evaluation and comparison results, a two-stage architecture is designed which outperforms the aforementioned detectors. The proposed architecture detects candidate regions of interest using LBP-AdaBoost in the first stage, which offers robustness to false positives in real-time conditions. The second stage is based on support vector machine classifiers that were trained using HOG features. The training data are generated from the novel dataset called large animal dataset, which contains common and thermographic images of large road animals.

Advantage:

- Two-stage architecture LBP-AdaBoost/ HOG-SVM has shown a good performance in daytime conditions.

Disadvantage:

- During the night time, the combination of LBP-AdaBoost and HOG-SVM has shown limited capabilities.

CHAPTER 3

SYSTEM REQUIREMENTS

3.1 SOFTWARE REQUIREMNTS

- Tool - Anaconda 3.
- Language – Python.

3.1.1 OpenCV :

OpenCV (Open Source Computer Vision Library) is an open source computer vision and machine learning software library. OpenCV was built to provide a common infrastructure for computer vision applications and to accelerate the use of machine perception in the commercial products. Being a BSD-licensed product, OpenCV makes it easy for businesses to utilize and modify the code. It is a cross-platform library using which we can develop real-time enhanced computer vision applications. The library has more than 2500 optimized algorithms, which includes a comprehensive set of both classic and state-of-the-art computer vision and machine learning algorithms. These algorithms can be used to detect and recognize faces, identify objects, classify human actions in videos, track camera movements, track moving objects, extract 3D models of objects, produce 3D point clouds from stereo cameras, stitch images together to produce a high resolution image of an entire scene, find similar images from an image database, remove red eyes from images taken using flash, follow eye movements, recognize scenery and establish markers to overlay it with augmented reality, etc. OpenCV has more than 47 thousand people of user community and estimated number of downloads exceeding 14 million. The library is used extensively in companies, research groups and by governmental bodies.

3.1.2 NumPy :

NumPy is a Python package which stands for 'Numerical Python'. It is the core library for scientific computing, which contains a powerful n-dimensional array object, provide tools for integrating C, C++ etc. It is also useful in linear algebra, random number capability etc. NumPy can also be used as an efficient multi-dimensional container for generic data. It provides a high-performance multidimensional array and basic tools to compute with and manipulate these arrays. It is an open source library available in Python. It helps to do the mathematical and scientific operation and is used extensively in data and science. It supports working with multi-dimensional arrays and matrices.

3.2 HARDWARE REQUIREMENTS

3.2.1 CAMERA

It is an optical instrument used for electronic motion picture acquisition, which are stored in a physical medium such as in a digital system or on photographic film. It consists of a lens which focuses light from the scene, and a camera body which holds the image capture mechanism.

3.2.2. HARD DISK

It is an electromechanical data storage device that uses magnetic storage to store and retrieve digital information using one or more rigid rapidly rotating disks (platters) coated with magnetic material. It is used to store the large number of trained datasets of various animals. In our demo we store the pictures which are frame and the videos in the hard disk for backup and storage.

CHAPTER 4

PROPOSED WORK

4.1 PROBLEM DEFINITON

Mortality from collision with vehicles is the most visible impact of road traffic on wildlife. Mortality due to roads can affect the dynamic of populations of many species and can, therefore, increase the risk of local decline or extinction. Highways passing through natural reserves have adverse impact on wild animals Amphibians and reptiles are slow to react to vehicles and this along with the drivers' ignorance probably leads to higher mortality among these species.

The idea is to build a user-friendly and reliable system to prevent roadkill circumstances with a high degree of accuracy. Initially the background is subtracted and an unintruded image of the region is stored for further comparison .The region is continuously captured in a video which in turn is converted into image frames. For every frame ,the background is eliminated and compared with the benchmarked image. If an intrusion is detected the intruded portion is segmented from the original to detect their identity. Haar feature-based cascade classifiers is applied on the segmented image which extracts feature using cascade function that is trained from a lot of positive and negative images. Finally, it is then used to detect objects in other images. If the algorithm discovers the segmented species to be a human or an animal, a warning signal is given out. This is a beacon for the drivers who can take the necessary steps to slow down their vehicle well in advance thus saving the wildlife.

