International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 /doi:10.14445/22315381/IJETT-V70I2P2230

Volume 70 Issue 2, 253-259, February, 2022

Original Article

Performance Evaluation of Support Vector Machine: Before and After Image Data Augmentation

M S Sunitha Patel[1], Srinath S[2]

[1]*Assistant Professor, Dept. of Computer Science and Engineering, ATME College of Engineering, Mysore, India*
[2]*Associate Professor, Dept. of Computer Science and Engineering, Sri Jayachamarajendra College of Engineering Mysore, India*

[1]mssunithapatel@gmail.com, [2]srinath@sjce.ac.in

***Abstract* — *Data to train the machine learning algorithms is a fundamental aspect to achieve the desired result for the given problem. Collecting the raw data and creating the datasets, pre-processing the data, and annotating for the given problem is a basic skill in data science engineering. Constructing the right dataset in automotive image processing problems usually takes 50% of the time in machine learning-based problem-solving techniques. Automotive image processing has more challenges considering the diversified weather conditions, road conditions, driving conditions, etc. Collecting diversified images in the automotive domain is one of the challenging tasks for researchers to study and implement machine learning algorithms. Image data augmentation will benefit from making required quantity and quality datasets for the automotive domain. In this paper, an effort has been made to show how to increase dataset size by utilizing image augmentation technique and also to create, test, train, validate the dataset for the multiclass vehicles. By utilizing the image data augmentation technique, validation and test dataset error have been reduced, which finally improved the performance of the machine learning model. Performance evaluation of the machine learning algorithm for the datasets with and without image augmentation has been analyzed. For analysis purposes, a Support Vector Machine (SVM) classifier has been utilized, and performance evaluation has been done using Receiver Operating Characteristics (ROC). Precision, recall, and F1 score has been compared for the dataset with and without image augmentation.*

Keywords — *Data Science, Dataset, Image Data Augmentation, Automotive Image Processing, SVM.*

I. INTRODUCTION

To develop a fully autonomous vehicle, the dataset quality should be very high, and also training images required are high. Dataset quality depends on the required accuracy in the output, development time, development cost. So, for finding the solution to a specific problem using machine learning methods, one should understand what kind of data has to be used for training. As a result, unnecessary development costs, lead time, and computation time can be avoided. Many automotive image processing systems need quick response time because necessary vehicle control action shall be completed in a few milliseconds. Few examples for active safety systems like Adaptive Cruise Control (ACC), Lane Keeping Assistance (LKA), etc., require quick response time, i.e., within milliseconds, to avoid any catastrophic incidences. Another important aspect here is the required dataset size to train ACC, LKA, NVC may not be the same because the Region of Interest (ROI) that has to be studied and trained may be different for different automotive features. Because in ACC important attribute is to control the vehicle speed and distance between vehicles ahead, here image processing plays a crucial role in predicting the gap between two vehicles or finding any sudden obstacle between two vehicles when driving in the longitudinal direction. In LKA, the vehicle control system should alert the driver if an unintentional lane change happens. So in LKA, image data has to be captured, which suites the scenarios of the unintentional lane change images like sudden lane mark changes, lane mark fading, poor visibilities of lane marks due to fog conditions, etc. Few of the automotive image processing features like Night Vision Camera Assistance (NVCA), Automatic Parking Assistance (APA) may need response time in a few seconds. In the NVCA & APA systems, the output is used by drivers to take the next control action, so processing the captured images with less response time is very important. Also, since human controls the next action, clarity of the image is very central in such systems. In NVCA, more focus is on the images that are captured during nighttime and assist drivers during nighttime for any foreseen risk. Therefore the dataset plays a major role in building such automotive image processing systems. In this article, the car, bus, and truck image dataset has been created, trained, validated, and tested using an SVM classifier. The objective to study multiclass vehicle problems is because multiclass vehicle identification is essential in advanced vehicle driver assistance systems like autopilot, driverless parking systems, vehicle platoon management, driverless vehicles, etc.

