NOVEL METHOD FOR IMPROVING ACCURACY IN DETECTING ROAD LANE WITH RECEIVER OPERATING CHARACTERISTIC USING SCALE-INVARIANT FEATURE TRANSFORM OVER SUPPORT VECTOR MACHINE

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Article History: Received: 12.12.2022 **Revised:** 29.01.2023 **Accepted:** 15.03.2023

Abstract

Aim: To improve the accuracy in detecting road lanes with Receiver Operating Characteristic using Novel Scale-Invariant Feature Transform over Support Vector Machine.
Materials and Methods: This study contains 2 groups namely Scale-Invariant Feature Transform (SIFT) and Support Vector Machine (SVM). Each group consists of a sample size of 1506 and the study parameters include alpha value 0.05, beta value 0.2, and the power value 0.8. Their accuracies are also compared with each other using different sample sizes.
Results: The Novel Scale-Invariant Feature Transform has an accuracy of 92.38% and the Support Vector Machine of 83.42% in Road Lane Detection. The significance value for performance and loss is 0.578 ($p>0.05$)
Conclusion: The SIFT model is significantly better than the SVM in identifying Road Lane Detection. It can be also considered as a better option for the Lane Detection in General.

Keywords: Novel Scale-Invariant Feature Transform, Support Vector Machine, Lane Detection, Feature Abstraction, Object Differentiation, Edge Detection.

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1. **Introduction**

A road lane detection system's ability to reliably recognise Road Lanes , beings and other vehicles is critical for a variety of applications, including abnormal event detection (Institute of Electrical and Electronics Engineers 2007). Road Lanes gait characterisation, congestion analysis, and fall detection for the elderly (Sudini 2017). The initial stage in the detecting procedure is to identify a canny edge, perform Background subtraction, optical flow, and spatio-temporal filtering methods might be used to identify lanes (Zheng et al. 2016). When a moving item is discovered, It can be categorised as an obstacle using shape-based, texture-based, or motion-based characteristics (Singh 2019).

There are about 32 articles in Google Scholar, Science direct and 21 in Scopus related to this study. In a study by Wen-Chang Wang. This paper aims at various detection techniques used to detect and separate lanes and other objects using the Novel Scale-invariant Feature Transform Algorithm (Zhu 2007). This paper tells about both supervised and unsupervised learning algorithms (Wu 2012). These two learnings combined to find and count the objects (Fu, Ma, and Xiao 2012)**.** This paper tells a simple and efficient bottom-up saliency detection model of a discriminative histogram feature metric by combining multiple colour space and gradient magnitude channels to handle complex images (Zheng et al. 2016). Shape-based, motion-based, and texture-based methods are the several types of object classification techniques. The benchmark datasets' properties are discussed, as well as the most common uses of lane detection (Rajahrajasingh 2019).

Our institution is keen on working on latest research trends and has extensive knowledge and research experience which resulted in quality publications (Rinesh et al. 2022; Sundararaman et al. 2022; Mohanavel et al. 2022; Ram et al. 2022; Dinesh Kumar et al. 2022; Vijayalakshmi et al. 2022; Sudhan et al. 2022; Kumar et al. 2022; Sathish et al. 2022; Mahesh et al. 2022; Yaashikaa et al. 2022). The research gap in Road Lane Detection and Object avoidance is the availability of real time data sets and the accuracy to be improved. The selection of the algorithm also plays a vital role in Road Lane Detection. So, this research focuses on improved accuracy in Road Lane detection using Scale-invariant Feature Transform Algorithm Over Support Vector Machine (Sudini 2017). This research aims to increase the size of the input dataset and also to improve the accuracy of the algorithms. Similar applications of Lane Detection are Vehicle Detection, Obstacle detection and Image Classification are some of applications.

Materials and Methods

This work is carried out at Saveetha School of Engineering, Department of Information Technology in the Data Analytics Lab. The study consists of two sample groups namely Scale-invariant Feature Transform Algorithm and Support Vector Machine. Each group consists of 10 samples with pre-test power of 0.18. The sample size kept the threshold at 0.05, G power of 80%, confidence interval at 95%, and enrolment ratio as 1. The classification dataset was obtained from the Kaggle (https://www.kaggle.com/soumya044/lane-line-detection(Sammarco and Detyniecki 2018) Database, an open-source data repository for Vehicle Detection using multiple machine learning approaches.

Data Preparation

To perform Road Lane Detection, the real time data sets used are images and videos. These input data sets for the proposed work are collected from the kaggle community (https:// www.kaggle.com/soumya044/lane-line-detection).