4.2 SYSTEM ARCHITECTURE

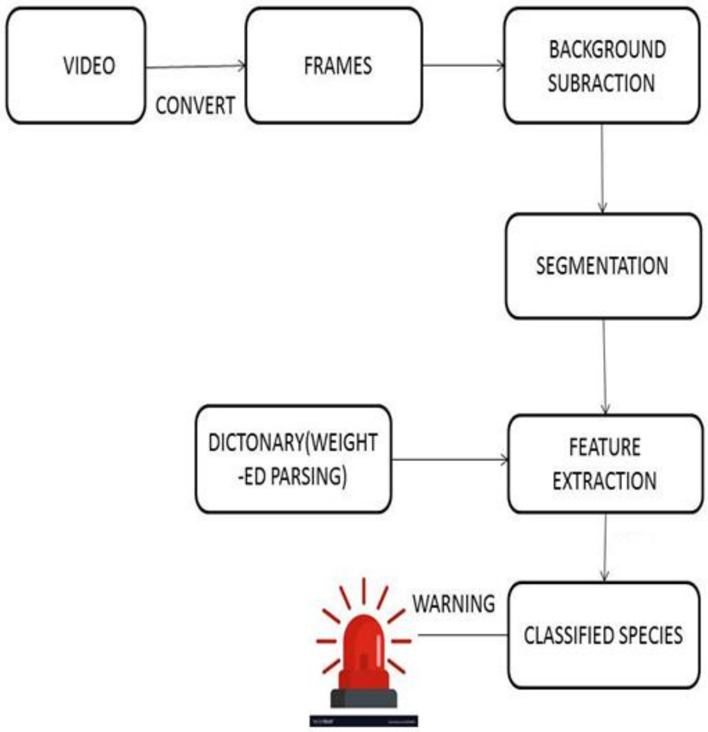

Figure 4.1 : System architecture

4.2.1 VIDEO

A video is captured continuously in a particular area of region, which is later converted to frames. The video is further used for this project as a main source to alert the drivers . The images are compared for the signalling. Video is much preferred over the camera trap images as in a video every moment of the object will be captured. But in the camera trapped images the time lapse will be a disadvantage. So taking video as the main source of input proves to be more efficient rather than the camera traps.

4.2.2 FRAMES

The video is converted to frames and the intruded image is compared to the actual trained image . The image captured is converted from RGB to gray scale as gray scale is more accurate in picking up the needed images. The videos are almost exclusively projected at 24 frames per second. Frame rate (expressed in frames per second or fps) is the frequency (rate) at which consecutive images appear on a display. The term applies equally to film and video cameras, computer graphics, and motion capture systems. Frame rate may also be called the frame frequency, and be expressed in hertz.