The paper has been divided into four sections, which start with the motivation of the work by addressing challenges & solutions in automotive image datasets with literature reviews. The second section explains the methodology used to execute the problem, and third part explains the implementation result for varying image count in datasets by using with and without image data augmentation, and the last section is the conclusion.

II. MOTIVATION

A. Automotive Image Processing Overview

In modern vehicles, the number of camera usage is increased to offer improved safety and driver comforts. Particularly, in modern cars, the number of cameras used can be more than 10 numbers [1] [2], which provides a lot of safety and driver comfort features. As the number of camera usage increases, challenges related to image processing and data analysis techniques also increase drastically. The challenge starts at the very initial step, i.e., in the image acquisition, as cameras are installed on the vehicle, which is in dynamic condition undergoes vibration, dust, rain [3], etc. Because of dynamic conditions, captured images will have a lot of noise and unwanted data. So, after capturing the image, the next step is image enhancement [4] which improves the quality of the images concerning resolution, colour rendition, etc., depending on the noise level in the captured images. After images are enhanced, the next step is image segmentation, which is very important for dataset creation. Image segmentation mainly deals with the required object detection and classification, so the data science engineer needs to capture the right objects in the datasets to train the machine learning model. For example, in the advanced vehicle driving systems like drive less vehicle, to have safe driving, the vehicle must recognize which area in the captured image or video is safe to drive the vehicle by a clear understanding of surrounding environments [5]. Pixel is the lowest level of feature which contains required information in representation and description. However, for automotive safety applications, a high level of representation and description are required. The final part of image pre-processing is representation and description, which is finally a suitable image that can be used for the required processing.

B. Dataset

Data science engineering in the automotive domain needs a very clear understanding of the different scenarios of images which needs training for machine learning algorithms. Once a clear understanding of required scenarios for the given problem is analyzed, then gathering the required images has to be initiated. As mentioned in Fig. 1, dataset modelling can be classified into 3 steps and explained as follows:

a) Open-Source Images: Through the World Wide Web, open-source image data for the automotive domain can be accessed. For the current problem analysis, the datasets are taken from the open-source dataset repository Mendeley Data(Poribohon-BD)[6]. The main challenge in these image datasets is the availability of the required quantity of images for the specific problem. The required quantity of images is one of the important aspects to train the machine learning algorithms. For example, in the current problem for multiclass vehicle analysis, through open-source image repositories, required quantities of images of nearly 5000 images for the car were obtained but could not get required quantities of images for bus and truck. Because of less quantity, performance for bus and truck was not good during analysis. In certain situations, the required quantity of images may be available but may fail to get the required diversity of the images, for in case, to implement Automatic Parking Assistance system, diversity of images scenarios like, day and night light conditions, different weather conditions like snow and fog conditions, parking symbol conditions, etc. will be not available in the dataset obtained through open-source repositories. If the required diversity of the image is not available, then the output quality of the learning algorithm may not cover the full scope of the problem.

b) Creating Image Dataset: Creating an image dataset for the problem is the best option but most of the time, developing images for all the required scenarios takes a lot of time and cost. If the research projects don't have enough budget and time, then the image dataset will impact the quality of the research output.

c) Image Data Augmentation: Image data augmentation is a technique to increase the dataset size by manipulating the available images. Various image manipulation techniques are available, [7] has explained different techniques like flipping, cropping, rotation, noise injection, translation, etc. But data science engineers must analyze and implement the required technique for the specific problem. Because, without proper analysis, if image augmentation is performed, then the wrong feature are given for training which can impact the training performance. The advantage of image augmentation is that required images for different scenarios can be created using existing images without impacting the quality of the new images.

As mentioned in the figure-1, the total image dataset required to analyze the performance of a machine learning algorithm can be created using open-source images or creating own images, and to improve the dataset size, image augmentation can be utilized. Once the data set is created then, training and testing will be performed using different machine learning algorithms. To solve the automotive image processing problems, a lot of machine learning algorithms are available, like SVM [8], Adaboost [9], Convolution Neural Network(CNN) [10]. SVM is a supervised machine learning algorithm, developed in 1995 [11], and for multiclass problems, SVM performance is superior to the Adaboost but inferior compared to CNN. From the literature survey, it is evident that SVM performance is in between CNN &Adaboost for the multiclass problem, so to start the problem, SVM has been selected considering to see any marginal difference in the performance.

