Evaluation of Manual and Video-Based Automated Classified Vehicle Counting Methods for Heterogeneous Traffic Flow

R.A.P.U.S. PERERA [a*], H.M.O.K. HERATH [b], Buddhi AYESHA [c], T. SIVAKUMAR [d], Amal S. KUMARAGE [e], A.S. PERERA [f]

[a,b,d,e] *Department of Transport and Logistics Management, Faculty of Engineering, University of Moratuwa, Sri Lanka*
[a] *E-mail: praveen@uom.lk*
[b] *E-mail: oshadhik@uom.lk*
[c] *E-mail: buddhiayesha.13@cse.mrt.ac.lk*
[d] *E-mail: tsivakumar@uom.lk*
[e] *E-mail: amalk@uom.lk*
[c,f] *Department of Computer Science Engineering, Faculty of Engineering, University of Moratuwa, Sri Lanka*
[f] *E-mail: shehan@cse.mrt.ac.lk*

Abstract: Video-based automated counting is a developing technology which will gradually replace the manual on-site counting. This study compares the accuracy of manual and video-based automated classified traffic counting. Original YoloV4 and a YoloV4 model with some preliminary custom training are used as automated vehicle counting. Preliminary model training was conducted using the tagged videos from survey locations. The manual and video data collections were conducted simultaneously at five locations for four one-hour time intervals. Seven vehicle categories were included in the preliminary model for heterogeneous traffic conditions. Classified vehicle counting in the laboratory by playing back the video data gathered at survey locations were considered as the actual vehicle counts. RMSE and MAPE are used to compare all three approaches to the actual vehicle count. Accuracy was tested for all vehicle categories at each location separately for variable vehicle composition and traffic conditions between locations and within a location.

Keywords: Traffic Flow, Classified Vehicle Counting, Video Processing, Deep Learning, YOLOv4

1. INTRODUCTION

Traffic data was not updated frequently as it was costly during the past to improve and manage passenger mobility in Sri Lanka. As the population has increased, the traffic congestion along the road network within the commercial district of Colombo and the expressways and corridors has increased with a rising number of vehicles entering the road network. To manage the traffic congestion, accurate traffic data collection is of paramount importance for transport planners, traffic controllers and policymakers. Therefore, a need has arisen to measure various traffic parameters to identify traffic patterns' variability during peak and off-peak periods under the existing road types.

As a developing country, Sri Lanka is not accustomed to using the high-end modern technologies used in several countries to measure traffic conditions. Hence, it is crucial to realize the effect and accuracy of various traffic data collection methods to identify the most

suitable local context method by comparing them. The traffic data collection methods are used to calculate vehicle speeds, traffic flow, traffic density and vehicle count. The two main methods used for the above purpose are automatic and manual data collection, though there are some situations where a hybrid method is used.

The manual data collection methods, which are widely used in Sri Lanka for Classified Vehicle Count (CVC), involve humans of various skill levels resulting in a human error that cannot be monitored, eventually leading to traffic data misinterpretation. An automated data collection method can be suggested as an alternative to manual counting where Deep Learning algorithms can be utilized. Real-time image processing is conducted where the video footage is fed to the developed model to monitor the classified vehicle count. In the ever-evolving technology, it is vital to use big data analytics wherever possible, which will provide data interpretations with fewer errors and human involvement.

With the recent developments in technology, there are rich data sources for transport professionals to calculate their jurisdictions' attributes. The advantages of video as an observational technique are proven to be entirely accurate, detailed and complete, than observations made by the bare human eye and human concentration. Unfortunately, there is no consensus on the best approach for estimating techniques for the above attributes.

To validate the manual and video-based automated methods' outputs, we must have an accurate data set. Hence, a classified vehicle count has been conducted manually using the video surveillance data collected at the locations. The classified vehicle count data from both methods have been validated using this data set. Video-based automated traffic counting will be assessed for accuracy while emphasizing the limitations and improvements to mitigate the existing drawbacks.

2. LITERATURE REVIEW

Counting the number of vehicles passing through a selected point on the road or an intersection is considered as traffic volume count. The traffic volume count's main objectives are to recognize the distribution of vehicles among different hours of the day, identify the peak hours, and compare and identify the progress and drawbacks in various models and plans related to traffic congestion (Powell, 1987).

The traffic on every branch of the selected location must be counted and recorded for each vehicle movement separately. It is vital to get the count carefully when the road contains more than one lane. For the data collection, several teams are placed in various locations at set intervals along the road, which are selected in advance. The technical staff managed the data collecting team to maintain the efficacy of the data. Tally sheets, mechanical counting boards, and electronic counting boards can record the manual counts (Zheng and Mike, 2012).