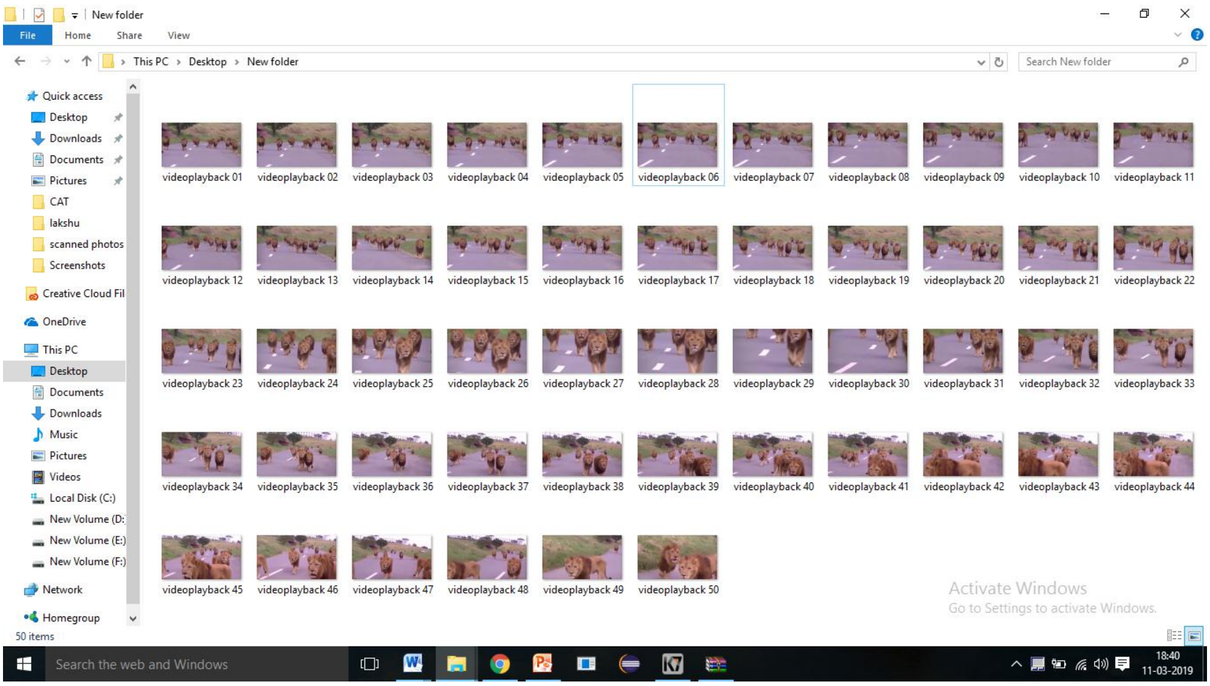

Figure 4.2: Frames

4.2.3 BACKGROUND SUBTRACTION

The unwanted region is eliminated from the frames captured. The background image is subtracted from the region to avoid unwanted objects that are on the road. The inner part of the lane is the only region considered, the outter part is the one that is subtracted.

4.2.4 SEGMENTATION

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super-pixels). The goal of segmentation is to simplify and change the representation of an image into something that is more meaningful and easier to analyze.

4.2.5 FEATURE EXTRACTION

Feature extraction starts from an initial set of measured data and builds derived values intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better interpretations. Feature extraction is a dimensionality reduction process, where an initial set of raw variables is reduced to more manageable groups (features) for processing, while still accurately and completely describing the original data set.

It is the process of collecting discriminative information from a set of samples. Feature classification is the grouping of features based on some criteria. Sometimes feature classification might also be related to feature selection which is to select a subset of the extracted features that would optimise the machine learning algorithm and possible reduce noise removing unrelated features.

4.2.6 DICTIONARY

Dictionary is the storage place for all the trained images. The benchmarked images are stored in the dictionary to be compared to the intruded image. It contains the possible angles of the target images to provide an improved result. The goal of dictionary learning is to capture high level information, that is, to select some items to describe the distribution of the input space.

4.2.7 CLASSIFIED SPECIES

Image classification refers to the labeling of images into one of the predefined categories. The object is detected based on two criteria negative and positive images. Animals are considered to be positive images and any other object detected are considered to be negative images. Classification includes image sensors, image pre-processing, object detection, object segmentation, feature extraction and object classification

4.2.8 INDICATION

When an animal is detected in the highway, a warning is given as an indication to the driver to take precautionary actions. The warning signal can be projected by a beam of light or with a siren in real time.

CHAPTER 5

MODULE DESCRIPTION

The animal detection system contains four important modules which are used to provide the safety features to the driver.

5.1 MODULES

- Conversion of video to frame
- Conversion of RGB to gray scale
- Background subtraction
- Display the extracted area of coverage
- Identification of objects in the area of coverage
- Recognition of animals
- Warning signal

5.1.1.Conversion of video to frame

A video is captured to monitor the activities on the highways and it is converted into individual frames. The video is preferred over the still images since the video continuously monitors the region and movement of the objects will not be missed. The live video is continuously converted to frames and compared to benchmarked image.