C. Training, Testing and Validation datasets

Once enough images are created for the given problem, then the total number of images can be grouped as datasets.

One should note that the available image datasets have to be divided into three parts training data set, validation dataset, and test dataset. Usually, the division of datasets is like 80% of images will be used for the training dataset, and the remaining 20% of images are used as testing datasets. Sometimes validation datasets can be used to fine-tune the parameter of the classifiers. Usually, 20% of the total train set

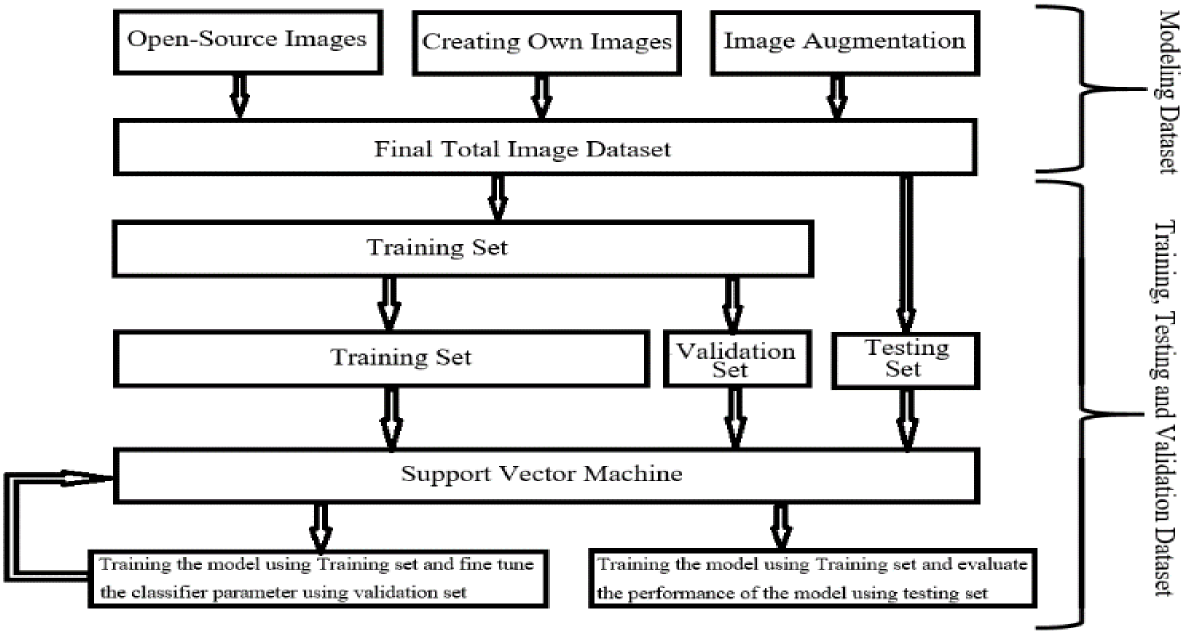

Fig. 1 Dataset Modelling, Training, Testing, and Validation

It can be used as the validation dataset. As mentioned in Fig. 1, the partition of the dataset has been shown considering the SVM algorithm.

III. IMPLEMENTATION

As explained in the previous section, the current problem has been implemented in three steps and explained as follows:

A. *Dataset Implementation*

As discussed earlier, performance evaluation of the SVM algorithms has been evaluated considering three sets of image datasets as mentioned in Table I.

a) Case-1: Images has been downloaded from the open-source repository [6] for all three class of Bus, Car, and Truck by considering the uniform number of the images. Since the availability of bus images were less than 2900 images, the same balanced image count has been considered for all three classes.

b) Case-2: Images has been downloaded from the open-source repository [6] for all three class of Bus, Car, and Truck, depending on the availability of the images. The case-2 dataset is imbalanced because the number of images in the datasets for each class is different.

