International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 8
DOI: https://doi.org/10.17762/ijritcc.v11i8.7944
***Article Received**: 05 May 2023 **Revised**: 29 June 2023 **Accepted**: 28 July 2023*

A Smart System for Detection of Road Lane and Divider

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Abstract— Road Lane and divider detection is a core part in environmental perception for driver assistance system. The paper discusses about machine learning and computer vision approach to identify road lanes and dividers and proposes a system for detection of road lane and divider. Driving assistance systems heavily rely on the road lane and divider recognition. Voting classification was implemented using 7 different classifiers. The combination of Scale Invariant Feature Transform (SIFT) and Oriented FAST and Rotated BRIEF (ORB) provided feature extraction. Principle Component Analysis (PCA) provided dimension reduction. The performance has been examined on the basis of accuracy (95.50%), precision (78.81%), recall (65.71%), and F1 score (71.67%). The proposed solution is helpful in solving issues related to road safety and reducing road accidents.

Keywords- Driver Assistance System, Detection of Divider, Detection of Lane on road, Smart System.

I. INTRODUCTION

World Health Organization (WHO) [1] highlights that minimum of 3,500 people died in traffic accidents on a daily basis. Advanced driver assistance systems (ADAS) are being designed [2] to facilitate safe driving. Researchers proposed models that monitor vehicles and lanes using camera vision to collect the surrounding information and group them into color information, lane markings, and feature information. The Process of lane detection is difficult [3] in presence of vehicles or shadows on the lane markings.

II. LITERATURE SURVEY

Line detection is a vast field of study as provided. CNN and RNN are used [4] to represent features and fusion of image processing methods. The LDTFE-based technique in [5] is better than the Line segment Detector method for lane detection. ACP parallel theory-based algorithms, obstacle detection, road printing detection, LIDAR, Multi-camera and GPS-based systems are integrated [6] to create a robust lanes detector. Probabilistic Hough transform and parallelogram region has been used in [7] for better runtime (30% less) and accuracy (3% more) in lane detection. The road lanes are identified [8] using a sliding window search. Gradient and HLS effectively detect the lane line in images in binary format. RANSAC algorithm increases the processing speed and generates improved results [9] for capturing lane markings. Kirsch operators enhance the robustness and adaptability of lane detection [10] and reduce the computational complexity. LLSS-Net framework extracts lane features from the enhanced

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images in DeeplabV3+ [11] with advanced semantic details to identify lanes.

The detection of lanes is carried out using geometry information [12]. The road picture is quantized to a binary image and utilized to detect lane markings. The accuracy of the model was reduced in fog and noise. Smartphone sensors-based techniques are used [13] for detecting road lanes, roadway intersections, and segments with 95% accuracy. Edge detection performed twice before and after selection of ROI [14] updates lane recognition rate. HT was unable to detect road dividers [15] in low light conditions. ML-based algorithms (Bayes classifier and neural network) are a more reliable solution. The algorithm helps to detect different conditions of lights. The MIT DARPA Urban Challenge vehicle's motion planning subsystem [16] follows the instructions of navigators for avoiding collisions, and obstacles. The system is based on the Randomly-exploring Random Trees Algorithm. Atrous Spatial Pyramid Pooling (ASPP) and Feature Pyramid Networks are used [17] for feature extraction. Feature map Pyramid Network (FPN) uses different sizes of convolutions [18] to map various images which indicate good improvement of performance. The polynomial curve model targets [19] the tangent relationship between line of road lane and the straight and curve models. Curve fitting method helps solve the equations of the curve model. The vanishing point detection and inverse perspective mapping are used in [20] providing lane detection accuracy of 97.7%. The robust edge detection in [21] is capable of generating lanes in case if lanes are not clearly visible. Inverse Perspective Projection (IPM) image's majority pixels [22] are road parts, cars, and other obstacles that become noise. The proposed solution for this noise is Gaussian Mixture Model (GMM) used efficiently for image segmentation. Morphological filtering is used for sharpening images and linear parabolic fitting [23]. Images were captured by the rear car camera and the dataset consists of video-captured images. Histogram Oriented Gradients (HOG) feature vectors of the POIs extracted [25] from all images for the unique type of road markings.

III. METHODOLOGY

The proposed model detects road lanes and dividers on the road. The design constitutes a camera and a processor-based system. Details of surrounding are captured by camera and fed to processor-based system. This model has the ability to differentiate between road lanes and dividers. A block diagram of the system for recognition of road lane and divider is shown in Fig. 1.

