Advanced Driver Assistance System

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Abstract- *In this paper a technique for identification for unwanted departure of travelling vehicles is proposed, along with pedestrian detection and drowsiness check of the driver. For lane departure identification a distance based departure measured is computed at each frame and a necessary warning message is issued to the driver when such measure exceeds a threshold. The principle of Hough transform is used to detect lanes for lane departure warning and Canny edge detectors to detect lane lines. To improve the lane detection accuracy we are using different image preprocessing techniques. To detect the pedestrians on the road based on HOG features and SVM classifier, and based on that proposed system will give an alert to the driver which will help to reduce various accidents on road. This paper also focuses on detecting the drowsiness of the driver by detecting the eye if it is open or closed by using Haar like features. Haar feature-based cascade classifiers are an effective object detection method first proposed by Viola and Jones. It's a machine learning based technique which uses a set of positive and negative images for training purpose.*

Keywords- Region of Interest, Lane departure, lane detection, Hough Transform, HOG, SVM, Haar like feature.

I. INTRODUCTION

The traffic envoirnment around the world is highly dynamic. This dynamicity causes the unique challenges for mobility and security. Most occurrences of the car accidents result from the use of smart phones, fatigue and drowsiness while driving and due to careless pedestrians. To improve security and traffic efficiency, research on Intelligent Transport Systems (ITS) has been conducted worldwide for many years. The main goal of the Intelligent Vehicle Systems is primarily to improve the road safety and to reduce the traffic capacity. A significant task of driver assistance system is the evaluation of image sequences saved with a mounted vehicle camera. In the coming future,vehicles are going to be more and more intelligent and they shall assist the driver both concerning comfort and safety. Advanced Driver Assistance Systems (ADAS) has a vast area to explore which includes various research for the driver safety like night vision assistance, *lane departure* warning system (LDWS), pedestrian detection system (PDS), smart airbags, cruise control, etc. As the dependence and the performance of the algorithms have been remarkably improved due to the gradual increasing performance of computers, vision systems have been appreciated in the automatic control community as a powerful and resourceful sensor to measure motion, position and structure of the environment. If well organized algorithms are developed in a proper manner in accordance to the need of society for such modern vision systems, then the performance of the system will increase to a larger extent.

Our main challenging task is to detect *lane departure* of the vehicles on road so as to prevent any harm. So a method is proposed in the system that detects unwanted departure of the lane and give necessary warning to the driver. This process of automation in driving will reduce the number of accidents that occurs due to departure of the vehicle from the specified lane. Identifying the road lanes in different environmental conditions is a challenging task, a robust algorithms must be used to mitigate the problems of poor *lane detection*. Many time roadlanes are fade and not visible the *Hough transform* is a widely used technique for the detection of regular curves such as lines, ellipses, and circles in an image by localizing them in a parametric space. It is particularly useful in lane marking detection because lines can be readily detected. Accordingly, it is necessary to detect the edge lane and to preprocess the road images for smoothing it for reducing any noise, picked up during image capture.

Another main challenging task is Pedestrian Detection System (PDS)which is one of the important system belonging to ADAS. The main objective of PDS is to detect pedestrians in front of an approaching vehicle and to anticipate the possibility of collision. The system provides a warning to the driver acoustically. PDS are highly significant now a days as the chances of a driver getting distracted by mobile phones have increased. Pedestrian detection is challenging as the posture of individuals differ and they could be carrying objects, both resulting in the variation of the normal shape of pedestrian. The variations in the colour of clothes worn by the pedestrian make it difficult for a detection algorithm based on colour. The system should satisfy the reaction time constraints for real time applications and must be robust to work without fail. However, it is still very challenging since it has high requirements for speed and accuracy. Currently, the typical pedestrian detection process is based on individual images, even though the applications are usually on videos. There is a

couple of consequent problems: 1) the detections are not stable, e.g. the bounding boxes are flickering; 2) the same object will be missed at current frame even though it is detected in previous frames. These problems happen because of no temporal constraint. In this paper, we introduce temporal priors to make the detections over continuous frames stable.
In some cases it may happen that the driver is not in the condition to drive because of drowsiness or mental condition, hence drowsiness detetction is also one of the important aspect of the proposed system. For detetcting drowsiness eye detetction techniques are used. *Haar like feature*s are widely used for detetcting eyes and face.

