An Iterative Morphological Fuzzy Rule Based Classifier For Moving Vehicle Recognition

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Abstract: A novel fuzzy rule based classifier to detect and recognize the type of moving vehicle from video frame using iterative morphological image processing operations is presented in this research work. A traffic video for a time period is captured, converted into still frames, pre-processed by iterative morphological filter, foreground objects are extracted by Background Subtractiontechnique,boundaries of the vehicles are extracted by morphological operation and the detected vehicles are isolated by Bounding Box method. Fuzzy Rule based classifier is constructed to categorize and recognize the vehicles into different types(Car, Bike, Bus, Container& Truck) based on the structural features Height, Width and Area of the bounding boxes. Finally the proposed method is evaluated with the classification metrics confusion matrix, precision and accuracy and the experimental results show that the performance of the proposed system goes beyond that of the existing video-based vehicle classification techniques yielding 84% of accuracy.

Keywords: Fuzzy Rule Based Classifier,Video frame,Vehicle Recognition,Iterative Morphological Filter, Background Subtraction, Bounding Box, confusion matrix.

1. Introduction

Now a day, moving vehicle recognition and classification plays a vital role in extracting the traffic density, finding out the evidence of traffic law infringement, controlling traffic, or reconciling the dispute over any accident. Significant ways or techniques are also essential to search suspicious vehicles during criminal investigations of traffic accidents. Recently, Electronic Toll Collection (ETC) system has become a common trend employed for toll collection in highways to avoid traffic delay. Automatic vehicle detection and classification is one of the major components in ETC. The advantages of classifying vehicles in traffic are below:

- Will be able to find the type of vehicles that travel in that given area.
- A count can be kept on the particular kind of vehicle that passes in front of the eyes of the camera.
- Useful in Security and Surveillance&Traffic Management Systems

In general, vehicles are manufactured with different sizes to suit diverse purposes and classified based on their sizes. The vehiclescan be classified as cars, buses, vans, trucks, trailers etc. To date, many vehicle classification methods have been proposed. Moving vehicles are detected from video frames by foreground extraction. There is a range of vehicle detection methods, based on the inter-frame difference method [4], background extraction method, and optical flow estimation method [5]. Background subtraction is the first step toward object detection and can be performed using frame averaging, a single Gaussian or a Gaussian mixture model (GMM)[6]. Friedman and Russel [7] proposed the basic idea of using a GMM for vehicle detection. They used three Gaussians to represent the road, shadow, and the moving vehicle. This method was then modified by Stauffer and Grimson [8], who used K Gaussians, where K was fixed. Zoran Zivkovic [9] used a Bayesian probability method to adaptively vary the number of Gaussian components required to model a pixel. Fuzzy logic control is well suited for classification of vehicles because it is capable of making inferences even under uncertainty [10]. It assists rules generation and decision-making. It uses set of linguistic Fuzzy rules to implement expert knowledge under various situations [11].

Video analytics play a significant role in most recent traffic monitoring and driver assistance systems. The installation and maintenance charges of hardware based vehicle recognition system are high compared to software based system as the detection is done using video frames or static images captured using cameras mounted on top of the road as well as in front of the lanes of the toll section. Whereas in vehicle classification method the image area of interest is part or whole vehicle image whereby size and shape of the vehicle are measured and subsequently used to determine their classes.

Classification of vehicles is a challenging problem and a process that is still going on. Difficulties in classification of vehicles can arise due to abrupt vehicle motion, changing background and scene, vehicles of non-standard size, vehicle occlusions, and camera motion. It is usually performed in the context of higher-level applications that require the location of the vehicle at every frame.

In this research work,a novel method to detect the vehicle from traffic video frame and recognize its type based on the structural features using Morphological image processing techniques and fuzzy classifiers is proposed. The paper is organized as follows: Section II describes the proposed methodology. Section III provides the experimental results and discussion. Finally, the research work is concluded in Section IV.

2.Proposed Methodology

An Iterative Morphological Fuzzy Rule Based Classifier for Moving Vehicle Recognition (IMFVR) is proposed in this section. The general schematic diagramof IMFVR is shown in figure 1 and discussed below.

Figure.1 Schematic Diagram of IMFVR

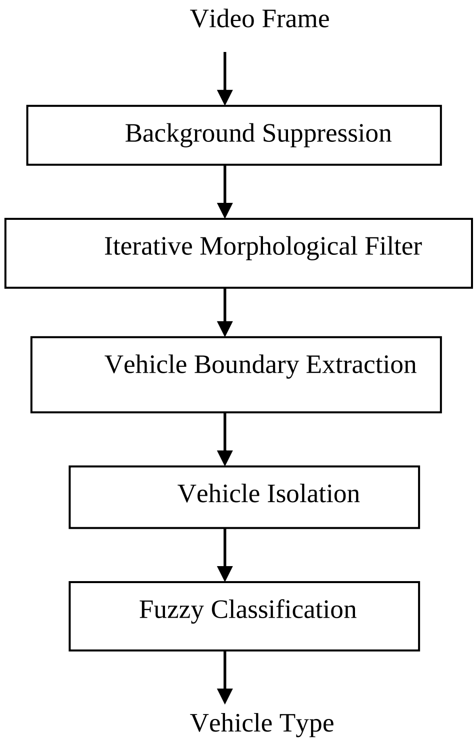


Image Acquisition

Real time traffic atTool Gate on NH7 in India is capturedas a video for a particular duration using CCTV camera mounted on the top. The video input is processed and the key frames are extracted for representing main visual content of each shot by using the video splitter method. The captured raw forms of videos are in MP4 format initially and then they are converted into AVI format. Each video frame is a still image containing different class of vehicles such as car, bike, auto etc. The real data set with each frame stored in AVI format is labelled and the samplestill image taken for processing is shown in figure 2.