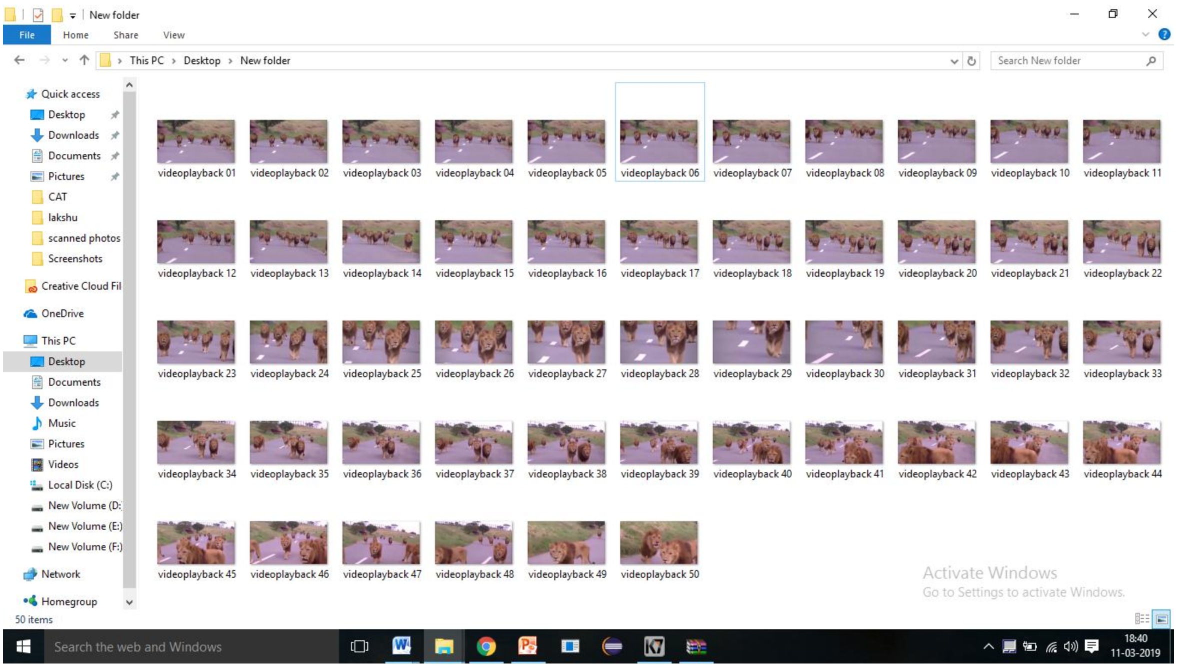

Figure 5.1 : Conversion of video to frames

5.1.2.Conversion of RGB to gray scale

The converted frame is converted from colored image to gray scaled image to perform further processing . An RGB Image consists of 3 layers R,G,B as it is clearly seen through its name. It’s a 3 dimensional matrix, whereas grayscale image is of only 2 dimensions, and the values ranges between 0–255 (8-bit unsigned integers). Some algorithms can only be applied on 2-D image rather than 3-D, hence conversion of RGB image into a grayscale image is done.

5.1.3.Background subtraction

Background Subtraction is a crucial step in many computer visions systems, as it is first applied to detect moving objects within a video stream. It is mainly used for video surveillance applications, since they first need to detect persons, vehicles, animals, etc before operating more complex process for intrusion detection, tracking, people counting, etc. The unwanted region is eliminated from the frames captured. The background image is subtracted from the region to avoid unwanted objects that are not on the road. The inner part of the lane is the only region considered, the outer part is the part that is subtracted.

Figure 5.2: Original image

Figure 5.3 : Image after background subtraction

5.1.4. Display the extracted area of coverage

The extracted area is displayed by the reference lines in the output. This is the inner part of the lane region. The extracted area is now taken and the objects are identified and the identified objects are segmented and compared to the benchmarked images.

5.1.4.1. Harr Cascade Classifer

Object Detection using Haar feature-based cascade classifiers is an effective object detection method. It is a machine learning based approach where a cascade function is trained from a lot of positive and negative images. It is then used to detect objects in other images.

The algorithm needs a lot of positive images (images of faces) and negative images (images without faces) to train the classifier. Then we need to extract features from it. For this, haar features are used. Fig 5.1 shows different types of features that can be extracted using the algorithm.