c) Case-3: Images has been downloaded from the open-source repository [6][18][19][20][21][22] for all three class of Bus, Car, and Truck, depending on the availability of the images. Since images of bus and truck were less, own dataset of 400 images was created by capturing photos. Later captured 400 images have been used for image augmentation to increase images nearly to 2000 for both classifiers to make the sum of the balanced image of 5000 for all three classifiers as mentioned in Table I. Different image augmentation techniques like crop, flip, blur, random erasing, noise injection, colour jittering, etc., have been implemented for the captured images. Depending on the image to achieve better performance, respective image augmentation techniques have been utilized. Two sets of examples are shown in Fig. 2 and Fig.3.

TABLE I.
THREE CASES OF IMAGE DATASET

Sl No	Number of Bus images	Number of Car images	Number of Truck images
Case-1	2900	2900	2900
Case-2	2900	5000	3400
Case-3	5000	5000	5000

B. *Training using SVM*

The proposed architecture to implement the current problem is as shown in Fig. 4. The proposed three cases of the dataset have been created separately and fed to the SVM classifier. As mentioned earlier, 80% of images dataset are used to train the algorithm, and 20% of dataset images are used for testing purposes. Input images are pre-processed, and RBF kernel has been used, and analysis has been performed on the individual case.

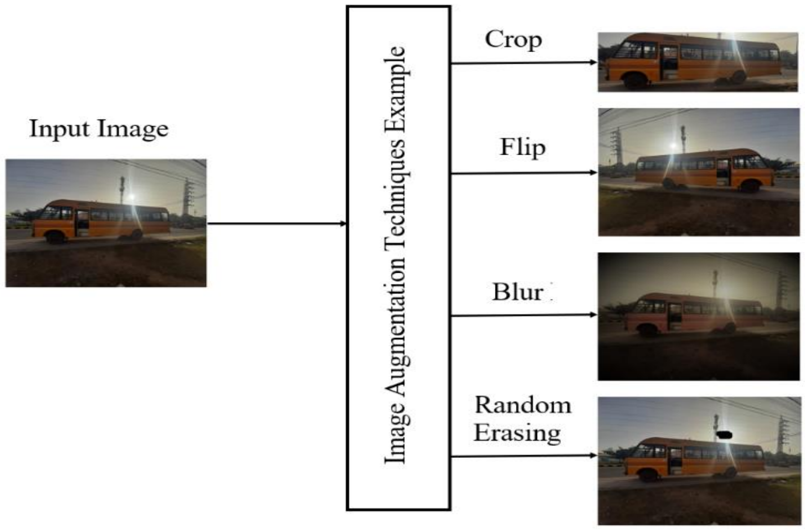

Fig. 2 Few examples of image augmentation techniques for the bus input image