Figure.2 Input Video Frame Image

Background Suppression

To extract and retain the moving vehicles, Background Suppression(*BS*) technique is proposed which often removes the relatively motionless background information from video frames. It is a common technique used for generating foreground moving vehicles. The BS operation is carried out as below

- *Read the Vehicle Frame Image and convert into a Grayscale Image(GI) using(1).*

  $GI = (VI(R) + VI(G) + VI(B) / 3)$……………(1)

WhereVI(R) – Red component , VI(G) – Green component, VI(B) – Blue component.

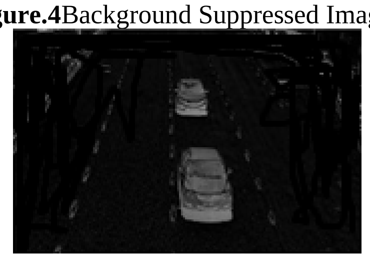
- *Capture an image without any vehicle on road (that means no traffic) and taken as Background Reference Image(BRI)*
- *Convert BRI into a Grayscale Image(BGI) using(1).*
- *Assign AI = GI;*
- *Find the difference between AI and BGI*

V = BGI – AI ....(2)

The background reference and Background Suppressed Images are shown in figures 3 & 4.

Figure.3 Background Reference Image

Figure.4 Background Suppressed Image



Iterative Morphological Filtering

Due to pollution and environmental factors the images may be occluded with noise particles. In this research, to retain the shape and size of vehicles, the image is enhanced to remove the undesired perturbations like impulse noises by applying the morphological operations iteratively with the selected size and shape of the Structure Element (SE)[2]. The process of Iterative Morphological Filter is given below:

1. *Let GI = V*
2. *Assign Reference Image RI = GI.*
3. *Apply morphological opening and closing on GI using disk shaped SE of size greater than that of noise particles.*

$$OGI = GI \circ B = (GI \Theta B) \oplus B \text{ …………(3)}$$

$$CGI = GI \bullet B = (GI \oplus B) \Theta B \text{ …………(4)}$$

4. *Find the average of OGI and CGI images.*

$$AI = (OGI + CGI)/2 \text{ ………………(5)}$$

5. *Find the difference between AI and RI.*

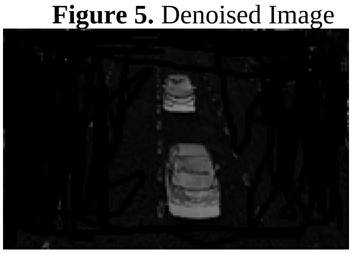
$$DI = (AI - RI) \text{ ………………(6)}$$

If DI is large
{
RI = AI;
GoTo Step 3;
}

6. *Return AI*

The impulse noises which are less than the size of the selected SE are removed effectively and this process is iteratively repeated. Any feature of size smaller than that may be treated as noise. The denoised image is shown in figure 5.

Figure 5. Denoised Image



Vehicle Boundary Extraction

The boundaries of the vehicles are extracted as below:

- *Apply Otsu threshold techniqueto binarize the image*

$$F(AI) = \begin{cases} 0 & if\ AI_1 < T \\ 1 & if\ AI_2 \geq T \end{cases} \qquad \text{...........(7)}$$

where, AI represents a grey image and T is the threshold value. The image AI is binarized and the output image stored as BI is shown in figure 6.

- *Apply Morphological erosion*

$$EV = BI \Theta B \qquad \text{...........(8)}$$

where BI is the binary image of the vehicle image, B is the structural element of size 3 X 3.

- *Subtract the eroded image from the input image.*

$$VBI = BI - EV \qquad \text{...........(9)}$$

The resultant Boundary Extracted image is shown in figure 7.

Figure 6. Grayscale Image

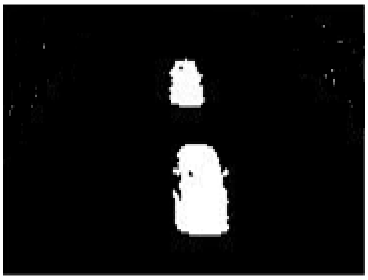
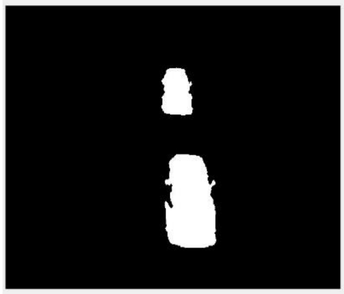


Figure 7. Boundary Extracted Image



Vehicle Isolation

A bounding box is an invented rectangle that provides a point of reference to detect the objects. It is a rectangle drawn over the image and outlines the object of interest within each image by defining its X and Y coordinates. The bounding box is created for eachvehicle and extracted from the frame as shown in figure 8.The extracted vehicles are stored in a data base for further recognition.