Scale-Invariant Feature Transform Algorithm

The scale-invariant feature transform(SIFT) is a computer vision algorithm to detect, describe, and match local features in images, invented by David Lowe in 1999. Applications include object recognition, robotic mapping and navigation, image stitching, 3D modelling, gesture recognition, video tracking, individual identification of wildlife and match moving.

SIFT keypoints of objects are first extracted from a set of reference images and stored in a database. An object is recognized in a new image by individually comparing each feature from the new image to this database and finding candidate matching features based on Euclidean distance of their feature vectors. From the full set of matches, subsets of keypoints that agree on the object and its location, scale, and orientation in the new image are identified to filter out good matches. The determination of consistent clusters is performed rapidly by using an efficient hash table implementation of the generalised Hough transform (Lapušinskij et al. 2021).

Each cluster of 3 or more features that agree on an object and its pose is then subject to further detailed model verification and subsequently outliers are discarded. Finally the probability that a particular set of features indicates the presence of an object is computed, given the accuracy of fit and number of probable false matches. Object matches that pass all these tests can be identified as correct with high confidence (Zhang, Li, and Li 2021).

Each identified cluster is then subject to a verification procedure in which a linear least squares solution is performed for the parameters of the affine transformation relating the model to the image.

Support-Vector Machine

Support-vector machines (SVM's, also support-vector networks) are supervised learning models with associated learning algorithms that analyse data for classification and regression analysis. Developed at AT&T Bell Laboratories by Vladimir Vapnik with colleagues SVM's are one of the most robust prediction methods, being based on statistical learning frameworks or VC theory proposed by (Chandran, Udaykumar, and Reinhardt 2010). Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier (although methods such as Platt scaling exist to use SVM in a probabilistic classification setting). SVM maps training examples to points in space so as to maximise the width of the gap between the two categories. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall (Scholkopf and Smola 2018).

More formally, a support-vector machine (Fig. 1), constructs a hyperplane or set of hyperplanes in a high - or infinite-dimensional space, which can be used for classification, regression, or other tasks like outlier detection. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training data point of any class (also-called functional margin), since in general the larger the margin, the lower the generalisation error of the classifier. The attributes are ridges, pattern, pores, edge contour, colour, image,etc. Dependent Variables are ridges, pattern, pores, edge contour. Independent variables are colour, image. Independent T- test is carried out in this research work.

Statistical Analysis

The minimum requirement to run the softwares used here are intel core i3 dual core Central Processing Unit @3.2 GHz, 4GB RAM, 64 bit OS, 1TB hard disk space personal computer and software specification includes Windows 8, 10, 11, Python 3.8 and MS-Office.

The Vehicle Detection is predicted by the randomised method, a forest of randomised trees is trained and the final prediction is based on the majority vote outcome from each tree. This method allows weak learners to correctly classify data points in an incremental approach that are usually misclassified.

Statistical package for the social sciences version 23 software tool was used for statistical analysis. An independent sample T-test was conducted for accuracy. Standard deviation, standard mean errors were also calculated using the SPSS software tool. The significance values of proposed and existing algorithms contains group statistical values of proposed and existing algorithms.

3. Results

The group statistical analysis on the two groups shows Novel Scale-Invariant Feature Transform Algorithm (Group 1=10) has more mean accuracy than Support-Vector Machines (Group 2=10) and the standard error mean is slightly less than Novel Scale-invariant Feature Transform Algorithm. The Novel Scale-Invariant Feature Transform algorithm scored an accuracy of 92.38% and Support-Vector Machine scored 83.42%. The accuracies are recorded by testing the algorithms with 10 different sample sizes and the average accuracy is calculated for each algorithm.

In SPSS, the datasets are prepared using 10 as sample size for Scale-Invariant Feature Transform Algorithm and Support-Vector Machines. Group id is given as a grouping variable and Lot area is given as the testing variable. Group id is given as 1 for Scale-Invariant Feature Transform Algorithm and 2 for Support-Vector Machines. Group statistics is shown in Table 4, Two Independent Sample T-Tests in Table 5.

4. Discussion

From the results of this study, Novel Scale-invariant Feature Transform Algorithms are proved to be having better accuracy than the Support-Vector Machines. SIFT has an accuracy of 92.38% whereas SVM has an accuracy of 83.42%. The group statistical analysis on the two groups shows that Novel Scale-Invariant Feature Transform Algorithm (Group 1=10) has more mean accuracy than Support-Vector Machines (Group 2=10) and the standard error mean including standard deviation mean is slightly less than Novel Scale-Invariant Feature Transform Algorithm.