The Automatic Traffic Count method can be used in scenarios where manual count method is not practicable. This method is an equipment-based method in which data is collected automatically without using human resources. Therefore, this method is labour extensive and time-consuming when compared to manual count methods. One of the methods used in automatic traffic counting is analyzing video surveillance data. This method uses the video image processing system. This system requires machine vision technology which could be used to direct the vehicles and capture information about any individual vehicle when it is required.

The above method contains some disadvantages regarding the latest achievements in modern technology. Generally, it can be mentioned as insufficient. Labour and resource

intensiveness, organizational complications, costly nature and requirement of more time are some drawbacks in these methods (Leduc, 2008).

Deep learning is a subfield and a new area of machine learning. Creation and function of algorithms are the same as machine learning. However, some differences exist, such as various layers of algorithms providing a different interpretation of the input data. Many deep learning models are based on Artificial Neural Networks (ANN). As the name suggests, the artificial neural networks function similar to human neural networks present in the brain. Deep learning can handle more complex data sets and produce high accuracy (Ahmad *et al.*, 2019).

YoloV3 network has been used to detect the vehicle type and location while the ORB algorithm was used in recognizing the driving direction and vehicle count on highways. Song *et al.*, (2019) have extracted the road surface area from the highway videos and segmented it before feeding YoloV3. Then, YoloV3 has been used to detect vehicles in two areas and the results were merged together which was fed to ORB algorithm to extract vehicle features (Multi-object tracking). A trajectory analysis was conducted in order to identify the driving direction of vehicles. A 0.88 precision and a 0.89 recall were observed from the trained model using 11,129 images where the dataset was split into an 80% training set and 20% testing set (Song *et al.*, 2019). Since cars, buses and trucks were the only vehicle categories used for the study, it can be developed to increase the number of vehicle types from three, for classified vehicle counting in mixed traffic conditions. As the road traffic is not consist of only those categories, it is extremely significant to include all the possible vehicle categories in order to improve the reliability of the model.

YoloV4 uses CSP darknet-53 classifier where it uses between19 and 53 layers for feature extraction. Also, it uses spatial pyramid pooling and Path Aggregation Network (PAN) to detect multiple objects in a single frame providing optimal speed and accuracy (Chethan Kumari et al., 2020). Aldo YoloV4 has a two times faster running time than EfficientDet while improving the Average Precision (AP) by 10% and Frames per Second (FPS) by 12% compared to the previous version which YoloV3 (Bochkovskiy *et al., 2*020). According to Mahto *et al* (2020), the mean absolute precision (mAP) of original YoloV4 model is around 60.93% which had encouraged them to develop a refined YoloV4 model with an mAP of 67.7% where they have added Anchor box optimization using k-means clustering (ABK), Non-maximum suppression using distance-IoU (DIoU-NMS), Spatial Attention Module (SAM), and Self-adversarial Training (SAT).

Mandal and Adu-gyamfi (no date) have conducted a study deploying several object detection and tracking algorithms. They have applied multiple combinations for above 2 purposes, and the most ideal 3 combinations were YoloV4 & DeepSORT, Detectron2 & DeepSORT, CenterNet & DeepSORT algorithms with a matching accuracy between 90% and 100%. The study focused on 4 main aspects which are; overall vehicle count, total count of only cars, total cars of only trucks and overall vehicle count for different times of the day for various roadways in New Orleans (Mandal and Adu-gyamfi, no date).

Root Mean Square Error, commonly known as RMSE, is more sensitive to outliers than Mean Absolute Error and Median Absolute Error (Hyndman *et al.*, 2006). It is widely used to measure the differences between predicted values and actual values. Therefore, RMSE is a better estimator for the standard deviation of the distribution of the errors. RMSE is always a positive value where "0" indicates a perfect fit which can hardly ever be achieved in real-life scenarios. Also, it is a scale-dependent measure of accuracy (Hyndman *et al.*, 2006).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \quad (1)$$

where,

$\hat{y}_i$: predicted value

y_i: actual value

n: the size of the data set

Mean Absolute Percentage Error (MAPE) is widely used when the prediction values exist way above zero. It is stated that MAPE is most suitable in forecasting where the availability of data is high (Myttenaere *et al.*, 2017). MAPE is essential when the value of a prediction is significant in evaluating its accuracy (Khair *et al.*, 2017).

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100\% \quad (2)$$

where,

A_t: Actual value

F_t: Predicted value

n: Size of the dataset

Therefore, both approaches will be considered to identify the value and percentage of the deviation in prediction compared to the actual value.