Figure 8. Bounding Box

Fuzzy Classification

Training Data Set

A real time vehicle image data set containing 300 images of various types of vehicles(Bike, Car, Bus, Container & Truck) with different models is created with size 256 X 256. Each vehicle type contains 60 images.

Feature Extraction

Since the vehicles are not in regular polygon shapes, in this research, it is aimed to recognize and classify the vehicles by extracting the structural features namely width, height and area. The objects, vehicles are detected by bounding box method and the structural features are computed from its dimensions. The sample feature values are listed in Table 1.

Table 1. Extracted Sample Feature Values

S.No	**Input Vehicle Attributes**		
	Height (Inches)	**Width (Inches)**	**Area (Inches)**
1	0.9081625	0.458639583	30.78125
2	0.7698	0.493153125	27.3333333

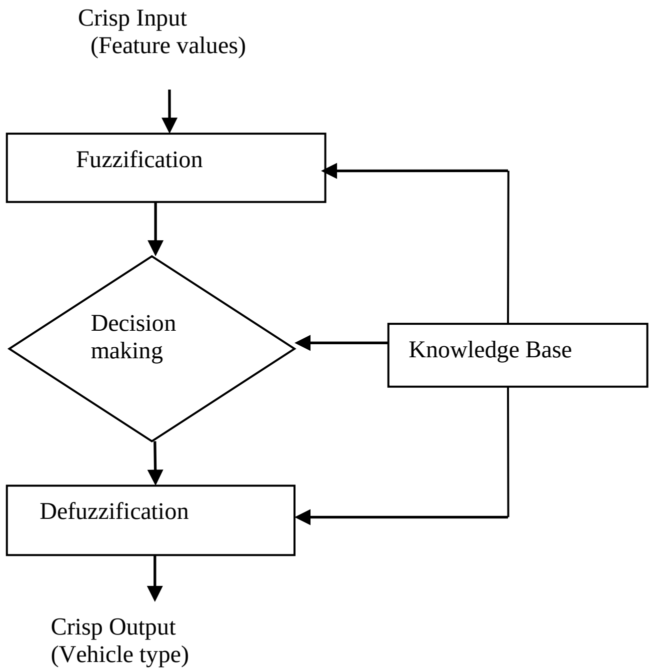
3	0.95902395	0.523771875	36.3125
4	0.56127187	0.306883333	12.8020833
5	0.74838437	0.475345833	26.6666666

Using these feature values fuzzy rule based classifier constructed as below.

Fuzzy Rule Based Classifier

Fuzzy classification system contains four modules as shown in figure 9.

Figure 9. Fuzzy Classification System



*Fuzzification*is the process that transforms the (crisp) input values into fuzzy values, by computing their membership to all linguistic terms defined in the corresponding input domain. The Vehicle Feature fuzzifier used for the feature values is shown in figure 10.

Figure10. Vehicle Feature Fuzzifier

From the training data setthe domain range of feature values for different vehicle classes are listed in Table 2.

Table 2. Feature Domain Range Values

S.No	Type	Height	Width	Area
1	Car	0.56-1.41	0.31- 0.73	12.8-55.1
2	Container	1.14-1.66	0.47-0.84	54.44-97.72
3	Bike	0.33-0.74	0.22 - 0.63	5.44-34.11

4	Bus	0.88- 1.25	0.45-0.69	31.99- 48.09
5	Truck	0.84-1.44	0.58 -0.84	40.83-85

The membership Function values assigned for each input variable is given Table 3,4& 5.

Table 3. Member Function Variables for Height

S.No	**MF Variables**	**Height**				
		>=0.33&& <=0.74	**>=0.56&& <=1.14**	**>=0.88&& <=1.24**	**>=1.14&& <=1.66**	**>=0.22&& <=0.63**
1	VL	✓				
2	L		✓			
3	M			✓		
4	H				✓	
5	VH					✓

Table 4. Member Function Variables for Width

S.No	**MF Variables**	**Width**				
		>=0.22&& <=0.63	**>=0.30 && <=0.74**	**>=0.45&& <=0.69**	**>=0.46&& <=0.84**	**>=0.57&& <=0.84**
1	VL	✓				
2	L		✓			
3	M			✓		
4	H				✓	
5	VH					✓

Table 5. Member Function Variables for Area

S.No	**MF Variables**	**Area**				
		>=5.4 && <=34.1	**>=12.8 && <=55**	**>=32 && <=48**	**>=40.8 && <=85**	**>=54 && <=97.8**
1	VL	✓				
2	L		✓			
3	M			✓		
4	H				✓	
5	VH					✓