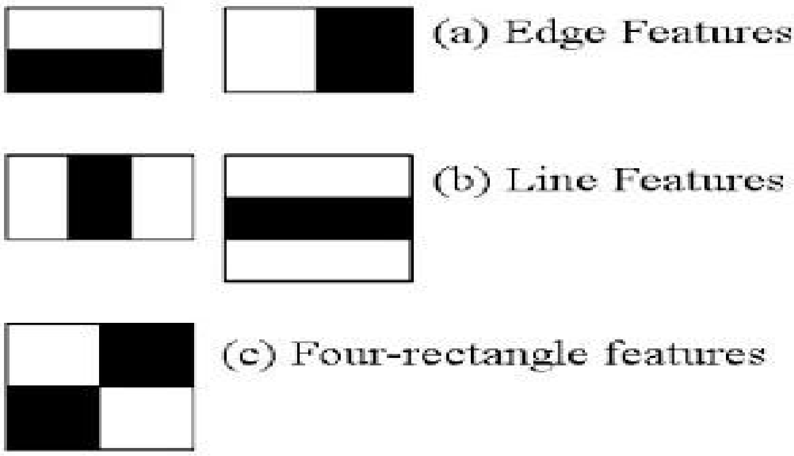

Figure 5.4: Haar Features

Each feature is a single value obtained by subtracting sum of pixels under white rectangle from sum of pixels under black rectangle. All possible sizes and locations of each are used to calculate plenty of features.

A 24x24 window results over 160000 features. For each feature calculation, we need to find sum of pixels under white and black rectangles. To select the best features out of 160000+ features, it is achieved by Adaboost. For this, we apply each and every feature on all the training images. For each feature, it finds the best threshold which will classify the faces to positive and negative images. We select the features with minimum error rate, which means they are the features that best classifies the face and non-face images. Take each 24x24 window. Apply 6000 features to it.

It is time consuming process, to make more efficient use the concept of cascade of classifiers. Instead of applying all the 6000 features on a window, group the features into different stages of classifiers and apply one-by-one. If a window fails the first stage, discard it. If it passes, apply the second stage of features and continue the process. The window which passes all stages is a face region.

Working with a boosted cascade of classifiers includes two major stages: the training and the detection stage. The detection stage using either HAAR or LBP based models.The training stage includes the following different stages: collecting training data, preparation of the training data and executing the actual model training. We can train our own classifier for any object like car, planes, animals etc. using OpenCV.

For the detection stage OpenCV already contains many pre-trained classifiers for face, eyes, smiles, etc. Those XML files are stored in the opencv/data/haarcascades/ folder. Similarly XML file for detecting animal is taken in our project. The part of that XML file is shown below.