3. METHODOLOGY

3.1. Data Collection

In order to achieve the objectives of this study, a classified vehicle count survey has been conducted at the carefully selected locations where both types of traffic data collection methods could be conducted. Therefore, 5 locations were selected within the Colombo Municipal Council, where a grade separation exists, and various road classes are available. The pilot survey was conducted at Wellawatte Railway Station. The surveys were conducted from Tuesday to Thursday to avoid the unusual traffic conditions at the start of the week and the week's end.

Table 1. Survey Locations and Road Classes

No.	Road Class	Road Name	Location Name
1	AB12	Marine Drive-Colombo 6	Wellawatte Railway Station, Overhead bridge
2	A002	Duplication Road – Colombo 4	Muslim Ladies College, Col-04, Overhead bridge
3	A001	Olcott Mawatha	Pettah Railway Station, Overhead bridge
4	A004	High Level Road	Overhead bridge at Dharmapala Vidyalaya, Pannipitiya
5	E002	Outer Circular Expressway	Horahena Road Overpassing Southern Expressway

3.1.1. Manual data collection

The classified vehicle count survey by video and manual counting will be conducted on one weekday (Tuesday, Wednesday or Thursday). The survey will be conducted for 12 hours (6:00 AM to 6:00 PM) in all five locations. The manual classified vehicle count survey at the site will be conducted simultaneously at the exact location for 4 hours split into four one-hour windows falling under morning peak, morning off-peak, afternoon off-peak and evening peak. It could tentatively be 0700-0800, 1000-1100, 1400-1500, 1600-1700, but adjusting can be done according to the traffic situation without compromising the total duration of 4hrs.

In the case of manual counting, Surveyors continuously count the number of vehicles by "60-minute band" by vehicle type according to Table 2. Surveyors shall record the number of vehicles on the app or survey sheet for each band.
The types of vehicles used during the manual traffic data collection are as follows, where ten vehicle types are considered.

Table 2. Vehicle categories used for manual classified vehicle counting.

Class	Identification	Class	Identification
1	Motorcycles	6	Large Bus
2	Three-wheeler	7	Light Goods Vehicles
3	Car/Jeep/4*4/Double Cabs (seats less than 6)	8	Medium Goods Vehicles
4	Passenger Van/Dual Purpose Van (more than six seats)	9	Heavy Goods Vehicles
5	Minibus	10	Heavy Goods Vehicles with Multi axel

3.1.2. Video-based counting method combined with Deep Learning

The video camera stationed on the overhead bridge captured the traffic flow in one direction continuously during the 12 hours. The video surveillance data was used as an input for Deep Learning models to classify vehicles according to the categories of Table 3. The videos from angular camera were also be used to recognize the accuracy of automated CVC via deep learning. The classified vehicle count survey was conducted in one direction.

Figure 1. Camera setup for simultaneous video surveillance for Deep learning

An HD 720p motorized varifocal HLC bullet camera with a 6 mm to 22 mm varifocal lens has been used for capturing video surveillance data. It had a 1.27MP CMOS image sensor where images can be captured even under low light conditions up to 0.001 lux. The types of vehicles used during the automatic traffic data collection using Deep Learning are as follows. Seven vehicle types are considered since the axel types cannot be monitored using video surveillance data.

Table 3. Vehicle categories used for Video-based traffic counting.

Class	Identification	Class	Identification
1	Motorcycles	5	Buses
2	Three-wheeler	6	Trucks
3	Car/Jeep/4*4/Double Cabs (seats less than 6)	7	Heavy Goods Vehicles with Multi Axel
4	Passenger Van/Dual Purpose Van (more than six seats)		

YoloV4 has been used for image classification and object detection in deep learning which is recognized as one of the best open-source real-time object detectors due to its high performance and speed (Bochkovskiy, Wang and Liao, 2020).

Original YoloV4 model was used for the initial automated classified vehicle counting where the video surveillance data from all the locations were fed to it after extracting the road surface area to exclude the surrounding data points. Then, YoloV4 was used to detect the vehicles in two areas of a video frame to make sure that the vehicles had passed the selected road section. The results were merged together, and a trajectory analysis was conducted to identify the driving direction of vehicles since only one direction was considered for vehicle counting. Finally, classified vehicle counting and individual speeds for motorcycles, three-wheelers, cars, buses and trucks were obtained.