Soour main aim is to prevent various casualties that occurs on roads such as accidents where in the loss of property is a major concern. So to implement such an idea we are constructing a system that includes *lane departure* warning system, pedestrian detection and drowsiness detction.

II. RELATED WORK

In recent years, a large amount of research has effectively addressed the lane marking detection. Pradnya N. Bhujbal et. al. [1] proposed color transformation, histogram equalization, ROI selection and thresholding as pre-processing technique. For detecting lanes hough tranform is used and lane depature warning is provided based on euclidian distance.Li et al. [2] proposed a model using a Adaptive *Hough Transform*. Firstly, the images are converted into gray scale form, using only the R and G channels of the color images. They have ignored the B channel relying on the good contrast of red and green channels on the white and yellow lane markings. A very low threshold Canny edge detection is then applied to the grayscale image. The next step consists in applying a particular HT, which they call RHT (Randomized HT) and pixels of RHT are sampled randomly according to their gradient magnitudes. This method ensures robust and accurate detection of lane markings, especially for noisy images. Z. Teng et al. [3] proposed an algorithm that integrates multiple cues, including bar filter and *Hough Transform*. The bar filter shows efficiency to detect bar-shape objects like road lane and color cue. To ensure robust *lane detection* in real time, a particular filtering technique was used. The algorithm has improved the accuracy of the *lane detection* in straight and curved road.

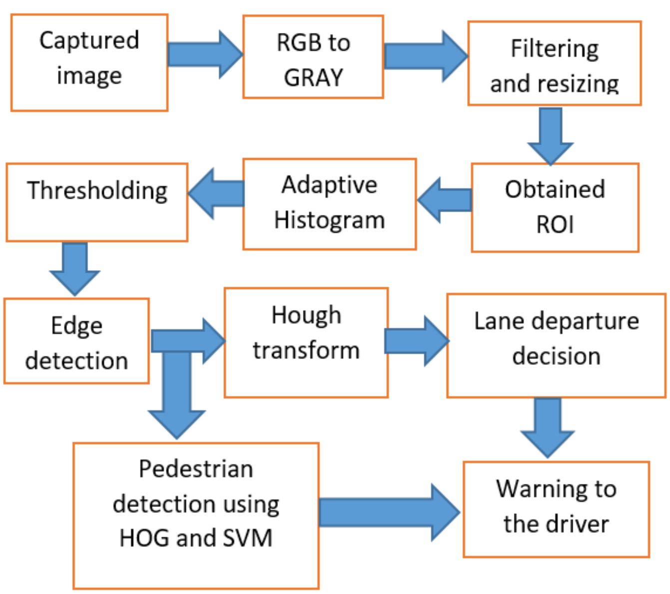
K. Ghazali et al. [4] proposed an algorithm based on H-Maxima and Hough Transform. The algorithm's excellent efficiency gives the ability to detect unexpected lane changes *and* excellent performance under straight and curved lane conditions, but failed to determine the farthest objects.Gaikwad and Lokhande [5]. In [5], at preprocessing step, piecewise linear stretching function (PLSF) is used to enhance the contrast of image. *Lane departure* identification is carried out on the basis of Euclidean distance based departure measure (i.e. absolute difference between Euclidean distance between center and midpoint of left lane and Euclidean distance between centre and right lane). Lee and Yi [6] proposed a lane boundary pixel extractor (LBPE) technique to increase the robustness of *lane detection*, which enhances the LDI by finding pixels that are possibly a part of lane boundaries. The ratios of the orientations and location parameters of the left and right lane boundaries are used to recognize the *lane departure*. However, an important condition is that the optical axis of a camera mounted on a vehicle coincides with the center of the lane. To improve *lane detection* accuracy, different image preprocessing techniques are used by many researchers. F. Bush et. al. [7]These techniques are the transformation of an image into hue–saturation– value and the application of morphological filters to reduce noise. For*lane detection*, Wang et al. [8] proposed the B-Snake method and achieved efficient tracking. Wu et al. [9] used a fan-scanning detection method but has the limitation of less accuracy. Mu and Ma [10] used piecewise fitting for *lane detection* but suffers from more false alarms. Parajuli et al. [11] obtained good *lane detection* results using local gradient features, but this approach shows poor performance in shadows and gives more false alarms.