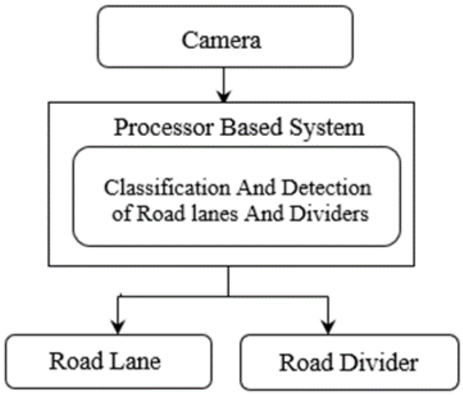

Fig. 1. Block Diagram for detection of road lane and divider

A) Dataset Collection

Table 1: Distribution of Dataset

Sr. No		Image Class	No. Of Images	Total
1	Training	Lanes	2000	6000
2		Dividers	2000	
3		Negative	2000	
4	Testing	Lanes	800	2400
5		Dividers	800	
6		Negative	800	
Total				8400

Fig. 2. Image Samples from Dataset

B) Design and Implementation of the system

The suggested system was developed over the course of five stages. - i) Feature Extraction, ii) Dimension Reduction, iii) Compilation of feature vector, iv) Data splitting, v) Classification.

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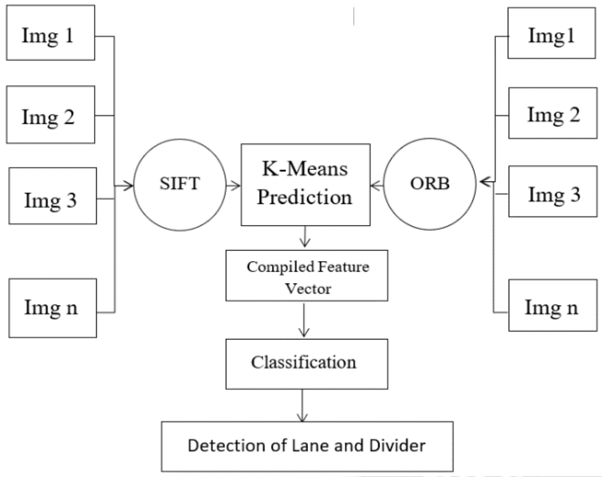

Fig. 3. Road Lane and Divider Detection Algorithm

Grayscale versions of each image are created and resized into 240x250 dimensions. Prewitt operator was utilized to detect edges. Prewitt yields superior results in comparison to Laplace, Sobel, Canny, and Robert. Prewitt edge detection performed better in most instances. Edge detected image helps to identify and highlight the edges of road lanes and dividers.

The Scale-Invariant Feature Transform (SIFT) is unaffected by scale, rotation and the translation. It performs feature extraction. By giving key points an orientation, feature descriptors were made to be rotation invariant. The magnitude and angle of gradient of a pixel are shown in eq. (1) and eq. (2).

$$n(a,b) = \frac{1}{\sqrt{(L(a,b+1) - L(a,b-1))^2 + ((a+1,b) - L(a-1,b))^2}} \quad (1)$$

$$\theta(a,b) = \left(\frac{L(a,b+1) - L(a,b-1)}{L(a+1,b) - L(a-1,b)}\right) \quad (2)$$

The descriptor was created by considering the 16x16 window kernel and further subdivided into 4x4 blocks. SIFT provides total 128 values for each descriptor. The final output of one image feature vector is of size Ax128 where A is the number of descriptors. The road lane and divider SIFT feature vector size is 329891×128 and 579242×128. The SIFT feature vector size of negative images is 737591×128. All these feature vectors are appended to get the compiled SIFT feature vector for all images of size 1646724×128. Oriented Fast and Rotated Brief (ORB) was used for feature extraction.

ORB is a mixture of the Feature from Accelerated Segment Test (FAST) key point detector and Binary Robust Independent Elementary Features (BRIEF) descriptor. Corner orientation as shown in eq. (3) was used to find moments of a patch and using moments the centroid shown in eq. (4).

$$m_{pq} = \sum_{x,y} x^p y^q \, I(x, y) \quad (3)$$

$$C = \left(\frac{m_{10}}{m_{00}}, \frac{m_{01}}{m_{00}}\right) \quad (4)$$

The size of feature vector of ORB for positive lane, divider and negative are 394436×32, 394436×32, and 855458×32 respectively. The compiled ORB feature vector is of size 1644330×32. The computational cost of processing this large sized vector was too high. An unsupervised K-Means clustering classification technique was applied on this data. K-Means clustering was employed to divide the huge size data into clusters. Euclidean distance as shown in (5) was used to find clusters in this algorithm.

$$d(a,b) = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2} \quad (5)$$

The value of 'k' has been determined using the elbow method. The optimal value of clusters obtained from elbow method was 25. The feature vector obtained from SIFT was divided into 25 clusters. The data obtained after K-Means prediction was normalized. The same process was carried out for feature vector obtained from ORB. SIFT and ORB K-Means predicted data was concatenated column wise obtain a single feature vector. Total dimension of the feature vector obtained for all images was (6000 x 50). Large feature vector of 50 columns was reduced to optimal size as presented in Algorithm1.

Principal Component Analysis (PCA) was incorporated to reduce the number of columns. PCA constructs new features by taking the linear combination of the original components. Sum of explained variance ratio was taken and it was observed that first 40 components contain 98% of total information. First 40 components were considered and the feature vector of size 6000 ×50 was reduced to 6000 ×40.