VL-Very Low L-LowM-Medium H-High VH-Very High

Knowledge base is a set of fuzzy rules and the descriptions of linguistic terms I/O linguistic variables.
Decision Making performs the fuzzy inference process and computes the output of each rule.
The fuzzy rules generated are:

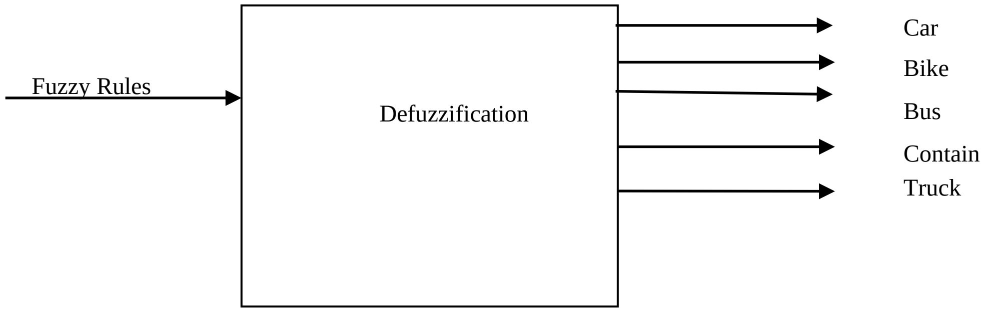
1. *If (HEIGHT is VL and WIDTH is VL and AREA is VL) Then VEHICLE TYPE = BIKE*
2. *If (HEIGHT is L and WIDTH is L and AREA is L) Then VEHICLE TYPE = CAR*
3. *If (HEIGHT is M and WIDTH is M and AREA is M) Then VEHICLE TYPE =BUS*
4. *If (HEIGHT is VH and WIDTH is H and AREA is VL) Then VEHICLE TYPE =CONTAINER*
5. *If (HEIGHT is H and WIDTH is VH and AREA is L) Then VEHICLE TYPE = TRUCK*

The fuzzy rules and output is shown in Table 6

Table 6. FuzzyRules and Output Types

Defuzzification derives the crisp output values by combining the rule outputs with specific transformation. The Vehicle Defuzzifier used in this research is shown in figure 11.

Figure 11. Vehicle Defuzzifier



3. Result & Discussion

A real time traffic video captured is converted into still frames. From the video frames totally 50 images of different vehicle types, 10 images of each type are captured and taken for analysis. The features of test vehicle images are computed, classified and the performance of the proposed model is estimated and compared with the existing Quadratic Discriminant (QD) and Medium Gaussian SVM (MGS) Classifiers based on various metrics.

Confusion matrix

Rule ID	**Input**	**VL**	**L**	**M**	**H**	**VH**	**TYPE**
1	Height	✓					**BIKE**
	Width	✓					
	Area	✓					
2	Height		✓				**CAR**
	Width		✓				
	Area		✓				
3	Height			✓			**BUS**
	Width			✓			
	Area			✓			
4	Height					✓	**CONTAINER**
	Width				✓		
	Area					✓	
5	Height				✓		**TRUCK**
	Width					✓	
	Area				✓		

Table7. Proposed Classifier IMFVR – Confusion Matrix

The Confusion matrix is the most intuitive and easiest metrics used for multi class output.The confusion matrix obtained from proposed model is given in Table 7.

Out of 10 Bike images, 9 are correctly classified, out of 10 Car images, 8 images are correctly classified, out of 10 Bus images, 9 are correctly classified, out of 10 Container images, 9 are correctly classified and out of 10 Truck images 7 are correctly classified.In the above confusion matrix, the diagonal elements indicate correct predictions, while the off-diagonals are incorrect predictions.

Correct classification rate= $\frac{\sum \text{Diagonal Elements}}{\text{sample size}}$ -----------(10)

= 42/50 = 84 %

The confusion matrices obtained by Quadratic Discriminant and Medium Gaussian SVM classifiers are shown in Tables 8& 9.

True Class	Predicted Class				
	Bike	**Bus**	**Car**	**Container**	**Truck**
Bike	9	0	1	0	0
Bus	0	9	0	1	0
Car	0	1	8	0	1
Container	0	0	0	9	1
Truck	0	1	1	1	7

Table 8. Quadratic Discriminant – Confusion Matrix

True Class	Predicted Class				
	Bike	**Bus**	**Car**	**Container**	**Truck**
Bike	6	0	4	0	0
Bus	0	8	1	0	1
Car	2	4	3	0	1
Container	0	0	0	8	2
Truck	0	0	1	0	9

Table 9. Medium Gaussian SVM Classifier – Confusion Matrix

The TPR/FNR rates for all classifiers are shown in Tables 10,11 and 12.

Table 10. True Positive Rates/False Negative Rates-IMFVR

Vehicle Type	TPR	FNR
Bike	90	10
Car	80	20
Bus	90	10
Container	90	10
Truck	70	30

Table 11. True Positive Rates/False Negative Rates - QD

Vehicle Type	TPR	FNR
Bike	60	40
Bus	80	20
Car	30	70
Container	80	20
Truck	90	10

Table 12. True Positive Rates/False Negative Rates – MGSVM

Vehicle Type	TPR	FNR
Bike	80	20
Bus	60	20
Car	40	60
Container	70	30
Truck	60	40

From the confusion matrices, the other metrics are calculated and tabulated in Table 13.