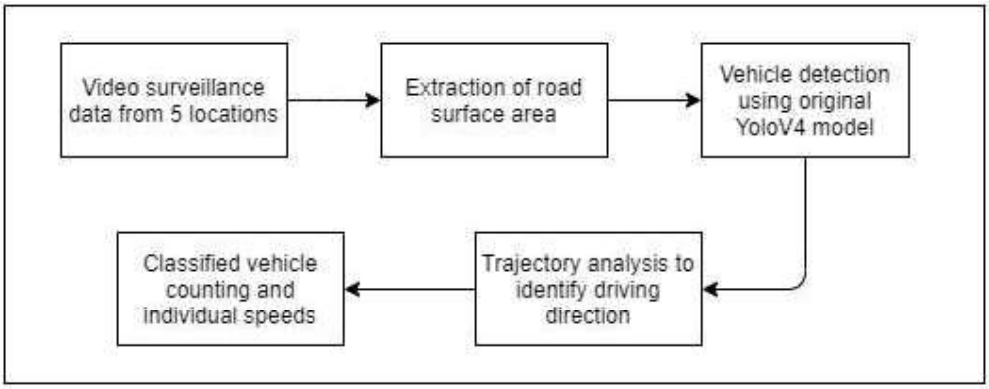

Figure 2. F Process for Video-based automated traffic counting for original YoloV4

The video footages were subjected to tagging in order to create a dataset to custom train the existing YoloV4 model since a number of vehicle categories were not available in the original model. A modified Microsoft VOTT was used to provide data points as the input, which is an open-source software for tagging. The tagging was conducted for seven categories which are motorcycles, three-wheelers, cars, dual purpose vehicles, buses, trucks and heavy goods vehicles with multi axels. DeepSORT algorithm was used to track objects while custom trained YOLOv4 was used to conduct the classified vehicle counting.

78,769 vehicle tags were selected from the initial 150,000 tags to mitigate double tagging of a single vehicle. Out of the selected tags, 70,893 were used for the model's training and the remaining 7,876 tags were selected for the validation of the model. The output was generated in CSV format for every video file containing Track ID, Vehicle type and time.

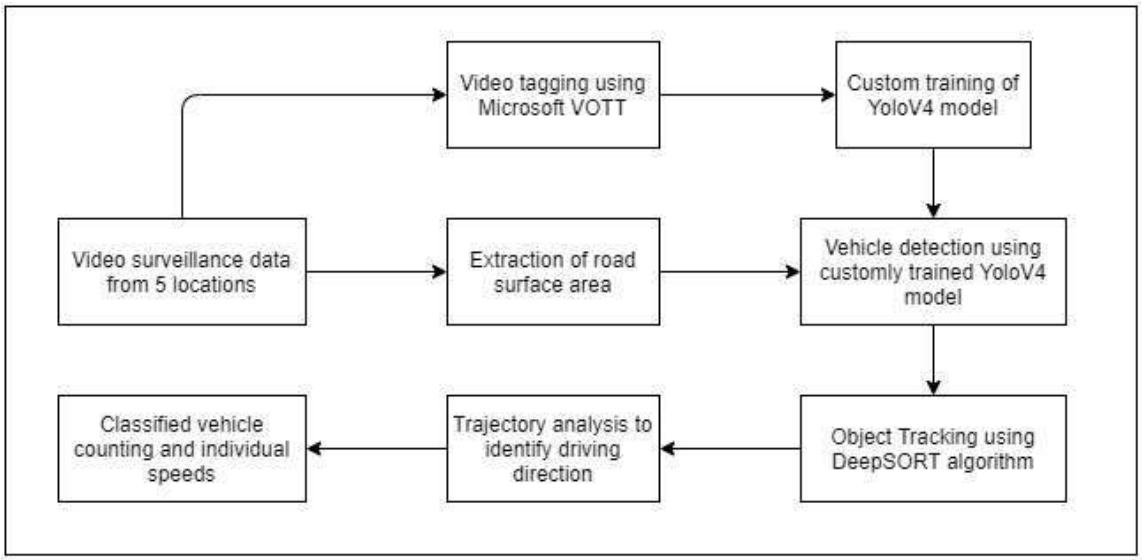

Figure 3. Process for Video-based automated traffic counting for preliminarily custom trained YoloV4

4. RESULTS & DISCUSSION

4.1. Limitations of the study

4.1.1. Sample size

A Deep Learning model consists of Artificial Neural Networks and requires thousands of data points for accurate prediction of classifiers (identification of vehicle categories in this study). The availability of tags (data points) is considered to be small compared with the required amount for model training. Since there are seven vehicle categories, an extensive data set is required to improve predictions' accuracy. Nevertheless, the available data set is provided below where fluctuations are very high among the categories resulting in mispredictions and missing predictions.