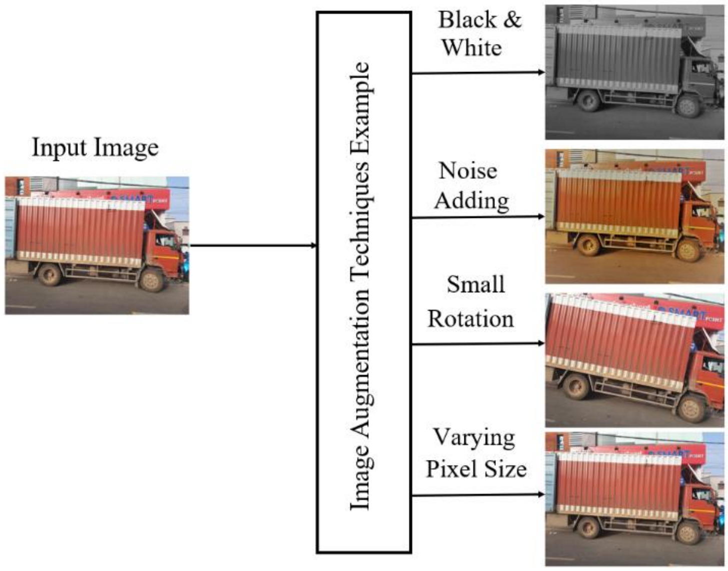

Fig. 3 Few examples of Image augmentation techniques for the truck input image

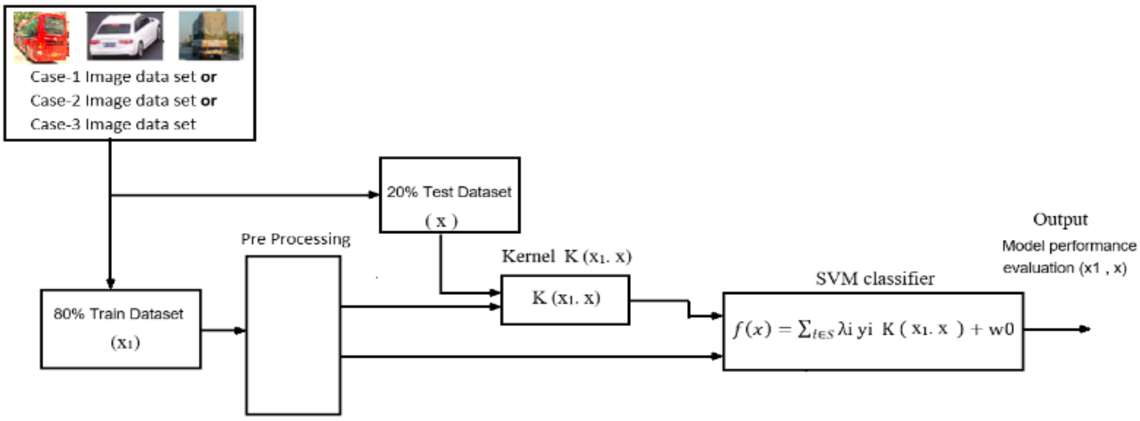

Fig 4: Proposed architecture

III. RESULT AND DISCUSSION

Performance evaluation of the SVM classifier with different data set has been experimentally done using a standard methodology like accuracy, precision, recall, and F1 score, the standard equation for the same has been explained as follows.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (1)$$

$$Precision = \frac{TP}{(TP + FP)} \quad (2)$$

$$Recall = \frac{TP}{(TP + FN)} \quad (3)$$

$$F1\ Score = \frac{2 \times TP}{((2 \times TP) + FP + FN)} \quad (4)$$

Where True Positive (TP) is correctly predicted class, False Positive (FP) is a label not belonging to class but predicted as positive, True Negative (TN) is the correctly predicted for class not belonging to, False Negative (FN) is wrongly predicted for class not belong to.

As mentioned in Table. I, image datasets have been executed individually for each case. In the output graph, label 0 represents bus vehicle, label 1 represents car vehicle, and label 2 represents truck vehicle as shown in Fig.5 on label convention. Performance evaluations like ROC, precision, and recall output graphs are shown in Figs 6 and 7 for case-1 and Figs. 8 and 9 for case-2 and Figs. 10 and 11 for case-3, respectively. Table. II shows the summary of the result for all considered three cases.

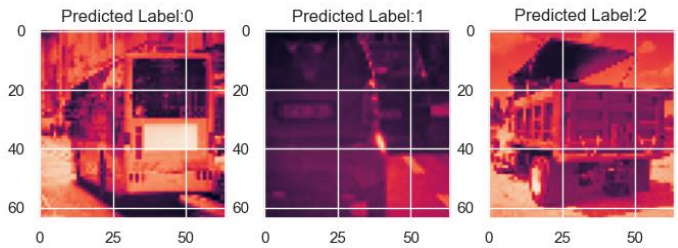

Fig. 5 Correctly predicted label, 0- Class bus, 1- class car, 2- class truck.