Several techniques for PDS have been proposed by researchers, a survey of various techniques for pedestrian detection was carried out by David Gero´ nimohor et.al [12] and it was observed that most of the techniques uses learning algorithms in combination with classification algorithms. An example of such a system is the use of HAAR features with Adaboost [13] or Histogram of oriented Gradients (*HOG*) with Support Vector Machine *SVM* [14][15]. Even though Adaboost helps to improve the speed of system with Haar features, it lack robustness and is found to be inferior to *HOG* with *SVM*. Jorge Martinez-Carballido et.al proposed a technique [16]which uses the shape of the shoes to identify pedestrian. The *Region of Interest* (ROI) considered in this approach was small hence it gave quick result for detecting pedestrian close to the vehicle. However this approach fails to detect pedestrians wearing no shoes or shoes with a different shape.Human body has symmetrical characteristics and this could be used to identify pedestrians as proposed by A. Broggi et.al [17]. A scheme of fusing the data from vision based system with that of Laser Scanner was proposed by A. Broggi et.al [18][19]. The Background Modeling approach in [20] by Kang et.al. requires knowledge of internal parameters of camera which makes it difficult. Amitha Viswanatha et.al [21] proposed a vision based technique of modeling dynamically varying background.

Many research works on emotion recognition and analysis have been carried out for a decade due to applications in the field of human-machine interaction. For real time emotion recognition system, a few approaches have been proposed. First step in process of emotion recognition is face detection in given image. In 2004, Viola and Jones [22] proposed an algorithm for face detection which has four stages Haar feature selection, creating an integral image, Adaboost training and Cascading classifiers. After face detection depending on facial feature extraction three types of approaches which geometric approaches, appearance based approach and hybrid approach combination of geometric and appearance can be used. In 2013, Rohit [23] used Local binary pattern (LBP) method to extract features, which is an appearance based approach depends on pixel values of facial image. In 2014, Myunghoon [24] used Active shape model (ASM) to extract 77 facial points. Active Shape Model is popular geometric based approach in which detected image is iteratively deformed to fit shape model and extract facial points after comparison with shape model. Least mean square method [25], Support Vector Machine (*SVM*) [26, 23, 22] and Adaboost [26] are different types of classifiers used for classification. In classification process first training has to be done to train the software later testing is done using test subject.For training many database are available which are Cohn-Kanade, FEEDTUM, JAFFE and CMU MultiPIE. Later the software developed can be deployed on system development kit or on mobile phones for further use.

III. PROPOSED METHODOLOGY

The methodology for LDWS and Pedestrian detection



The methodology for Drowsiness detection

A: LANE DEPARTURE WARNING SYSTEM

We aim to develop a robust algorithm and ensure a real-time detection, because we are interested on a real-time implementation. For this purpose, our optimization techniques will take into consideration image preprocessing, edge detection and line tracking steps for detection of lane. As a Smoothing filter, we will use an average filter. The choice of this filter is due to its simplicity on comparison with the median filter. Lower area of a lane image, shown in Fig. 1, is considered as *region of interest* (ROI). This ROI contains road lanes. This is the lower region of the view seen by a camera which can be situated inside a car near rear view mirror. This ROI is further divided into left and right subregions. Lane marking using *Hough Transform* (HT) will be carried out in segmented regions of an image. Processing an image without ROI segmentation will detect many Hough lines. All lanes which come in ROI will be detected. Otherwise, all these lines will create vagueness in identifying exact lane markings which are required for *lane departure* indication purpose.

Fig.1. *Region of Interest*

The purposes for the construction of the ROI are the reduction of processing time and the reduction of memory space required for each video frame. Moreover, we limit the number of memory access. Then, the RGB color image is converted to an intensity image and the rest of operations are performed on intensity image. Next, we apply to the ROI of the image an average filter to reduce noise effects. Finally, we threshold the intensity image to obtain road lines. A good choice of a threshold value allows us to detect both yellow and white lane boundary lines.

A.1 Hough Transform

Hough Transform is one of the extensively used technique for detection of shapes or any parametric curves, if we can represent that shape in terms of mathematical form. It can accurately detect the shape even if it is broken or distorted a little bit. The mathematical treatment of *Hough Transform* is Shown as follows:

It is represented as **y = mx+c** or in parametric form, as**ρ =x*cosΘ + y*sinΘ** where ρ is the perpendicular distance from origin to the line, and 'Θ' is the angle formed by the perpendicular line and horizontal axis measured in anti-clockwise (A line That direction varies on how you represent the coordinate system. This representation is used in OpenCV). So if a line is passing below the origin, it will have a positive ρ and angle which will be less than 180. If the line is going above the origin, an angle is taken less than 180, and ρ is taken negative. Any line can be represented in these two terms (ρ, Θ) i.e in parametric form. So first of all it creates a 2D array or accumulator (to hold values of two parameters) and it is set to 0 initially. Rows denote the ρ and columns denote the Θ. Size of any array on which the *Hough Transform*is applied its array depends on the accuracy need of users parameters. Suppose that we want the accuracy of angles to be 1 degree, then what you need is n 180 columns. For ρ, the maximum distance possible is the diagonal length of the image on which HT is being applied.