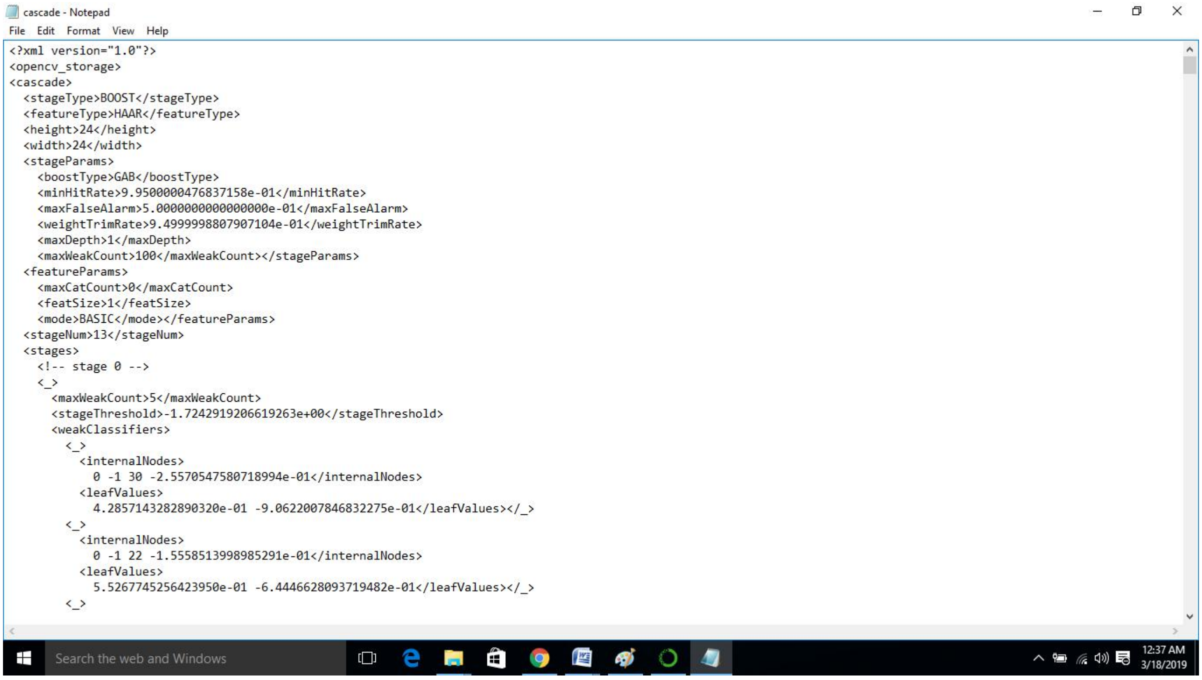


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Figure 5.5: XML document

For training a boosted cascade of classifiers a set of positive samples (containing actual objects you want to detect) and a set of negative images (containing everything you do not want to detect) is needed.