TABLE II
CONFUSION MATRIX FOR CASE-1

	Correctly Classified
	Misclassified
	False Positive
	False Negative
	Average accuracy

Actual Class \ Predicted Class	Bus	Car	Truck	
Bus	2350	202	348	550
Car	250	2400	250	500
Truck	353	197	2350	550
	600	400	600	85%

As mentioned in Table. I, for case-1 image consideration, where each class of bus, car, and truck has 2900 images in the dataset, and the experimental result has been captured in table II. From Table. II correctly classified images are 2350,2400 and 2350 images for bus, car, and truck class, respectively. Misclassified images are mentioned in the red colour box. Based on the misclassified images, the false positive is 600,400 and 600 images for bus, car, and truck class, respectively. False-negative is 550,500 and 650 images for bus, car, and truck class, respectively. ROC for the case-1 dataset is shown in figure 6.

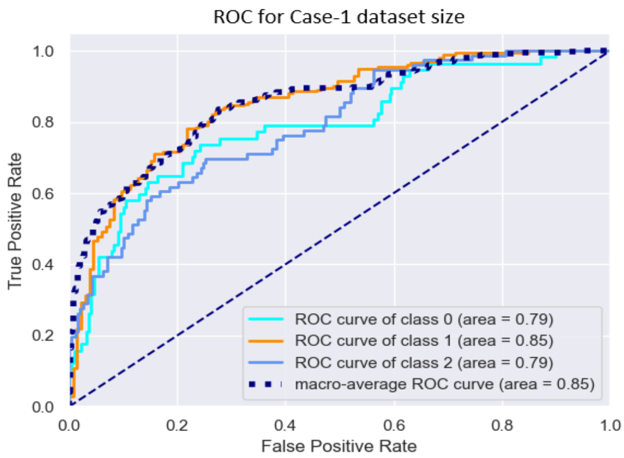

Fig. 6 ROC curve for Case-1 dataset

As mentioned in Table I, for case 2 image consideration, the experimental result has been captured in Table III. From table 2, correctly classified images are 1895, 4600, and 2300 images for bus, car, and truck class, respectively. Misclassified images are mentioned in the red colour box. Based on the misclassified images, the false positive is 650,500 and 650 images for bus, car, and truck class, respectively. A false negative is 1005,400 and 400 images for bus, car, and truck class, respectively. ROC output for the case-2 dataset is shown in figure 7.

TABLE. III
CONFUSION MATRIX FOR CASE-2

	Correctly Classified
	Misclassified
	False Positive
	False Negative
	Average accuracy

Actual Class \ Predicted Class	Bus	Car	Truck	
Bus	1895	450	555	1005
Car	300	4600	100	400
Truck	350	50	3000	400
	650	500	655	87%

As mentioned in Table I, for case 3 image consideration, the experimental result has been captured in Tabel IV. From Tabel III, correctly classified images are 4480, 4900 and 4750 images for bus, car, and truck class, respectively. Misclassified images are mentioned in the red colour box. Based on the misclassified images, the false positive is 150,80 and 240 images for bus, car, and truck class, respectively. False-negative is 220,100 and 150 images for bus, car, and truck class, respectively. ROC output for the case-3 dataset is shown in figure 8.

