NOVEL METHOD FOR IMPROVING ACCURACY IN DETECTING ROAD LANE WITH RECEIVER OPERATING CHARACTERISTIC USING SCALE-INVARIANT FEATURE TRANSFORM OVER CONVOLUTIONAL NEURAL NETWORK

Rohan Raju Gorule[1], G. Charlyn Pushpa Latha[2*]

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 Noval Scale-Invariant Feature Transform over Convolutional Neural Network.

Materials and Methods: This study contains 2 groups i.e Scale-Invariant Feature Transform (SIFT) and Convolutional Neural Network (CNN) Each group consists of a sample size of 5301 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 Noval Scale-Invariant Feature Transform has an accuracy of 92.38% and the Convolutional Neural Network of 84.2% in Road Lane Detection. The significance value for performance and loss is 0.965 ($p>0.05$)

Conclusion: The SIFT model is significantly better than the CNN in identifying Road Lane Detection. It can be also considered as a better option for the Lane Detection in General.

Keywords: Noval Scale-Invariant Feature Transform, Convolutional Neural Network, Lane Detection, Feature Abstraction, Object Differentiation, Novel Method, Edge Detection.

[1]Research Scholar, Department of Information Technology, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, Tamil Nadu, India. Pincode: 602105.

[2*]Department of Information Technology, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, Tamil Nadu. India, Pincode: 602105.

1. Introduction

A road lane detection system's ability to reliably recognise Road Lanes beings and the road lane and other vehicles is critical for a variety of applications, including abnormal event detection, Road Lanes gait characterisation, congestion analysis, and fall detection for the elderly. The initial stage in the detecting procedure is to identify a canny edge(Lapušinskij et al. 2021), perform Background subtraction, optical flow, and spatio-temporal filtering methods might be used to identify lanes. When a moving item is discovered, It can be categorized as an obstacle using shape-based, texture-based, or motion-based characteristics.

There are about 32 articles in Google Scholar Science direct and 21 in Scopus related to this study. This paper aims at various detection techniques used to detect and separate lanes and other objects using the Novel Scale-invariant Feature Transform Algorithm(Lindeberg 2012). This paper tells about both supervised and unsupervised learning. These two learnings combined to find and count the objects(Tsuji et al. 2001)**.** This paper tells a simple and efficient bottom-up saliency detection model of a discriminative histogram feature metric by combining multiple color space and gradient magnitude channels to handle complex images. 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(Venturi and Korda 2020).

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 Convolutional Neural Network(Singh 2019). 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, Image Classification.

2. 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 Convolutional Neural Network. 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.

Data Preparation

To perform the real time data sets used are images and videos. The input data sets for the proposed work is collected from kaggle.com (“Kaggle: Your Machine Learning and Data Science Community”).

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 modeling, 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(Alfakih 2018). 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 generalized Hough transform(Talib and Ramli 2015). 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(Ghazali, Xiao, and Ma 2012). Object matches that pass all these tests can be identified as correct with high confidence.

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(Rui 2013).

Convolutional Neural Network

A Convolutional Neural Network (CNN) is a class of neural networks, generally normally applied to break down visual symbolism. They are otherwise called shift invariant or space invariant counterfeit neural organizations (SIANN) (Arulampalam and Bouzerdoum 2003), in view of the common weight engineering of the convolution bits or channels that slide along input includes and give interpretation equivariant reactions known as component maps. Illogically, most convolutional neural organizations are just equivariant, instead of invariant, to interpretation. They have applications in picture and video acknowledgment, recommender frameworks, picture order, picture division, clinical picture investigation, regular language handling, cerebrum PC interfaces and monetary time series(Kim et al. 2017).

CNNs are regularized forms of multi-facet perceptrons. Multi-facet perceptrons typically mean completely associated networks, that is to say, every neuron in one layer is associated with all neurons in the following layer. The "full availability" of these organizations make them inclined to overfitting information(Kim et al. 2017; Rassabin, Yagfarov, and Gafurov 2019). Common methods of regularization, or forestalling overfitting, include: punishing boundaries during preparing, (for example, weight rot) or managing availability (skipped associations, dropout, and so on) CNNs adopt an alternate strategy towards regularization: they exploit the various leveled design in information and gather examples of expanding intricacy utilizing more modest and easier examples embellished in their channels. Along these lines, on a size of network and intricacy, CNNs are on the lower side(Choi and Oh 2010).