A.2 Lane Departure Warning (LDW)

Considered as an essential part of the Advanced Driver Assistance system (ADAS), the *lane departure* warning (LDW) plays an essential role in the proposed system. At this stage, lines markings extraction is already done at the end of the *Hough transform.* LDWS uses lane information to determine the position of the vehicle relative to the lane. If a *lane departure* is happening, LDWS gives the driver alarm signal and textual warning. For one image even if we use history information to improve results of *Hough transform*, the result is not enough reliable. The camera is placed in the middle of the vehicle so that the two line markings appear in the middle of the image and are symmetrical to each other when the driver is on the right way. Connected line markings are detected using the improved *Hough transform*.

Steps for lane departure warning :

1. H0is the origin (centre)of *Hough transform* placed at the coordinate (W/2, 0). Where W is width of the frame.
   Minneg = W/2 ; Minpos = W/2
2. Initializing the height and width for ROI
3. Obtaining required points in the frame, necessary for defining the warning to the driver.
   New height = 0.6* height ;
   New width = 0
   Accordingly ROI will be defined as follows
   ROI = new height :height,0:width
4. X_samples are the points on line obtained by equation of straight line using two point form.
   slope = (y2 - y1) / (x2 - x1)
   X_sample = x1 + int((y - y1)/slope)
5. Select the range for slope to elliminate unwanted hough lines
   Diff = W/2 – X_sample
   if diff > 0
   if diff < minpos
   minpos = diff
   elif diff < 0:
   diff = -diff
   if diff < minneg:
   minneg = diff
6. Defining threshold point
   threshold = int(0.9 * wd/4)
   if (minneg) < threshold
   "Right departure warning "
   elif (minpos) < threshold
   "Left departure warning "
   Else
   "No departure "

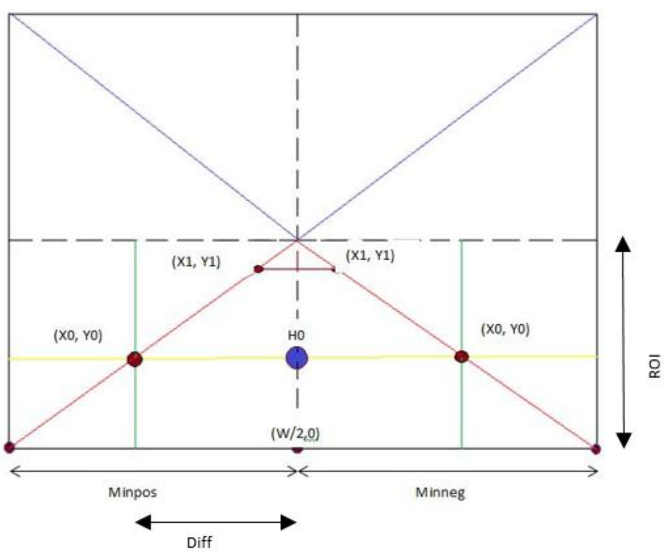


Fig. 2. Lane departure decision

B:PEDESTRIAN DETECTION

Pedestrian detection is one of the most important steps in a Advanced Driver Assistance System. Histogram of Oriented Gradients (*HOG)* features introduced by Dalal and Triggs are now the most widely used in the field of vision-based pedestrian detection. Often the *HOG* features are learned by the use of Support Vector Machine (*SVM*) for detecting pedestrians. The *HOG* plus *SVM* approach scans an image at different scales, and it examines all the subimages at each scale. In each subimage, a *HOG* feature vector is extracted. Then, *SVM* classifier is employed to make a decision between human and nonhuman. Although this approach is by far one of the most successful human detection methods, it is very slow . This is a critical problem when applied to a fast-moving vehicle. This paper presents an adaptive method of using *HOG+SVM.*Rather than computing *HOG* features on a whole image, we select image regions that have high possibility of human existence. And *HOG*features are obtained only from the selected regions.