Table 4. Tags available for each vehicle category

Category	No. of Tags	Category	No. of Tags
Motorcycles	16,783	Buses	5,433
Three-wheeler	29,758	Trucks	2,554

Car/Jeep/4*4/Double Cabs (seats less than 6)	25,406	Heavy Goods Vehicles with Multi Axel	10
Passenger Van/Dual Purpose Van (more than six seats)	2,544		

4.1.2. Traffic density

When the traffic density increases, the visibility of the complete vehicle decreases dramatically creating tagging harder. It also raises the possibility of overlapping in tagging and missing vehicles in predictions which can be overcome with the increased sample size.

Figure 4. High density traffic flow in heterogeneous traffic

4.1.3. Stationary vehicles

Stationary vehicles are taken into consideration several times by the model increasing the final output, and all the vehicle categories predicted by the model are considered. However, we can see only a single vehicle in the provided frame below.

.

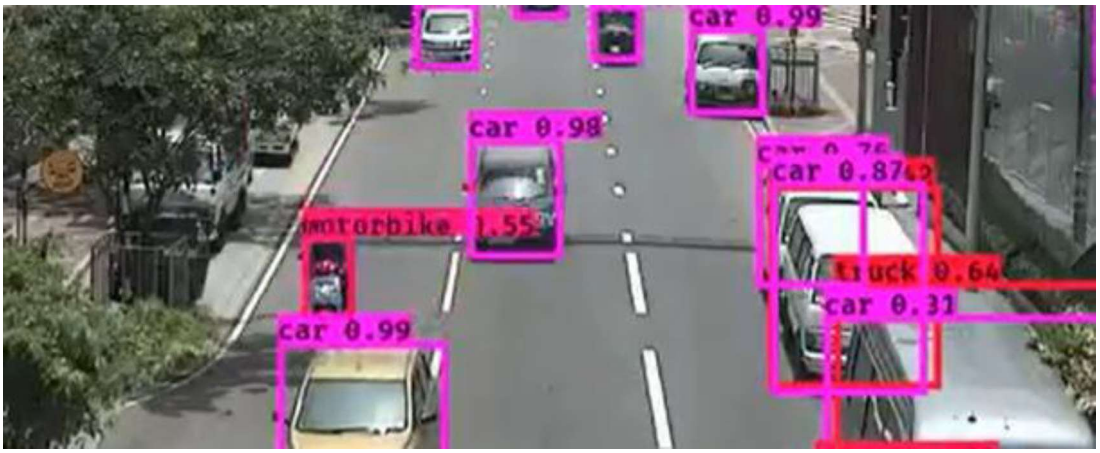

Figure 5. Stationary vehicles resulting in many predictions

4.2. Actual Classified Vehicle Counting

The actual classified vehicle counts for all the locations have been found in the laboratory by playing back the video footages during the respective time intervals. Tally counters have been used for the counting which was thoroughly supervised. The accuracy of vehicle counting in the laboratory was calculated using a sample 5 minutes from each video. The counting was reconducted until the accuracy of sample reached 100% for each video. Since the road types and the locations were different, the vehicles' composition has fluctuated differently throughout the hours that the counting was conducted. The types of vehicles are limited to 7 categories in the actual classified vehicle, same as in automated methods.