Convolutional networks were motivated by natural cycles in that the availability design between neurons looks like the association of the creature's visual cortex. Individual cortical neurons react to boosts just in a confined district of the visual field known as the responsive field(Cai et al. 2018). The responsive fields of various neurons to some degree crossover with the end goal that they cover the whole visual field.

CNNs generally utilize little pre-handling contrasted with other picture grouping calculations. This implies that the organization figures out how to enhance the channels (or parts) through robotized learning, though in conventional calculations these channels are hand-designed. This autonomy from earlier information and Road Lanes intercession including extraction is a significant benefit(Graves 2012).

3. Results

The group statistical analysis on the two groups shows Novel Scale-Invariant Feature Transform Algorithm (Group 1) has more mean accuracy than Convolutional Neural Networks (Group 2) 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 91.39% and Convolutional Neural Network scored 84.2%. 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 Convolutional Neural Networks . 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 Convolutional Neural Networks . 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 Convolutional Neural Networks . SIFT has an accuracy of 91.39% whereas CNN has an accuracy of 84.2%. The group statistical analysis on the two groups shows that Novel Scale-Invariant Feature Transform Algorithm (group 1) has more mean accuracy than Convolutional Neural Networks (group 2) 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%. Attention based on Road Lane Detection paper provided an accuracy of 84.2%.

The limitation in this model is that the accuracy of CNN requires full labeling of input data. Most of the data is simulated from nature which is far from reality. Effective data preprocessing techniques, 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 Convolutional Neural Networks (CNN). 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.

Author Contributions

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 organizations 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.

6. References

Alfakih, Abdo Y. 2018. Euclidean Distance Matrices and Their Applications in Rigidity Theory. Springer.

Arulampalam, Ganesh, and Abdesselam Bouzerdoum. 2003. “A Generalized Feedforward Neural Network Architecture for Classification and Regression.” Neural Networks: The Official Journal of the International Neural Network Society 16 (5-6): 561–68.

Cai, Yichao, Dachuan Li, Xiao Zhou, and Xingang Mou. 2018. “Robust Drivable Road Region Detection for Fixed-Route Autonomous Vehicles Using Map-Fusion Images.” Sensors 18 (12). https://doi.org/10.3390/s18124158.

Choi, Hyun-Chul, and Se-Young Oh. 2010. “Illumination Invariant Lane Color Recognition by Using Road Color Reference & Neural Networks.” The 2010 International Joint Conference on Neural Networks (IJCNN). https://doi.org/10.1109/ijcnn.2010.5596304.

Dinesh Kumar, M., V. Godvin Sharmila, Gopalakrishnan Kumar, Jeong-Hoon Park, Siham Yousuf Al-Qaradawi, and J. Rajesh Banu. 2022. “Surfactant Induced Microwave Disintegration for Enhanced Biohydrogen Production from Macroalgae Biomass: Thermodynamics and Energetics.” Bioresource Technology 350 (April): 126904.

Ghazali, Kamarul, Rui Xiao, and Jie Ma. 2012. “Road Lane Detection Using H-Maxima and Improved Hough Transform.” 2012 Fourth International Conference on Computational Intelligence, Modelling and Simulation. https://doi.org/10.1109/cimsim.2012.31.

Graves, Alex. 2012. Supervised Sequence Labelling with Recurrent Neural Networks. Springer.

Kim, Jihun, Jonghong Kim, Gil-Jin Jang, and Minho Lee. 2017. “Fast Learning Method for Convolutional Neural Networks Using Extreme Learning Machine and Its Application to Lane Detection.” Neural Networks. https://doi.org/10.1016/j.neunet.2016.12.002.

Kumar, J. Aravind, J. Aravind Kumar, S. Sathish, T. Krithiga, T. R. Praveenkumar, S. Lokesh, D. Prabu, A. Annam Renita, P. Prakash, and M. Rajasimman. 2022. “A Comprehensive Review on Bio-Hydrogen Production from Brewery Industrial Wastewater and Its Treatment Methodologies.” Fuel. https://doi.org/10.1016/j.fuel.2022.123594.

Lapušinskij, Aleksandr, Ivan Suzdalev, Nikolaj Goranin, Justinas Janulevičius, Simona Ramanauskaitė, and Gintautas Stankūnavičius. 2021. “The Application of Hough Transform and Canny Edge Detector Methods for the Visual Detection of Cumuliform Clouds.” Sensors 21 (17). https://doi.org/10.3390/s21175821.