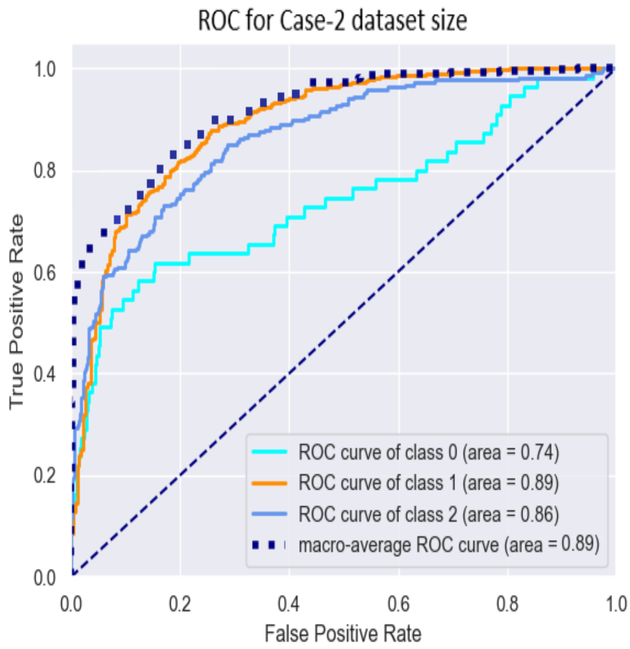

Fig 7. ROC curve for Case-2 dataset

TABLE. IV CONFUSION MATRIX FOR CASE-3

(green)	Correctly Classified
(orange)	Misclassified
(blue)	False Positive
(grey)	False Negative
(yellow)	Average accuracy

Actual Class		Bus	Car	Truck	
	Bus	4880	30	190	220
	Car	50	4900	50	100
	Truck	100	50	4750	150
		150	80	240	97%

Predicted Class

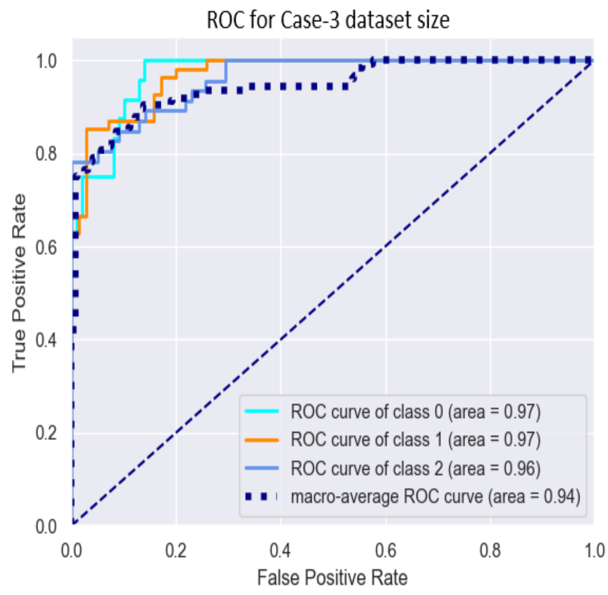

Fig. 8 ROC curve for Case-3 dataset

Similar to accuracy, performance output result for precision, recall, and F1 Score has been validated from the experimental result. Performance result for three different image dataset sizes, as mentioned in Table I, has been captured in Table V. From the result summary, it is quite evident that in multiclass analysis, imbalanced dataset size can degrade the performance. In the case-2 scenario, it is evident that the imbalance dataset size for bus, car, and truck has degraded the performance of the bus class. After adding images by considering Image augmentation, the performance of the output has been increased more than 15% compared to the case-1 scenario.

TABLE. V
SUMMARY OF THE PERFORMANCE RESULT FOR 3 CASES

Image Dataset	Class	Accuracy in %	Precision in %	Recall in %	F1 Score %	Average in %
Case-1	**Bus**	79	79	81	80	81
	Car	85	85	82	84	
	Truck	79	79	81	80	
Case-2	**Bus**	84	74	65	70	84
	Car	83	90	92	91	
	Truck	80	82	88	85	
Case-3	**Bus**	97	96	97	96	97
	Car	97	96	96	98	
	Truck	96	97	97	98	

IV. CONCLUSIONS

Machine learning algorithms need good datasets to train the algorithms. SVM segregates two classes by using an equal distance hyperplane, so dataset imbalance in the multiclass analysis will degrade the performance of the training. Image augmentation has a quite excellent benefit in automotive image processing to increase dataset size, in turn improving the learning algorithm capability. However, the data science engineer has to thoroughly analyze the given problem and implement the required image augmentation technique carefully. Each image augmentation technique has its performance output, and in our next work, a detailed analysis of image augmentation will be carried out, and performance evaluation of each technique shall be analyzed using the CNN algorithm.

REFERENCES

[1] Rafael C. Gonzalez, Richard E Woods, Digital Image Processing, Third Edition, Dorling Kindersley (India) Pvt. Ltd, (2014).