Table 13. Performance Analysis of Classification Results

Classifier	Accuracy (%)	Mis Classification(%)	Precision	Recall/ Sensitivity	Specificity	F1-Score
QD	68	32	0.686	0.68	0.84	0.6829
MGS	62	38	0.626	0.62	0.836	0.6229
IMFVR	84	16	0.824	0.84	0.914	0.8319

The performance analysis based on various metrics is plotted and shown below in figures 12 & 13.

Figure 12. Performance Analysis with different Classifiers

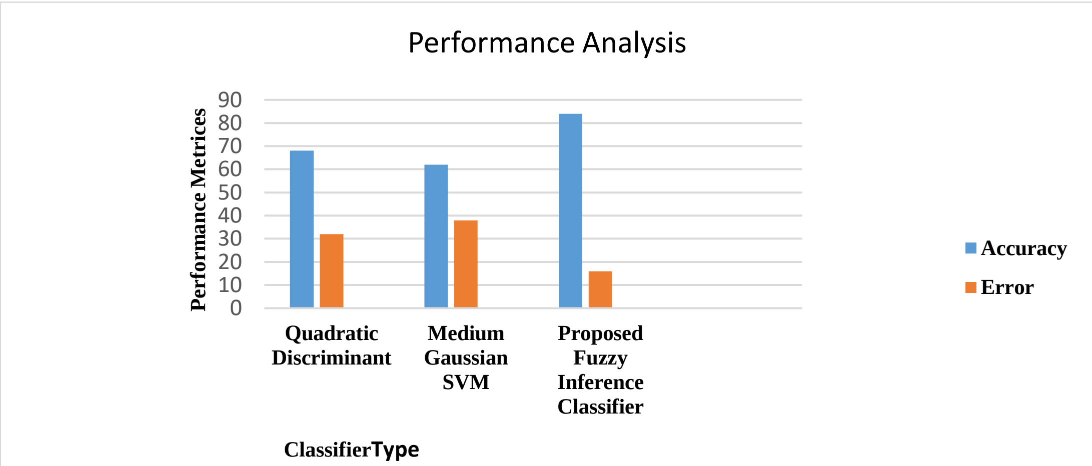
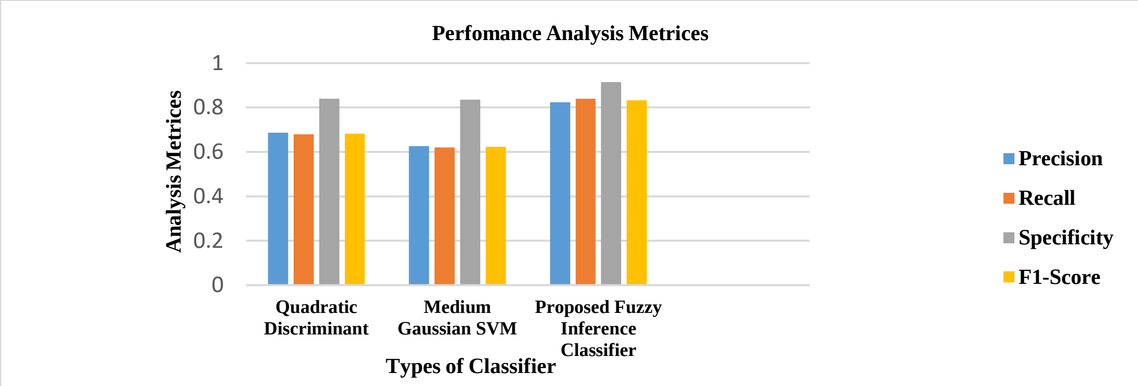
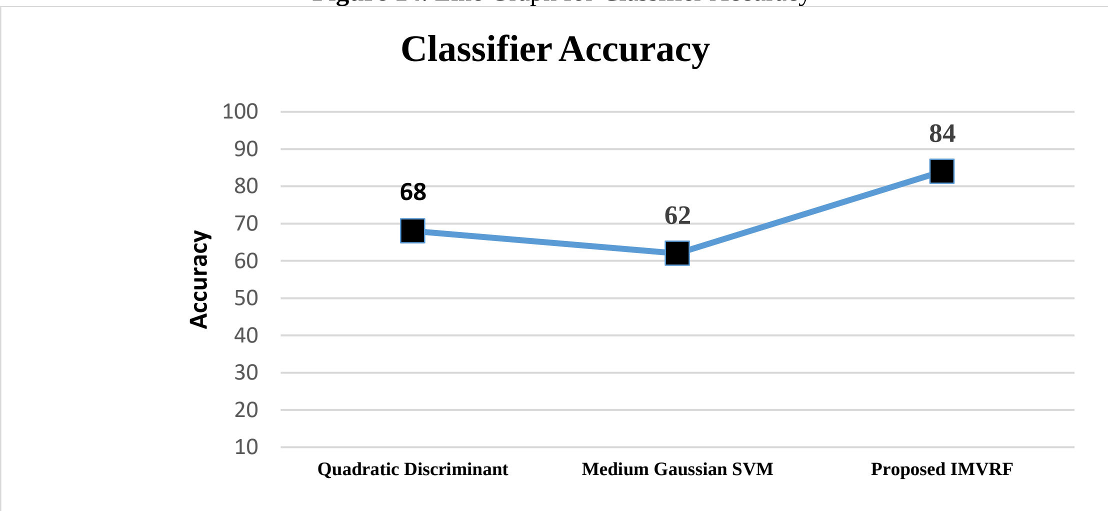