Lindeberg, Tony. 2012. “Scale Invariant Feature Transform.” Scholarpedia. https://doi.org/10.4249/scholarpedia.10491.

Mahesh, Narayanan, Srinivasan Balakumar, Uthaman Danya, Shanmugasundaram Shyamalagowri, Palanisamy Suresh Babu, Jeyaseelan Aravind, Murugesan Kamaraj, and Muthusamy Govarthanan. 2022. "A Review on Mitigation of Emerging Contaminants in an Aqueous Environment Using Microbial Bio-Machines as Sustainable Tools: Progress and Limitations." Journal of Water Process Engineering. https://doi.org/10.1016/j.jwpe.2022.102712.

Mohanavel, Vinayagam, K. Ravi Kumar, T. Sathish, Palanivel Velmurugan, Alagar Karthick, M. Ravichandran, Saleh Alfarraj, Hesham S. Almoallim, Shanmugam Sureshkumar, and J. Isaac JoshuaRamesh Lalvani. 2022. "Investigation on Inorganic Salts K2TiF6 and KBF4 to Develop Nanoparticles Based TiB2 Reinforcement Aluminium Composites." Bioinorganic Chemistry and Applications 2022 (January): 8559402.

Ram, G. Dinesh, G. Dinesh Ram, S. Praveen Kumar, T. Yuvaraj, Thanikanti Sudhakar Babu, and Karthik Balasubramanian. 2022. "Simulation and Investigation of MEMS Bilayer Solar Energy Harvester for Smart Wireless Sensor Applications." Sustainable Energy Technologies and Assessments. https://doi.org/10.1016/j.seta.2022.102102.

Rassabin, Maksim, Rauf Yagfarov, and Salimzhan Gafurov. 2019. "Approaches for Road Lane Detection." 2019 3rd School on Dynamics of Complex Networks and Their Application in Intellectual Robotics (DCNAIR). https://doi.org/10.1109/dcnair.2019.8875560.

Rinesh, S., K. Maheswari, B. Arthi, P. Sherubha, A. Vijay, S. Sridhar, T. Rajendran, and Yosef Asrat Waji. 2022. "Investigations on Brain Tumor Classification Using Hybrid Machine Learning Algorithms." Journal of Healthcare Engineering 2022 (February): 2761847.

Rui, Xiao. 2013. Lane Markings Detection Based on E-Maxima Transformation and Improved Hough.

Sathish, T., V. Mohanavel, M. Arunkumar, K. Rajan, Manzoore Elahi M. Soudagar, M. A. Mujtaba, Saleh H. Salmen, Sami Al Obaid, H. Fayaz, and S. Sivakumar. 2022. "Utilization of Azadirachta Indica Biodiesel, Ethanol and Diesel Blends for Diesel Engine Applications with Engine Emission Profile." Fuel. https://doi.org/10.1016/j.fuel.2022.123798.

Singh, Himanshu. 2019. Practical Machine Learning and Image Processing: For Facial Recognition, Object Detection, and Pattern Recognition Using Python. Apress.

Sudhan, M. B., M. Sinthuja, S. Pravinth Raja, J. Amutharaj, G. Charlyn Pushpa Latha, S. Sheeba Rachel, T. Anitha, T. Rajendran, and Yosef Asrat Waji. 2022. "Segmentation and Classification of Glaucoma Using U-Net with Deep Learning Model." Journal of Healthcare Engineering 2022 (February): 1601354.

Sundararaman, Sathish, J. Aravind Kumar, Prabu Deivasigamani, and Yuvarajan Devarajan. 2022. "Emerging Pharma Residue Contaminants: Occurrence, Monitoring, Risk and Fate Assessment – A Challenge to Water Resource Management." Science of The Total Environment. https://doi.org/10.1016/j.scitotenv.2022.153897.

Talib, Muhamad Lazim, and Suzaimah Ramli. 2015. "A Review of Multiple Edge Detection in Road Lane Detection Using Improved Hough Transform." Advanced Materials Research. https://doi.org/10.4028/www.scientific.net/amr.1125.541.

Tsuji, Masafumi, Ryota Shirato, Hiroshi Furusho, and Kiyoshi Akutagawa. 2001. "Estimation of Road Configuration and Vehicle Attitude by Lane Detection for a Lane-Keeping System." SAE Technical Paper Series. https://doi.org/10.4271/2001-01-0799.