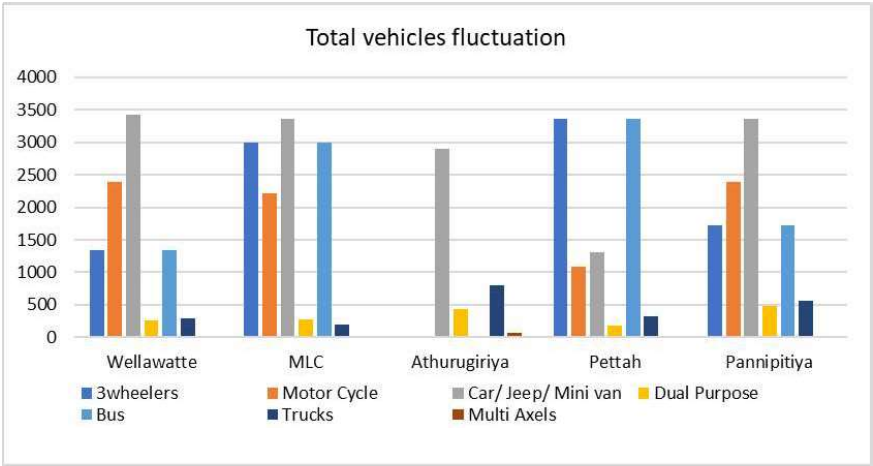

Figure 6. Actual total vehicle fluctuation

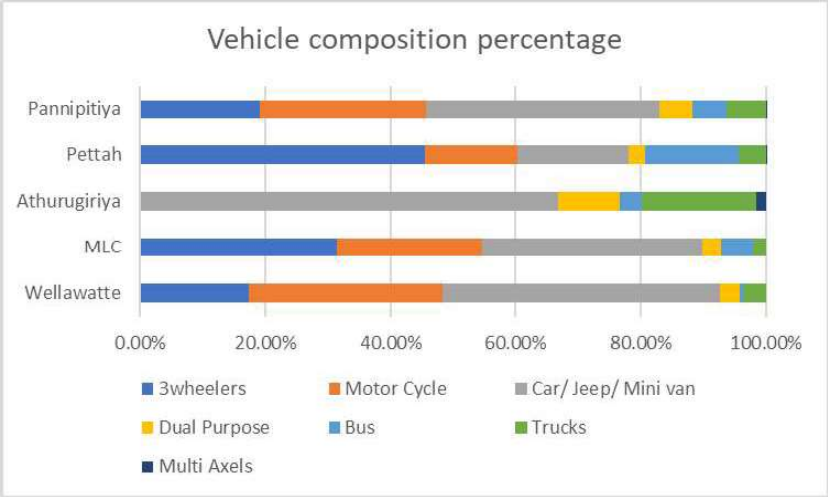

Figure 7. Vehicle composition by location

4.3. Manual Classified Vehicle Counting

The accuracy of on-site manual classified vehicle counting was also measured using both MAPE and RMSE approaches.

Due to Car, Three-wheeler, and Motorcycle categories' high availability, they have the highest RMSE values varying from 23.989 to 184.487, from 7.583 to 405.351 and from 11.467 to 126.377, respectively. Furthermore, Multi Axels have the least RMSE values up to 5.148.

Cars and Motorcycles have the least percentage error values fluctuating from 3.114% to 16.364, while trucks have the highest error percentage differing from 6.271% to 66.853%. The error percentages never exceed 100%.

4.4. Video-based Automated Classified Vehicle Counting using Original YoloV4

The video surveillance data collected from the survey locations was directly fed to the original YoloV4 model in order to find the accuracy of the existing model. Due to the unavailability of the vehicle categories such as three-wheelers, dual purpose vehicles and multi axels in the original YoloV4 model, they were not identified from the original model. Therefore, the MAPE values for above vehicle categories are 100% since no outputs were available for them.

For existing vehicle categories, motor bicycle category shows the least MAPE values varying from 15.68% to 34.36%. The vehicle categories with a smaller number of tags have a higher error percentage. The bus category has mean absolute error percentages between 22.34% to 155.54% when it fluctuates from 180.30%; 1106.59% for trucks category, since many dual -purpose vehicle categories were identified as trucks in the original model. The car category also expresses a large error values since three-wheelers which addressed a higher composition in road traffic were identified as cars from the original YoloV4. The MAPE values vary from 25.49% 340.65%.

Car category has the highest RMSE values resulting it as the least accurate category varying from 170.87 to 1235.58. From the existing vehicle categories, motorcycles show the highest accuracy in classified counting which has RMSE values from 46.34 to 283.89.

4.5. Video-based Automated Classified Vehicle Counting using preliminarily custom trained YoloV4

Due to the study's limitations, and the less amount of tagging available, the vehicle counting accuracy is not very high. Since this study focuses on initiating a Deep learning model for seven vehicle categories, the primary results satisfy several vehicle categories. We have tried to include the missing vehicle categories in the original YoloV4 model for mixed traffic conditions in order to reduce the number of missing vehicles in vehicle classification.

For example, the MAPE for Motorcycle category varies between 14.357% and 30.136% while error level for Car category fluctuates from 10.427% to 52.676%. The vehicle categories with a smaller number of tags have a higher error percentage. The truck category has error percentages between 61.184% and 717.637% when it varies from 57.828% to 100% in Multi Axel category.

Three-wheelers have the highest RMSE values resulting least accuracy varying from 243.9969 to 604.3403 and Multi axels have the least RMSE values up to 14.534 due to the number of vehicles on the road during the period of the survey,

4.6. Results Comparison & Discussion

The outputs from both original and preliminarily custom trained YoloV4 models have less accuracy compared to manual on site classified vehicle counting. However, the original model shows more accuracy than the custom trained model for car and bus categories at Athurugiriya and motorcycle category at Pettah. The smaller number of data points available in bus category for model training has resulted in the increased MAPE value compared to the original model.

The composition of training data set in the preliminarily custom trained model has also affected the final results. The MAPE values for three-wheelers (36.08% from total training dataset) varies between 68.85% and 89.22% while it fluctuates from 61.18% to 717.64% for trucks (3.09% from total training dataset) which clearly depicts the above statement.