If there is a human in a scene, it is likely to show high strength of gradient, particularly in vertical direction. A Sobel mask is employed to compute the gradient.The gradient image is then converted into a binary image by the use of a threshold. The threshold value is determined automatically using Basic Global Thresholding method as described below.

Step 1: An initial guess of threshold T is selected as the meanvalues of all the pixel values
Step 2: Pixels are grouped into two classes, G1 and G2 by comparing with T.
Step 3: Compute the mean value of each class, m1 and m2.
Step 4: A new threshold value is computed by TN=(m1 and m2)/2.
Step 5: Compute 'T=|TN-T|. If 'T is considerably large, then go to Step 2. Otherwise, TN is the final threshold value.

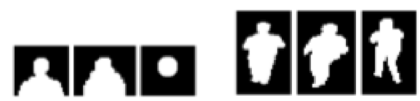
After obtaining a binary image consisting of pixels of high gradient, the image is vertically projected by

$$S(x) = \sum_{y-1}^{n} (\mathrm{B}(x, y))$$

where B is the binary image. We repeat this projection process horizontally too, and find pixels having strong vertical and horizontal projection values. It presents a clue where humans likely exist and the *HOG* window should be moved around. *HOG* features obtained are fed into *SVM*. The *SVM* is a binary classifier, which makes a decision for an input vector to belong +1(human) or -1(non-human). Since any human detection method including those using *HOG* and *SVM* can fail occasionally, we count the detection number in image sequences, and a warning is made when multiple detections are made at the same region in a short sequence.

B.1 HumanDetection

Our human detection is based on conventional *HOG* descriptive features . Since *HOG* has the highest computational time in the human detection processes, we use regions of interest to find a candidate area to perform human detections. A *region of interest* (ROI) is an area with foreground pixels that can possibly be a human. A bounding box is cropped over a dilated foreground to get a bounding box slightly larger than the segmented foreground. And the size of these extracted bounding boxes, from the small image, is then converted to their original size. These regions on the full-sized image are computed for *HOG* and are classified using support vector machine (*SVM*). These regions are very useful for reducing *HOG* feature extraction and also reducing numbers of false positives since an area without segmented foregrounds is not likely to contain human. With our approach, we do not need to perform multiscale *HOG* computation as a sliding window on the whole image, but rather, only on the candidate regions. Thus, the computational time is largely reduced.



(a) upper body (b) full body

The full body templates contain silhouettes of different walking actions as shown in Figure(b). The lowest distance (most similar) is selected from the six templates to be used for the human shape classification.

C: DROWSINESS DETCTION

This paper also focuses on detecting the facial expression of the driver and by identifying the mood in accordance with the facial expression the system will alert the driver providing a certain warning to the driver. Facial expressions includes drowsiness of the driver i.e. when driver's eye remains close for a specific amount of time (It may be any threshold amount of time, In this project we have kept our threshold at 3 sec.) ,the system will issue an alert to the driver. To make this possible we have used *Haar like feature*s to detect the human eye. A Haar-like feature considers neighboring rectangular regions at a specific location in a detection window and sums up the pixel intensities in each region and calculates the difference between these sums. This difference is then used to categorize subsections of an image.

Each Haar-like feature consists of two or three connected "white" and "black" rectangles as shown in Fig. 3.The extended set of Haar-like feature which was proposed by Lienhart and Maydt.The value of a Haar-like feature is difference between the sums of the pixel values in the black and white rectangles.

$$f(x) = \sum_{\text{black}} (\text{pixel value}) - \sum_{\text{white}} (\text{pixel value})$$

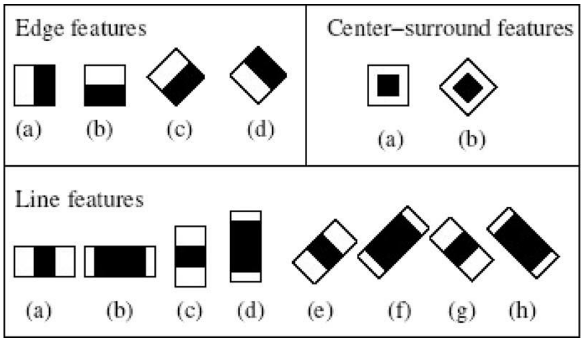


Fig. 3. Extended set of *Haar like features.*

The cascade classifier consists of several number of stages, where each stage consists of a list of weak learners.