Road Lane Detection was performed using Scale-invariant Feature Transform Algorithm based categorization which gave an accuracy of 91.77% (Stewart 1994). Attention based on Road Lane Detection paper provided an accuracy of 83.42% (Institute of Electrical and Electronics Engineers 2007).

The limitation in this model is that the accuracy of SVM requires full labelling of input data. Most of the data is simulated from nature which is far from reality. Effective data preprocessing techniques (Astorino et al. 2011), and the combination of SIFT with other machine learning algorithms such as PCA, LDA and CNN may give better accurate results in the future.

5. Conclusion

Based on the experimental results, the Novel Scale- Invariant Feature Transform Algorithm (SIFT) has been proved to detect Road Laness more significantly than Support-Vector Machines(SVM). It can be used in Road lane Detection and Navigation for Self driving in Future.

Declarations

Conflicts of Interest

No conflicts of interest in this manuscript.

Authors Contribution

Author RRG was involved in data collection, data analysis, data extraction, manuscript writing. Author CPG was involved in conceptualization, data validation, and critical review of the manuscript.

Acknowledgement

The authors would like to express their Gratitude towards Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (Formerly known as Saveetha University) for providing the necessary infrastructure to carry out this work successfully.

Funding

We thank the following organisations for providing financial support that enabled us to complete the study.

1. Best Enlist
2. Saveetha University
3. Saveetha Institute of Medical and Technical Sciences.
4. Saveetha School of Engineering.

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Tables and Figures

Table 1: Pseudocode for Novel Support Vector Machine

// I : Input dataset records
1. Import the required packages.
2. Convert the image into machine readable after the extraction feature.
3. Assign the image or video to the output variables.
4. Using the model function, assign it to the variables.
5. Compiling the model using metrics as accuracy.
6. Evaluate the output
7. Get the accuracy of the model.
OUTPUT //Accuracy

Table 2: Pseudocode for Scale Invariant Feature Transform

// I : Input dataset image
INPUT: Capture Image or Video Stream
Step 1. Pre-process the image to detect Canny Edges
Step 2. Segment and Normalise the Frames
Step 3. Extract the feature vector of each normalised candidate
Step 4. Train SIFTs based on a saved sample database.
Step 5. Recognize the Lanes by the set of SIFTs trained in advance.
Step 6. If there are no more unclassified samples, then STOP.

Step 7. Add these test samples into their corresponding database for further training. OUTPUT: Lane detected / mapped
OUTPUT //Accuracy

Table 3: Accuracy of Road Lane Detection using Novel Scale Invariant Feature Transform

Test Size	**Accuracy**
Test 1	91.47
Test 2	95.72
Test 3	92.48
Test 4	96.37
Test 5	94.72
Test 6	97.81
Test 7	90.37
Test 8	91.98
Test 9	91.25
Test 10	93.08

Table 4: Accuracy of Road Lane Detection using Support Vector Machine

Test Size	**Accuracy**
Test 1	85.86
Test 2	83.96
Test 3	84.75
Test 4	82.55
Test 5	88.86
Test 6	87.55
Test 7	86.98
Test 8	81.99
Test 9	90.98
Test 10	91.97

Table 5: Group, Accuracy and Loss value uses 8 columns with 8 width data for Road Lane Detection .

SI.NO	Name	Type	Width	Decimal	Columns	Measure	Role
1	Group	Numeric	10	2	10	Nominal	Input
2	Accuracy	Numeric	10	2	10	Scale	Input
3	Loss	Numeric	10	2	10	Scale	Input

Table 6: Group Statistical analysis for Novel Scale-Invariant Feature Transform and Support Vector Machine. Mean, Standard Deviation and standard error mean are determined.