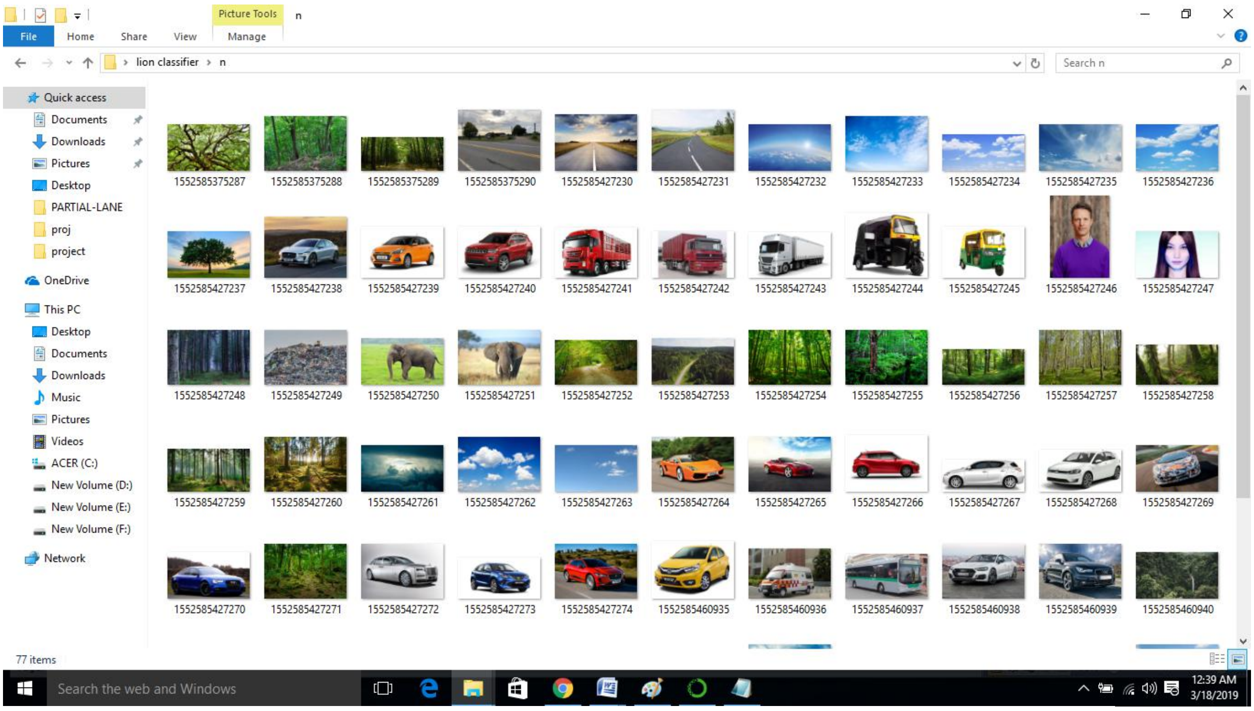

Figure 5.6: Negative images

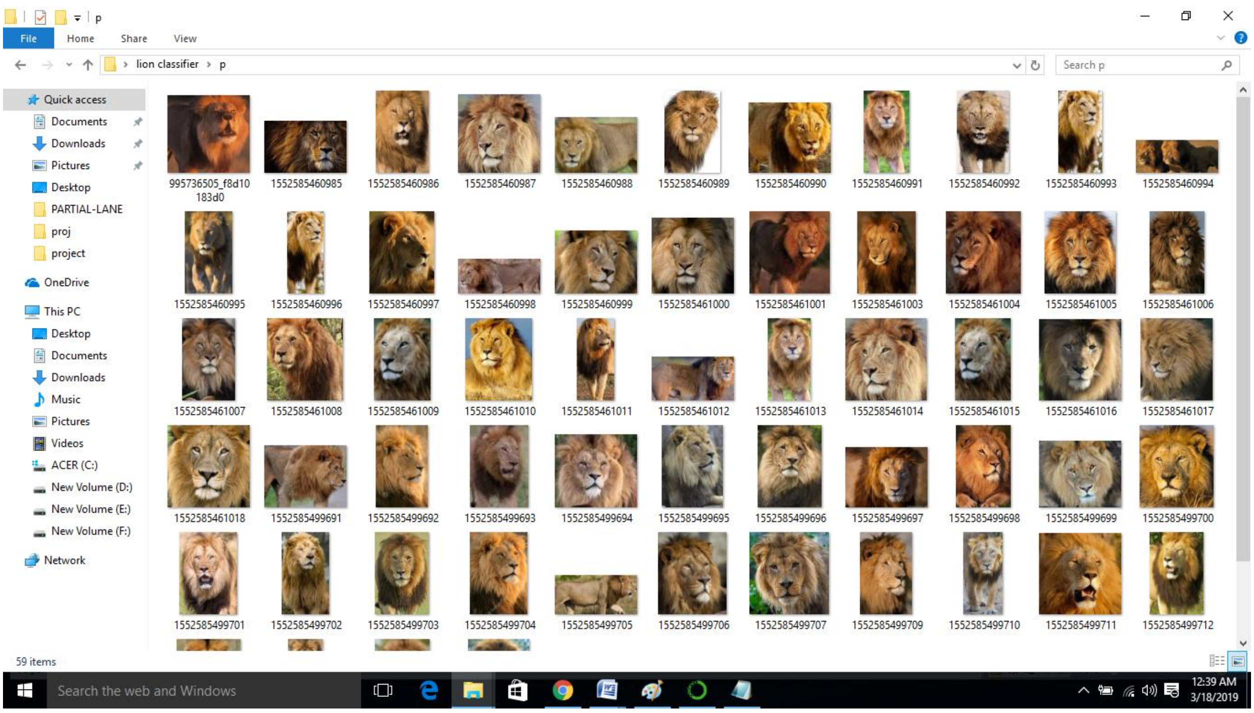

Figure 5.7: Positive images

5.1.5. Identification of objects in the area of coverage

Any objects that enter the area of coverage is recognized. After the outer region is eliminated and the inner part is on continuous observation, now any object that is intruded in the inner region will be detected and compared to the benchmarked images. The identified objects are segmented and compared.

Figure 5.8 : Detection of all the objects

5.1.6. Recognition of animals

The animals are only recognized from all the objects that are identified. And when the intruded image matches the benchmarked image, the alert signal is notified such that the driver gets cautioned and prevents the fatal accident.