Algorithm 1: Extraction of optimal feature vector

Input:

1. Feature vector of SIFT (1646724 x 128)

2. Feature vector of ORB (1644330 x 32)

Output:Optimized feature vector (6000 x40)

1. Data1 = [], Data2 = []

2. For each image Feature vector of SIFT in F

// Dimension of F = (Z, 128)

3. X = pre-Trained k-means [k =25]

[Dimension of X = (1, 25)]

4. N = Normalize(X)

5. Data1.append(N)

6. End For

7. For each image Feature vector of ORB in F

// Dimension of F = (Z, 32)

8. Y = pre-Trained k-means [k =25]

// Dimension of Y = (1, 25)

9. M = Normalize(Y)

10. Data2.append(M)

11. End For

12. final_data = Concatenate (Data1, Data2)

// Dimension of final_data is 6000*50

13. FV = PCA with [n =40] // Dimension of data is 6000*40

The data is split into dependent variables (x) and independent variables (y). The train-test (80-20) split procedure was used to gauge the functionality of the machine learning algorithms. This model was also evaluated using an unknown dataset of 2400 images.

A. Train Dataset: Used to fit the machine learning model.

B. Test Dataset: Used to evaluate the fit machine learning model.

Image classification was performed using 7 different classifiers - i) Decision tree (DT), ii) Random Forest (RF), iii) K-Nearest Neighbor (KNN), iv) Logistic Regression (LR), v) Support vector machine (SVM), and vi) Gaussian NB, vii) Decision Tree Classifier. Voting Classifier combines the results of each classifier fed into it. Based on the largest vote majority, it forecasts the output class. Individual 7 pre-trained classifier models were ensembled and soft voting classifier was developed. The ensemble classifier prediction can be mathematically represented as in (6).

$$\hat{y} = arg\ arg\ max \sum_{j=1}^{m} w_j X_A\left(C_J(x) = i\right) \qquad (6)$$

where, C_j represents the classifier, w_j represents the weight associated with the prediction of the classifier.

Soft voting classifier works as a global classifier and improves the classification accuracy. Using the probabilities of each prediction provided by every classification model, it classifies the input data.

IV. RESULTS AND DISCUSSIONS

The voting classifiers have an accuracy of 95.50%. The voting classifier provides maximum accuracy among 7 used classifiers. The maximum F1 score obtained with voting classifier is 71.67 % for lane, 84.57 % for divider and 81.87 % for negative. Calculation of F1 score enabled the performance evaluation with respect to imbalanced dataset.

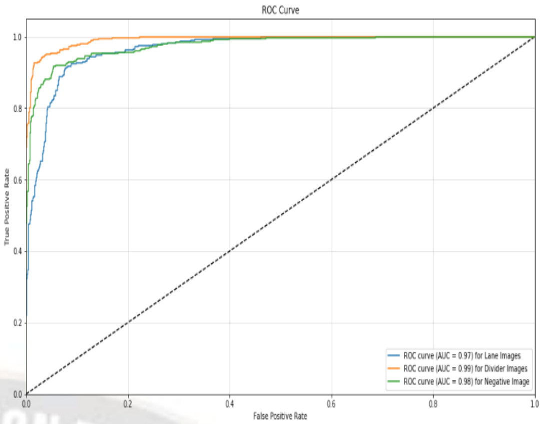

Fig. 4. Receiver Operating Characteristics (ROC) and Area under the ROC Curve (AUC) for soft voting on training data

The visualization of Receiver Operating Characteristics (ROC) and Area under the ROC Curve (AUC) for trained data is shown in Fig.4. The plot represents AUC of soft voting for lane, divider and negative image are 97%, 99% and 98% respectively on training data.

The classifier with the maximum accuracy was chosen for prediction. The accuracy, precision, recall, F1 score for road-lane and divider are shown in Table 2.

Table 2. Evaluation of performance of the proposed model

Classifier	Train Accuracy	Test Accuracy	Precision	Recall	F1 Score
Decision Tree	95.10%	83.66%	77.45	82.07	79.69
			83.81	88.29	85.99
			90.21	80.80	85.24
Random Forest	99.54%	95.83%	75.62	87.01	80.91
			92.07	85.75	88.80
			91.56	84.83	88.06
KNN	92.33%	83.33%	84.75	82.33	83.53
			90.31	84.91	92.55
			89.58	87.67	88.62
SVM (RBF)	94.72%	91.91%	87.18	90.12	88.63
			85.50	95.16	85.28
			93.17	93.17	91.82
Gradient Boost	80.06%	79.75%	78.81	65.71	71.67
			85.45	83.71	84.57
			75.91	88.86	81.87
Voting Classifier	97.97	95.50%	78.81	65.71	71.67
			85.45	83.71	84.57
			75.91	88.86	81.87

V. CONCLUSION

This paper proposes a design for road lane and divider identification. Voting-based model provides an accuracy of 95.50% on the test dataset and the Random Forest classifier model accuracy is 95.23%. This system is capable of detecting road lanes and dividers and helps in driver assistance system. The system lacks to detect the road lanes and dividers when road lanes and dividers are not clearly visible. The proposed method is helpful in reducing road accidents and safe driving assistance.

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