The system can detect gestures in problem statement by moving a window over the image. Every stage of the cascade classifier identifies the specific region by providing an appropriate labels to it, which is further defined by the current location of the window as either positive or negative, where positive means that an object was found or negative means that the specified object was not found in the image.

The basic mechanism which we have implemented to check the drowsiness of the driver is the amount of time which will be calculated, when the eyes of the driver are closed. When the eyes are open, no warning will be issued to the driver but when the eyes are closed for more than threshold time, the system will issue an alert.

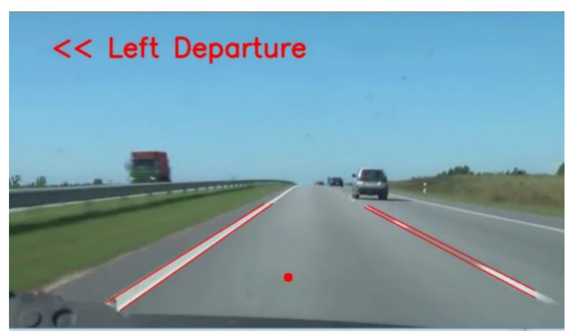
IV. RESULTS

Fig.4(a) Original image

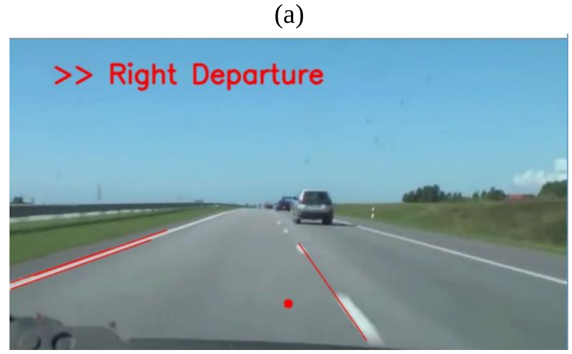
Fig. 4(b) Thresholding

Fig.4(c) Output of *Hough transform*

Above are the images for which *lane detection* was carried out Fig.4(a) is the actual image which has undergone through extraction of ROI and thresholding in Fig.4(b) and the image fig.4(c) shows the lane detected using *Hough Transform*



(a)



(b)

Fig 5 (a) (b) Warning issued for *lane departure*

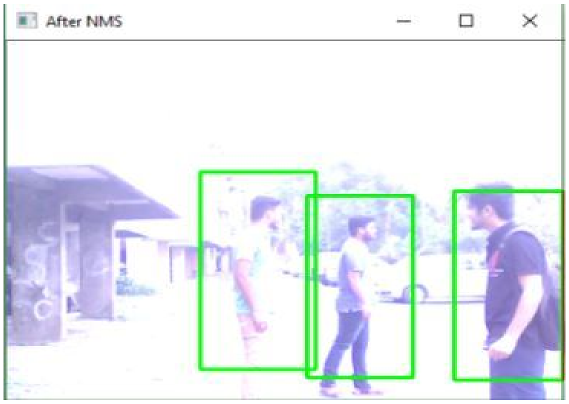


Fig. 6. Pedestrian detection

The fig. 6 shows pedestrian is detected on the road.

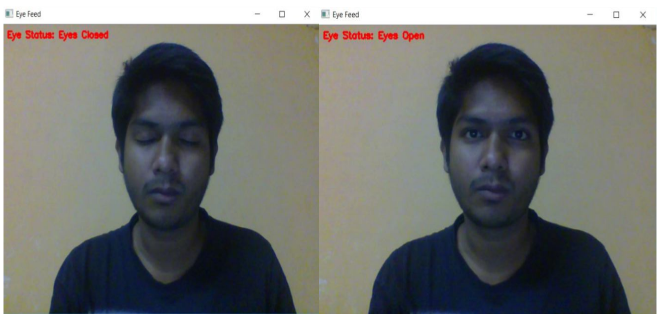
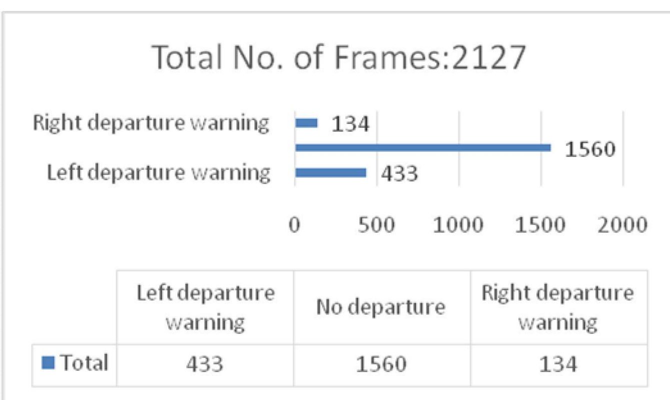