	Group	N	Mean	Std Deviation	Std.Error Mean
Accuracy	**Scale-Invariant Feature Transform**	10	92.3880	1.77610	0.56165
	Support Vector Machine	10	83.4220	1.81097	0.57268
Loss	**Scale-Invariant Feature Transform**	10	7.612	1.77610	0.56165
	Support Vector Machine	10	16.5780	1.81097	0.57268

Table 7: Independent sample T-Test t is performed on two groups for significance and standard error determination. p value is greater than 0.05 (0.355) and it is considered to be statistically insignificant with 95% confidence interval

		Levene's test for Equality Of variance		T-Test for equality of mean						
				t	df	Sig(2 tailed)	Mean difference	Std.Error Difference	95% confidence of Difference	
		F	Sig						Lower	Upper
Accuracy	Equal variances assumed	.096	.760	11.178	18	.005	8.96600	0.80213	7.28079	10.65121
	Equal Variances not assumed	-	-	11.178	17.993	.005	8.96600	0.80213	7.28074	10.65126
Loss	Equal variances assumed	.321	.578	-11.178	18	.005	-8.96600	0.80213	-10.65121	-7.28079
	Equal Variances not assumed	-	-	-11.178	17.993	.005	-8.96600	0.80213	-10.65126	-7.28074

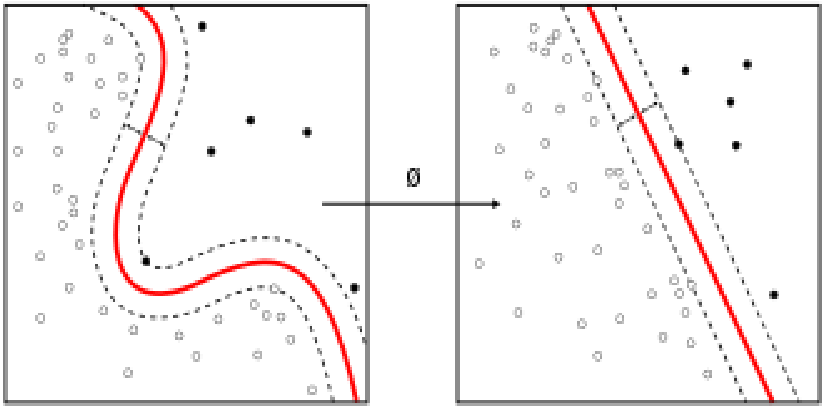

Fig. 1. Constructs a hyperplane or set of hyperplanes in a high - or infinite-dimensional space, which can be used for classification, regression, or other tasks like outlier detection. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training-data point of any class (so-called functional margin).

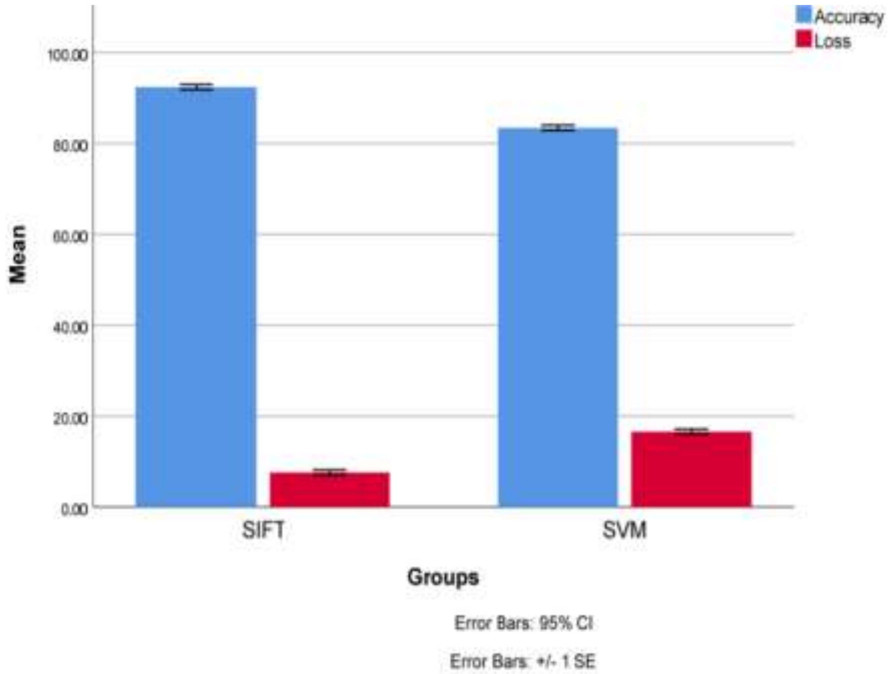

Fig. 2. Comparison of Novel Scale-Invariant Feature Transform and Support Vector Machine in terms of mean accuracy. The mean accuracy of the Novel Scale-Invariant Feature Transform is better than the Support Vector Machine algorithm. The standard deviation of Scale-Invariant Feature Transform is slightly better than Support Vector Machine. X Axis: Scale-Invariant Feature Transform vs Support Vector Machine.Y Axis: Mean accuracy of detection ± 1 SD.