The motorcycle counting from both automated models have a minimum variation from each other which are 16.16% and 16.23% for original model and custom trained model respectively. Considering the vehicle categories, motorcycles show the least error percentage fluctuating from 14.366% to 34.36% in both automated counting. Even the bus category has a better accuracy except for one location where MAPE is 155.54% in the original model.

Compared to the original YoloV4 model, preliminarily custom trained model shows better accuracy for almost all the vehicle categories in the five locations though it is not as accurate as the onsite manual counting. Car counting at MLC shows the best accuracy compared to all the outputs from automated methods where the MAPE value is only 10.43% which is provided by our model. The classified counting accuracy is better where the density values are low such as Athurugiriya compared to highly dense Pannipitiya when considering the RMSE values.

Misclassification of vehicle categories and multi-tracking of a single stationary vehicle have affected the accuracy of both original and preliminarily custom trained YoloV4 models. While the original YoloV4 model misclassified some vehicles due to the unavailability of certain highly dense vehicle categories in the original dataset such as three-wheelers emphasizing its ineptness for heterogeneous traffic conditions. Moreover, custom trained model tends to be inaccurate for its misclassification of dual-purpose category as trucks due to the less availability of tags and the similarity between them

Multi-tracking of a single vehicle from both the automated models could not be removed in the preliminary stage since some vehicles were parked encouraging the driving lane. Therefore, it became an issue to draw a virtual line separating the moving vehicles and parked vehicles. When the traffic density increased on the road, tagging the complete vehicle or identifiable part of the vehicle without overlapping was challenging, resulting in a high error percentage at some locations in preliminarily custom trained YoloV4 model since it was trained using our own data points.

Table 5. MAPE values for All three methods

Type		3wheelers	Motor Cycle	Car/ Jeep/ Mini van	Dual Purpose	Bus	Trucks	Multi Axels
WELLAWATTE	Manual	2.04%	3.76%	3.11%	13.08%	17.50%	28.36%	
	Original YoloV4	100%	27.77%	57.80%	100.00%	155.54%	180.97%	
	Custom YoloV4	68.85%	25.05%	28.32%	71.74%	71.03%	151.71%	
MLC	Manual	4.72%	6.60%	8.39%	29.76%	3.12%	48.62%	
	Original YoloV4	100%	15.68%	151.70%	100%	22.34%	1106.59%	
	Custom YoloV4	68.79%	14.36%	10.43%	81.40%	10.52%	717.64%	
ATHURUGIRIYA	Manual			14.14%	25.01%	20.47%	6.27%	14.02%
	Original YoloV4			25.49%	100.00%	34.44%	180.30%	100%
	Custom YoloV4			48.42%	66.33%	53.96%	61.18%	57.83%
PETTAH	Manual	42.17%	3.02%	8.97%	10.74%	11.70%	66.85%	
	Original YoloV4	100%	16.16%	340.65%	100%	32.92%	265.99%	
	Custom YoloV4	69.53%	16.23%	52.68%	69.46%	21.08%	160.19%	
PANNIPITIYA	Manual	16.58%	16.36%	15.69%	29.29%	17.69%	40.86%	66.67%
	Original YoloV4	100%	34.36%	103.79%	100%	39.01%	223.03%	100%
	Custom YoloV4	89.22%	30.14%	33.78%	91.27%	29.15%	119.11%	100%

5. CONCLUSION

This paper deals with classified vehicle counting and its different approaches, one of the most significant aspects in traffic data collection . The video-based automated counting is gradually replacing manual CVC using deep learning approaches involving models like YoloV4. To evaluate and enhance the existing YoloV4 model, we have custom trained a preliminary model using YoloV4.

The preliminary custom trained model indicates better accuracy than the original YoloV4 model except for three occasions where the results show an insignificant deviation among the automated models. The availability of more vehicle categories in our model due to new tagged videos which were used to train the model has reduced the MAPE values from 25.056% to 20.948%

Based on the outputs of all three classified counting methods, manual CVC still surpasses the video-based automated CVC methods due to the initial Deep Learning model's limitations for all the locations and selected vehicle categories. The manual classified vehicle counting has the best accuracy among the methods which as depicted from its lower MAPE value as a mere 7.475%.

The custom trained YoloV4 model requires further training using more tagged video surveillance data, to improve the accuracy for highly congested heterogenous traffic flows and stationary vehicles such as recognizing more accurately the dual-purpose and truck categories. This could be done by carrying out more vehicle tags to the existing dataset to train the model effectively so that the data points are distributed more equally for all the vehicle categories identified in a heterogenous traffic flow condition since the past studies using YoloV3 and YoloV4 were conducted on homogeneous traffic conditions.