Fig 13. Performance Analysis with different Metrics



The accuracy analysis for the different classifiers types are shown in figure 14.

Figure 14. Line Graph for Classifier Accuracy



The TPR and FPR values obtained by different classifiers for different vehicle types is plotted in figures 15, 16 and 17.

Figure 15. IVFMR TPR/FPR Rate

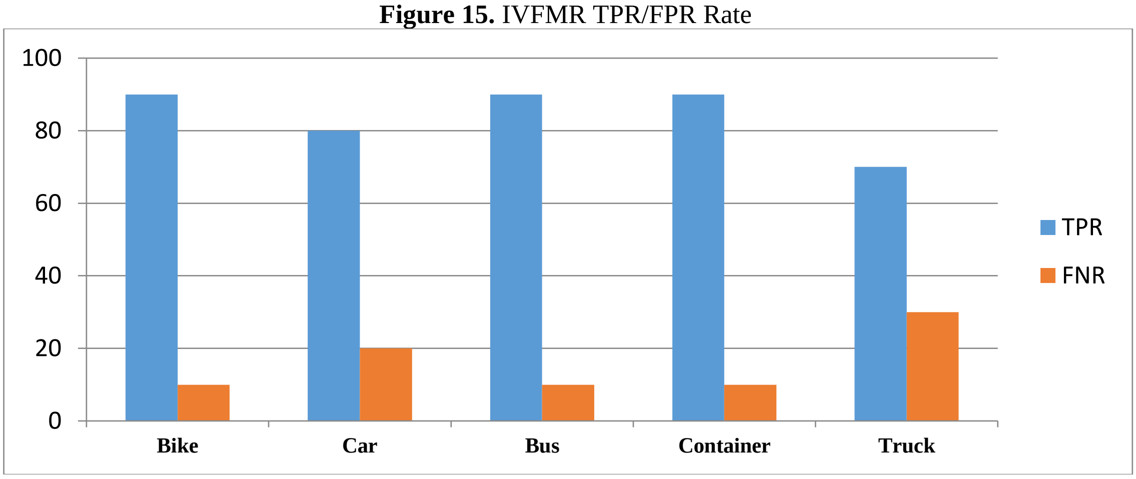


Figure 16. QD TPR/FPR Rate

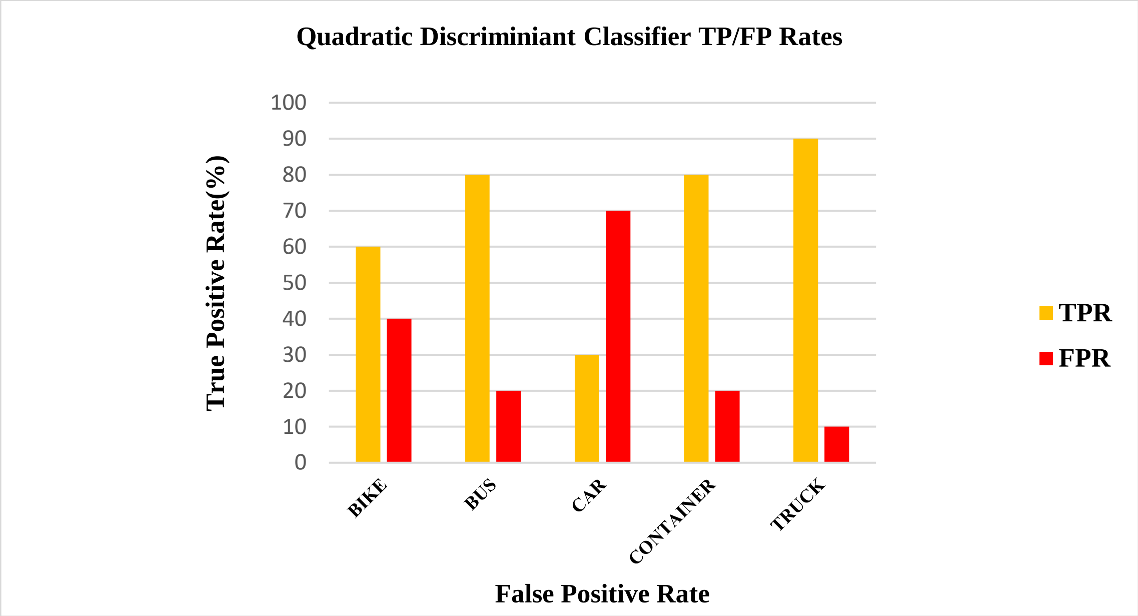
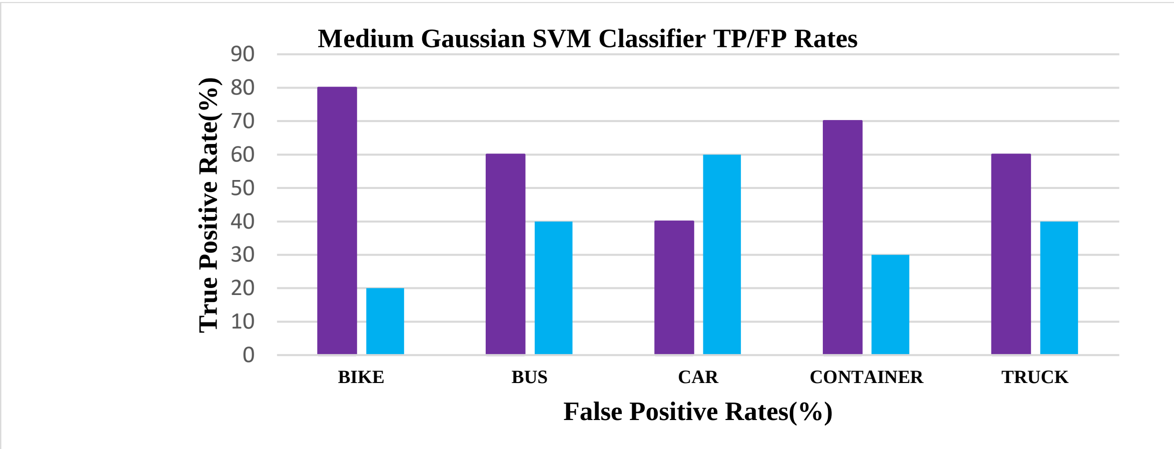