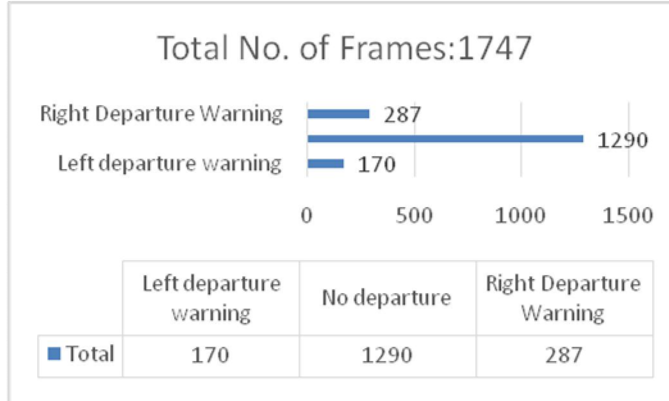
Fig 7. Drowsiness Detection

When the driver's eyes are closed for 3 sec. it shows drowsiness of driver and system is providing an alert to the driver.

V. RESULTS ANALYSIS



(a)



(b)

Fig. 8. Graph of the No. of departures for (a) video sequence 1 and (b) video sequence 2.

Table 1.Result analysis for pedestrian detection.

Atmospheric Condition	Pedestrain Present	Pedestrain Detected	Accuracy in %
Day Time	7	6	85.71
Night time	7	2	28.57
Cloudy Day	7	4	57.14
Evening	7	4	57.14

Overall average accuracy is found to be 56.39%.

VI. CONCLUSION

In this paper of Advanced Driver Assistance System we are implementing three techniques viz. *Lane departure* warning system, Pedestrian detection system and mood detection. Adaptive histogram equalization method is used to enhance the contrast level and provide a proper intensity to the image present in the frame which in turn provides better lanes images. An adaptive method of using *HOG+SVM* has provided a better result for pedestrain detecion and accuracy of detection during daytime was found to be 85.71%.*Haar like features* is an effective and fast technique of detecting an object. This project will results in reducing the number of road accidents and thus saving many lives. The ADAS system has a huge market in upcoming future. So the market point of view and society benefit point of view this project will have a great impact.

REFERENCES

[1] P. Bhujbal, S.Narote "*Lane departure* warning system based on *Hough transform* and Euclidian distance" *IEEE 2015* Third International Conference on Image Infonmation Processing.

[2] Q. Li, N. Zheng, et H. Cheng, “A prototype Autonomous vehicle and its algorithms for *lane detection*,” IEEE Transactions Conference on Intelligent Transportation Systems, vol. 5, Dec. 2004.

[3] Z. Teng, D.J. Kang et J.H. Kin, “Real-time *Lane detection* by using multiple cues,” IEE Conference on control Automation and Systems (ICCAS), pp. 2334 - 2337, Oct. 2010.

[4] K. Ghazali, R. Xiao, et J. Ma, “ Road *Lane Detection* Using H-Maxima And Improved *Hough transform*,” IEEE Conference on Computational Intelligence, Modelling and Simulation (CIMSiM), pp: 2166-8531, 2012.

[5] V. Gaikwad and S. Lokhande, "*Lane Departure* Identification for Advanced Driver Assistance," IEEE Trans. on Intelligent Transportation systems, 2014, pp. 1-9.

[6] J. W. Lee and U. K. Yi, “A lane-departure identification based on LBPE, *Hough transform*, linear regression,” Comput. Vis. Image Understanding, vol. 99, no. 3, pp. 359–383, Sep. 2005.

[7] F. N. Bush and J. M. Esposito, “Vision-based *lane detection* for an autonomous ground vehicle: A comparative field test,” in Proc. 42nd Southeastern Symp. Syst. Theory, 2010, pp. 35–39.

[8] Y. Wang, E. K. Teoh, and D. Shen, “*Lane detection* and tracking using B-Snake,” Image Vis. Comput., vol. 22, no. 4, pp. 269–280, Apr. 2004.