ACKNOWLEDGEMENT

This work was supported by the Accelerating Higher Education Expansion and Development (AHEAD) Operation of the Ministry of Higher Education funded by the World Bank [grant number - Credit/Grant #:6026-LK/8743-LK].

APPENDIX

Table 6. RMSE values for All three methods

Type		3wheelers	Motor Cycle	Car/ Jeep/ Mini van	Dual Purpose	Bus	Trucks	Multi Axels
WELLAWATTE	Manual	7.58	25.55	23.99	8.08	0.71	20.95	
	Original YoloV4	341.05	260.92	364.87	66.84	7.83	131.90	
	Custom YoloV4	244.00	171.97	410.50	50.53	4.97	101.57	
MLC	Manual	42.57	38.98	83.41	19.10	4.15	37.94	0.71
	Original YoloV4	751.50	103.48	1235.58	75.08	29.79	514.74	
	Custom YoloV4	514.64	110.13	102.66	61.76	17.51	334.34	0.71
ATHURUGIRIYA	Manual			129.45	33.05	8.44	16.59	5.15
	Original YoloV4			170.87	109.65	12.75	377.44	18.53
	Custom YoloV4			396.40	76.29	23.34	135.79	14.53
PETTAH	Manual	405.35	11.47	31.62	6.24	34.37	55.02	0.71
	Original YoloV4	854.83	46.34	1094.20	47.61	87.89	167.68	0.50
	Custom YoloV4	604.34	73.20	182.89	34.43	53.85	104.02	0.71
PANNIPITIYA	Manual	87.83	126.38	184.49	37.63	49.95	47.27	1.22
	Original YoloV4	430.16	283.89	874.90	120.59	52.95	228.58	1.22
	Custom YoloV4	383.71	273.62	296.17	109.77	34.19	119.57	1.22

REFERENCES

Ahmad, J., Farman, H. and Jan, Z. (2019) 'Deep Learning Methods and Applications', *SpringerBriefs in Computer Science*, pp. 31–42. doi: 10.1007/978-981-13-3459-7_3.

Bochkovskiy, A., Wang, C. Y. and Liao, H. Y. M. (2020) 'YOLOv4: Optimal Speed and Accuracy of Object Detection', *arXiv*.

Chethan Kumar, B., Punitha, R. and Mohana (2020) 'YOLOv3 and YOLOv4: Multiple object detection for surveillance applications', *Proceedings of the 3rd International Conference on Smart Systems and Inventive Technology, ICSSIT 2020*, (Icssit), pp. 1316–1321. doi: 10.1109/ICSSIT48917.2020.9214094.

Hyndman, R. J. and Koehler, A. B. (2006) 'Another look at measures of forecast accuracy', *International Journal of Forecasting*, 22(4), pp. 679–688. doi: 10.1016/j.ijforecast.2006.03.001.

Khair, U. *et al.* (2017) 'Forecasting Error Calculation with Mean Absolute Deviation and Mean Absolute Percentage Error', *Journal of Physics: Conference Series*, 930(1). doi: 10.1088/1742-6596/930/1/012002.

Leduc, G. (2008) 'Road Traffic Data : Collection Methods and Applications', *EUR Number: Technical Note: JRC 47967*, JRC 47967(May), p. 55. Available at: http://ftp.jrc.es/EURdoc/EURdoc/JRC47967.TN.pdf.

Mahto, Pooja and Garg, Priyamm and Seth, Pranav and Panda, J. (2020) 'REFINING

YOLOV4 FOR VEHICLE', in, pp. 409–419. doi: 10.34218/IJARET.11.5.2020.043.
Mandal, V. and Adu-gyamfi, Y. (no date) '2007.16198'.
Myttenaere, A. De *et al.* (2017) 'Mean Absolute Percentage Error for regression models To cite this version : HAL Id : hal-01312590', *Advances in artificial neural networks, machine learning and computational intelligence - Selected papers from the 23rd European Symposium on Artificial Neural Networks (ESANN 2015)*, pp. 38–48.
Powell, S. (1987) 'Transportation Planning Models', *Journal of the Operational Research Society*, 38(12), pp. 1218–1219. doi: 10.1057/jors.1987.200.
Song, H. *et al.* (2019) 'Vision-based vehicle detection and counting system using deep learning in highway scenes', *European Transport Research Review*, 11(1). doi: 10.1186/s12544-019-0390-4.
Zheng, P. and Mike, M. (2012) 'An Investigation on the Manual Traffic Count Accuracy', *Procedia - Social and Behavioral Sciences*, 43, pp. 226–231. doi: 10.1016/j.sbspro.2012.04.095.