[2] M S Sunitha Patel and Dr Srinath S, Soft Computing Approaches for Automotive Image Processing: Opportunities & Challenges, Advances in Automation, Signal Processing, Instrumentation, and Control, Scopus Indexed Springer Proceedings – Lecture Notes in Electrical Engineering., (2020).

[3] Fei Han, Weiwen Deng, Sumin Zhang, Bei Ren, and Ying Wang, A Vision-based Forward Collision Warning System Developed under virtual Environment, SAE International Journal of TransportationSafety, 2(2) (2014).

[4] Yunbo Rao, Leiting Chen, A Survey of Video Enhancement Techniques, Journal of Information Hiding and Multimedia Signal Processing3(1) (2012).

[5] J. McCall and M. M. Trivedi, Video-based lane estimation and tracking for driver assistance: Survey, algorithms, and evaluation, IEEE Trans. Intell. Transp. Syst., 7(1) (2006) 20–37.

[6] https://data.mendeley.com/datasets/pwyyg8zmk5/2

[7] Connor Shorten*and Taghi M. Khoshgoftaar: A survey on Image Data Augmentation for Deep Learning, Journal of Big Data, (2019).

[8] L. Torresani, M. Summer, and A. Fitzgibbon: Efficient Object Category Recognition Using Classemes. European Conference of Computer Vision .,(2010) 776–789.

[9] Abhishek N, S Gopalswamy, S Rathinam, Vision-based Techniques for Identifying Emergency Vehicles, SAE Technical Paper, 2019-01-0889, (2019).

[10] Shiker Srivastava, Ayush Nigam, Madiajagan Mauthaiyan, Low-cost Driver Assistance System for drivers suffering from Dyslexia or Colllor-Blindness using Machine Learning, International Journal of Engineering Trends and Technology, 69(12) (2021).

[11] Jun Hu, Wei Liu, Shuai Cheng, Huan Tian, Huai Yuan, and Hong Zhao: Real-time Pedestrian Detection using Convolutional Neural Network on Embedded Platform, SAE Technical Paper, 2016-01-1877, (2016) .

[12] Corinna Cortes, Vladimir Vapnik: Support-Vector Network, Kluwer Academic Publishers, Boston, Machine Learning, 20 (1995) 273-297.

[13] Jafar Tanha, Yousef Abdi, Negi Samadi, Nazil Razzaghi, Mohammad Asadpour: Boosting methods for multiclass imbalanced data classification: an experimental review, Journal of Big Data, (2020).

[14] Yun Wei, Qing Tian, Jianhua Guo, Wei Huang, Jinde Cao: Multi-vehicle Detection algorithm through combining Haar and HOG Features, International Association for Mathematics and Computers in Simulation 155(2019) 130-145, Elsevier Publisher.

[15] H Angrish, N Kaur, R ChadhaA Novel Technique to Detect Local Features in Digital Images., IJSTE - International Journal of Science Technology & Engineering - September , (2015).

[16] Abhishek Nayak, Swaminathan Gopalswamy, Sivakumar Rathinam: Vision-Based Techniques for Identifying Emergency Vehicles, SAE Technical Paper 2019-01-0889, (2019). DOI:10.4271/2019-01-0889.

[17] Sivaraman, S. and Trivedi, M.M.: Looking at Vehicles on the Road: A Survey of Vision-Based Vehicle Detection, Tracking, and Behavior Analysis, IEEE Transactions on Intelligent Transportation Systems 14(4) (2013)1773-1795.

[18] 5. Chapelle, O., Haffner, P., and Vapnik, V.N., Support Vector Machines for Histogram-Based Image Classification, IEEE Transactions on Neural Networks 10(5) (1999) 1055-1064.

[19] https://www.kaggle.com/brsdincer/vehicle-detection-set

[20] https://data.mendeley.com/datasets/pwyyg8zmk5/2

[21] http://ai.stanford.edu/~jkrause/cars/car_dataset.html

[22] https://github.com/datacluster-labs/Indian-Vehicle-Image-Dataset

[23] https://www.gti.ssr.upm.es/data/Vehicle_database.html