Venturi, Luca, and Krishtof Korda. 2020. Hands-On Vision and Behavior for Self-Driving Cars: Explore Visual Perception, Lane Detection, and Object Classification with Python 3 and OpenCV 4. Packt Publishing Ltd.

Vijayalakshmi, V. J., Prakash Arumugam, A. Ananthi Christy, and R. Brindha. 2022. "Simultaneous Allocation of EV Charging Stations and Renewable Energy Sources: An Elite RERNN-m2MPA Approach." International Journal of Energy Research. https://doi.org/10.1002/er.7780.

Yaashikaa, P. R., P. Senthil Kumar, S. Jeevanantham, and R. Saravanan. 2022. "A Review on Bioremediation Approach for Heavy Metal Detoxification and Accumulation in Plants." Environmental Pollution 301 (May): 119035.

TABLES AND FIGURES

Table 1.Pseudocode for Novel Convolutional Neural Network

// 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 Normalize the Frames
Step 3. Extract the feature vector of each normalized 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 Convolutional Neural Network

Test Size	**Accuracy**
Test 1	84.86
Test 2	81.96
Test 3	88.75
Test 4	83.55
Test 5	81.86
Test 6	85.55
Test 7	84.98
Test 8	87.99
Test 9	90.98

Test 10	89.97

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 Convolutional Neural Network. 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
	Convolutional Neural Network	10	79.0190	4.33118	1.36964
Loss	Scale-Invariant Feature Transform	10	7.612	1.77610	0.56165
	Convolutional Neural Network	10	25.9810	2.44340	0.77267

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						
		F	Sig	t	df	Sig(2 tailed)	Mean difference	Std.Error Difference	95% confidence of Difference Lower	Upper
Accuracy	**Equal variances assumed**	19.288	.001	9.031	18	.003	13.36900	1.48033	10.25895	16.47905
	Equal Variances not assumed			9.031	11.944	.003	13.36900	1.48033	10.14196	16.59604
Loss	**Equal variances assumed**	.002	.965	-19.230	18	.003	-18.36900	.95523	-20.37587	-16.36213
	Equal Variances not assumed			-19.230	16.435	.003	-18.36900	.95523	-20.38966	-16.34834

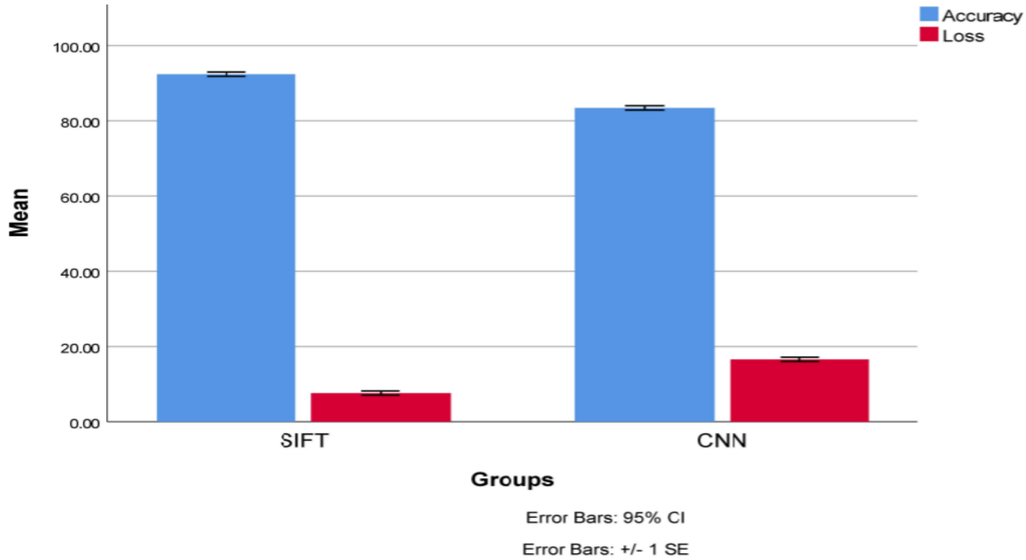

Fig. 1 Comparison of Novel Scale-Invariant Feature Transform and Convolutional Neural Network in terms of mean accuracy. The mean accuracy of the Novel Scale-Invariant Feature Transform is better than the Convolutional Neural Network Algorithm. The standard deviation of Scale-Invariant Feature Transform is slightly better than Convolutional Neural Network.
X Axis: Scale-Invariant Feature Transform vs Convolutional Neural Network.
Y Axis: Mean accuracy of detection ± 1 SD.