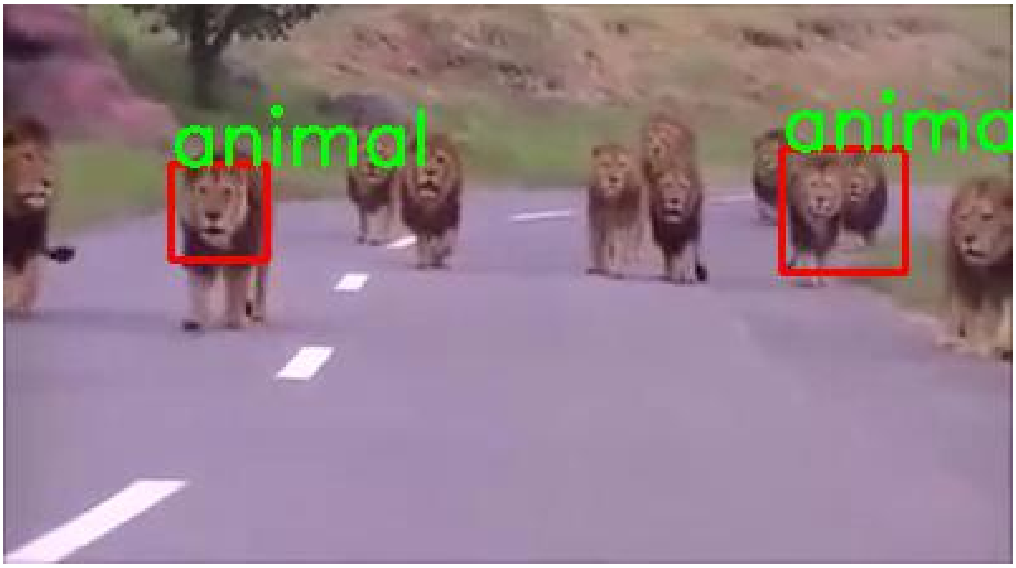

Figure 5.9 : Recognition of animals

5.1.7.Indication

Whenever an animal is identified, an indication is given. The indication is in the form of a spotlight such that the driver can get notified of the animal on the road from a far-off distance and can avoid the accidents.

CHAPTER 6

EXPERIMENTAL RESULTS

6.1 BACKGROUND SUBTRACTION

The place where the region is continuosly monitored by the video camera is called the area of coverage, the rest of the region is eliminated. The intruded objects in the area of coverage will be recognized and and compared to the benchmarked image.

Figure 6.1 : Background subtraction

6.2 OBECT DETECTION

The objects intruded are detected and compared. Every object would be detected including the vehicles, trees and any living or non living object. All the objects will be recognized and compared to the trained data sets continuously.

Figure 6.2 : Object detection

6.3 ANIMAL RECOGNITION

The animals are only recognized from all the objects that are identified. And when the intruded image matches the benchmarked image, the alert signal is notified such that the driver gets cautioned and prevents the fatal accident.

Figure 6.3: Animal recognition

6.4 INDICATION

Whenever an animal is identified, an indication is given. The indication is in the form of a spotlight such that the driver can get notified of the animal on the road from a far-off distance and can avoid the accidents.

6.5 SAMPLE RESULT

No. of samples	Condition	Expected result	Actual result
1	Car	No Alarm	No
2	Lorry	No Alarm	No
3	Donkey	Alarm	Yes
4	Elephant	Alarm	Yes

CHAPTER 7

CONCLUSION AND FUTURE WORK

CONCLUSION

This project proposes a reliable method for the detection of wildlife in highways applicable to unconstrained wildlife video. There are no strong assumptions about the video material and the environment, such as the number of animals present, their poses to the camera, the amount of background clutter, and the camera operation. As a consequence, the system detects and tracks animals of different sizes and poses on the road.

The proposed system effectively helps in preventing roadkills in the highway regions. This reduces the fatality of drivers, vehicles and animals. With an accuracy of 80%, it efficiently helps in reducing the number of accidents occurring on highways. Though the proposed work has been focused on automatic animal detection in context to Indian highways, it will work in other countries also. The proposed method can easily be extended for detection of other animals too after proper training and testing. The proposed system can be used with other available, efficient pedestrian and vehicle detection systems and can be offered as a complete solution (package) for preventing collisions and loss of human life on highways.

FUTURE WORK

Though our proposed system can detect the animals (cow) on roads and highways as well as gives alert to the driver, it cannot give warning signals before-hand if the vehicle is only at a distance of 5 metres or less from the animal . In that case, though animal gets detected time is not sufficient to prevent animal-vehicle collision. Some means or method of finding a solution for this needs to be done so that driver gets sufficient time for applying brakes or take any other action for preventing the collision. High-end resolution cameras can be used to detect animals during the night, which is expected to be done in our future scope of study and research. The method does not make hard constraints on the species themselves and can thus be easily adapted to other animal species.

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