Figure 17. MGSVM TPR/FPR Rate



The number of vehicles counted by different classifier models is shown in figures 18, 19 and 20.

Figure 18 Vehicle Counting-Proposed IVFMR Method

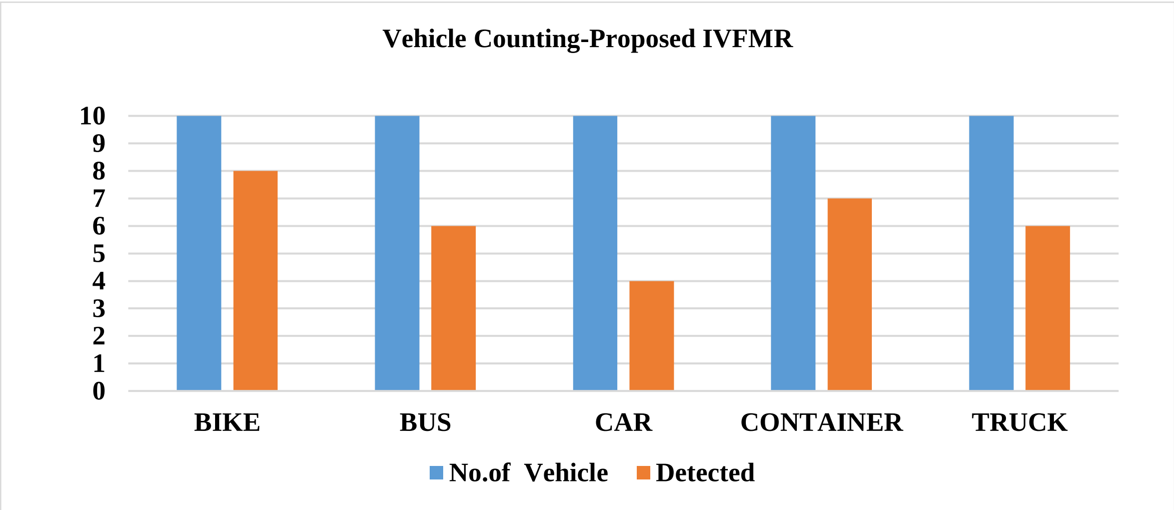


Figure 19. VehicleCounting-Quadratic Discriminant Method

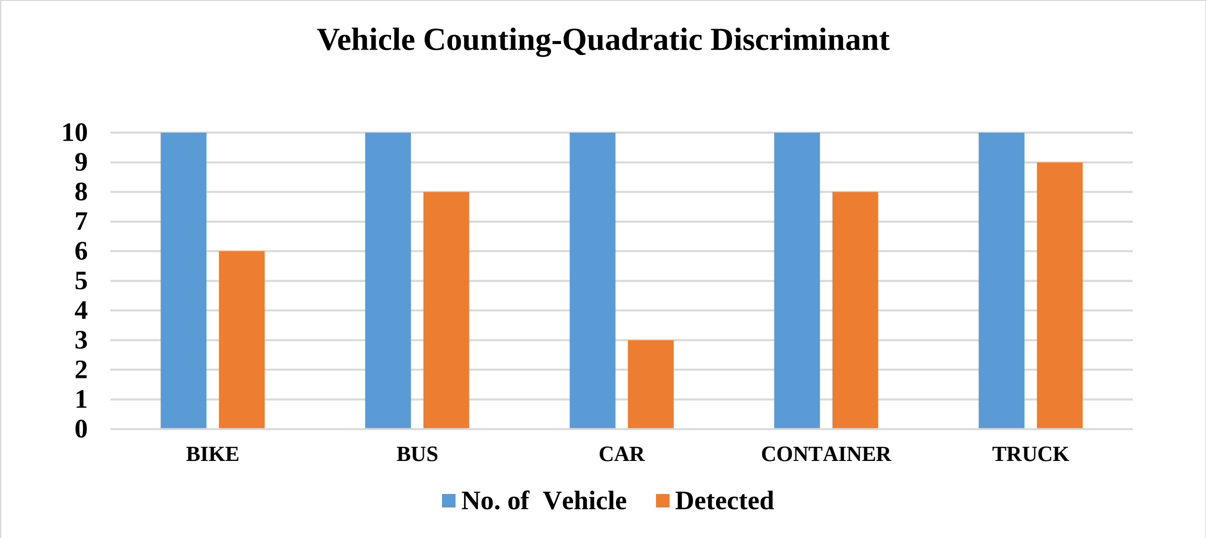
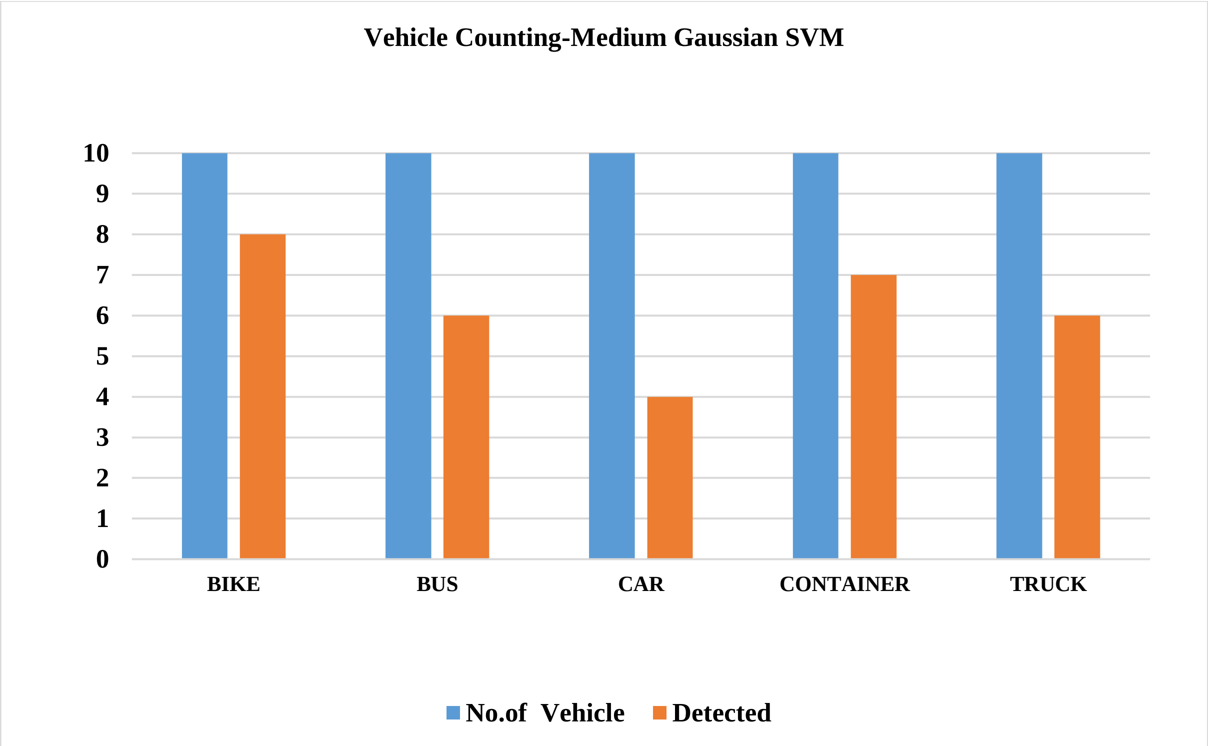


Figure 20 Vehicle Counting-Medium GaussianMethod



The proposed classification model **IMFVR** yields 84% of accuracy where QD and MGS yield 68% and 62%.The main reasons for misclassifications are:

- Occlusion of vehicles
- Shadow Effect which increase the values of the size features
- The size factors are similar for some container and Truck models.

4.Conclusion

An iterative morphological fuzzy rule based classifier is proposed in this research work to recognize the vehicle type from real time traffic video. The vehicles are detected and classified into Bike, Car, Bus, Container or Truck based on their size features. The performance of this method is evaluated with various metrics and found that it yields 84% accuracy compared to QD and MGS classifiers. The performance of the methodology can be enhanced with occlusion and shadow management processes in future.

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