[9] C.-F.Wu,C.-J.Lin, and C.Y.Lee,“Applying a functional neuro fuzzy network to real-time *lane detection* and front-vehicle distance measurement,”IEEE Trans. Syst., M n, Cybern.C, Appl.Rev., vol.42, no.4, pp.577–589, Jul. 2012.

[10] C. Mu and X. Ma, “*Lane detection* based on object segmentation and piecewise fitting,” TELKOMNIKA Indonesian J. Elect. Eng., vol. 12, no. 5, pp. 3491–3500, May 2014.

[11] A. Parajuli, M. Celenk, and H. Riley, “Robust *lane detection* in shadows and low illumination conditions using local gradient features,” Open J. Appl. Sci. , vol. 3, no. 1B, pp. 68–74, Mar. 2013.

[12] Geronimo, D., Lopez, A. M., Sappa, A. D., & Graf, T. (2009). Survey of pedestrian detection for advanced driver assistance systems. IEEE Transactions on Pattern Analysis & Machine Intelligence, (7), 1239-1258.

[13] Viola, P., Jones, M. J., & Snow, D. (2005). Detecting pedestrians using patterns of motion and appearance. International Journal of Computer Vision, 63(2), 153-161.

[14] Zhang, L., Wu, B., & Nevatia, R. (2007, June). Pedestrian detection in infrared images based on local shape features. In Computer Vision and Pattern Recognition, 2007. CVPR’07. IEEE Conference on (pp. 1-8). IEEE.

[15] Dalal, N., & Triggs, B. (2005, June). Histograms of oriented gradients for human detection. In Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on (Vol. 1, pp. 886-893). IEEE

[16] Martinez-Carballido, J., & Morales-Velázquez, M. (2012, February). Using adaptive threshold to detect pedestrians crossing on a street for Advanced Driver Assistance Systems. In Electrical Communications and Computers (CONIELECOMP), 2012 22nd International Conference on (pp. 179-182). IEEE.

[17] Broggi, A., Bertozzi, M., Fascioli, A., & Sechi, M. (2000, October). Shape-based pedestrian detection. In Proceedings of the IEEE Intelligent Vehicles Symposium (pp. 215-220).

[18] Broggi, A., Cerri, P., Ghidoni, S., Grisleri, P., & Jung, H. G. (2009). A new approach to urban pedestrian detection for automatic braking. Intelligent Transportation Systems, IEEE Transactions on, 10(4), 594-605.

[19] Broggi, A., Cerri, P., Gatti, L., Grisleri, P., Jung, H. G., & Lee, J. (2009, June). Scenario-driven search for pedestrians aimed at triggering non-reversible systems. In Intelligent Vehicles Symposium, 2009 IEEE (pp. 285-291). IEEE.

[20] Kang, S., Paik, J. K., Koschan, A., Abidi, B. R., & Abidi, M. A. (2003, April). Real-time video tracking using PTZ cameras. In Quality Control by Artificial Vision (pp. 103-111). International Society for Optics and Photonics.

[21] Viswanath, A., Behera, R. K., Senthamilarasu, V., & Kutty, K. (2015). Background Modelling from a Moving Camera. Procedia Computer Science, 58, 289-296.

[22] Paul V., Michael J., ‘Robust Real-time Face Detection’, International Journal of computer vision, May 2004, Volume 57, Issue 2, pp 137-154

[23] Rohit Verma and Mohamed-Yahia Dabbagh, Fast facial expression recognition based on local binary patterns, IEEE, Electrical and Computer Engineering (CCECE), 2013 26th Annual IEEE Canadian Conference, pp 1 – 4, 2013.

[24] Myunghoon Suk, Balakrishnan Prabhakaran, Real-time Mobile Facial Expression Recognition System – A Case Study, Computer Vision and Patter Recognition Workshops (CVPRW), IEEE Conference , pp 132 – 137, 2014.

[25] Peng Zhao-yi, Zhu Yan-hui, Zhou Yu, Real-time Facial Expression Recognition Based on Adaptive Canny Operator

[26] Edge Detection, IEEE, Multimedia and Information Technology (MMIT), SecondInternational Conference on (Volume:2), pp 154 – 157, 2010.

[27] F. Abdat, C. MAAOUI And A. Pruski, Human-computer interaction using emotion recognition from facial

expression, IEEE, Computer Modeling and Simulation (EMS), Fifth UKSim European Symposium, pp 196 – 201, 2011