Vehicle detection using machine learning model with the Gaussian Mixture Model (GMM)

by Rika Rosnelly

Vehicle detection using machine learning model with the Gaussian Mixture Model (GMM)

Rika Rosnelly*, Bob Subhan Riza, Linda Wahyuni, Edy Victor Haryanto S, Annas Prasetio

Faculty of Engineering and Computer Science, University of Potensi Utama, Medan, Indonesiai

Corresponding Email: rikarosnelly@gmail.com

***Abstract* –** Motion tracking apps are used for a lot of different things, like finding traffic jams and counting the number of cars going through a traffic light. The datasets come from many places on the internet, like YouTube and public dataset archives. There are about 20 videos that are tagged with the words "traffic" and "traffic camera video" and run for 10 to 30 seconds. The Gaussian Mixture Models (GMM) method is the proposed model. It separates the background from the tracked object, which is needed to do motion tracking. Then, the GMM method groups pixel data based on the background color of each pixel. After the cluster is made, the input is matched as a distribution, with the most common distribution used as the background. The analysis was done using MATLAB2019B. The results of this study show that the GMM method can adapt to the background. This is shown by the fact that testing of some of the given conditions went well.

***Keywords* –** Vehicle detection, Gaussian Mixture Models, MATLAB2019B, Background, Motion tracking.

1. Introduction

The rapid growth and development of digital technology and the availability of video capture-based devices such as digital cameras and mobile phones with cameras are driving the explosive rise of network storage devices[1–3]. This is consistent with the nearly daily increase in the number of cars, but it is not accompanied by major volume changes [4]. Consequently, with a substantial increase in the number of vehicles and a constant volume of roadways, there will be an accumulation of vehicles, which ultimately leads to congestion [5, 6]. Congestion is a prevalent issue in cities, which in turn leads cities to become inefficient and generates considerable economic losses due to a number of factors, including the ratio of transportation infrastructure to land area, an inadequate network, unregulated spatial planning, and vehicle expansion [7, 8].

A moving vehicle is an intriguing research subject. Counting the number of vehicles, segmentation, feature extraction, classification, and the elimination of minor motions of objects that are deemed noise are interesting research objects [9–11]. Obviously, this can be a solution to the problem of extremely rapid vehicle growth [12]. Manually calculating the vehicle's parameters is possible, but inefficient. Several factors, such as the human condition, atmosphere, and work environment, contribute to its error-prone nature. In order for the technology to assist humans with traffic control, we need an alternative approach that can execute computations and produce more reliable data [13–16]. Computer vision is one approach for processing information from photos or movies [17, 18]. The goal of this study is to count the number of cars by looking at video clips. This will help two groups of people directly: people who use the roads and the people in charge of traffic. Users of the roads can avoid traffic jams and choose the best way to get where they need to go if they know how the traffic is right now. On the other hand, traffic administrations can use traffic information in their systems for controlling traffic, which makes traffic management better. In the past few years, video detection has come a long way. There are many ways that video detection could be done, such as (Kavya et al., 2020) [19] a study that suggested a good way to find and follow vehicles from moving video frames. The Viola-Jones algorithm is used to find vehicles, and the Nonlinear Kalman Filter is used to keep track of the vehicles found. Simulations and tests show that a nonlinear Kalman filter can be used to solve the tracking problem. Pan & Zhang[20] did more work that solves some of the biggest problems with detecting and recognizing video objects. These problems include accurately separating the target from the background, dealing with shadows in complex scenes, accurately classifying extracted foreground targets, and recognizing targets in complex backgrounds. Next by Marzouk & El Azeem[21], who proposes that IoT technology and modified video processing techniques be used to find and count vehicles. The results showed that IoT-based technology and modified techniques for taking out the background worked well together. By applying GMM Filter [22, 23] to reduce unwanted small items, this research completes and continues object detection on video.

There are several other motion tracking methods that were considered before settling on the Gaussian Mixture Models (GMM) method. Some of these include:

a. Kalman Filters: These are a type of mathematical model that can be used to predict the state of a system based on previous observations. They are often used in tracking applications because they can handle uncertainty in the observations and model errors.

b. Particle Filters: These are a type of estimation algorithm that can be used to track a moving object in a noisy environment. They work by representing the state of the object using a set of particles, each of which has a probability of representing the true state.

c. Optical Flow: This is a method for tracking the motion of objects in a video by analyzing the movement of pixels from one frame to the next. It can be used to estimate the motion of rigid or non-rigid objects.

d. Optical Flow based on Deep Learning: Optical flow method is also very popular in deep learning methodologies. The deep learning-based method can give better results compared to traditional methodologies.

e. Condensation Algorithm : It is a Monte Carlo method which approximates the posterior density of the state using a set of sample points.

f. Ultimately, the choice of motion tracking method depends on the specific requirements of the application and the trade-offs between accuracy, computational complexity, and robustness.

According to statistics, GMM is one of the most used statistical models and is most commonly utilized when adaptive background subtraction in movies is needed [24]. When used in settings with relatively little background movement, this approach performs exceptionally well.

2. Research methodology

A total of 20 movies with a duration between 10 and 30 seconds were acquired from various online sources, including YouTube, using the search terms "traffic" and "traffic camera video" as well as from publicly accessible dataset repositories. In addition, vehicle video data is subdivided according to its scale, i.e., quiet, normal, and congested cars. The following is an example of a CCTV camera's vehicle video dataset.

(a)

(b)

(c)

Figure 1. (a) The condition of the vehicle is calm, (b) the condition of the vehicle is normal, and (c) the condition of the vehicle is crowded

MATLAB 2019B software is utilized for the analysis of automatic vehicle detection systems in video sequences. The entire implementation procedure has been broken down into ten steps. Each step has been adequately explained. The following is a flowchart analysis of the automatic vehicle detection system as depicted in the video sequence in Figure 2.

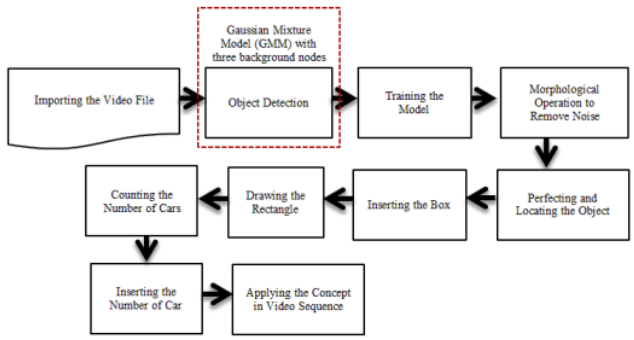

Figure 2. Proposed model

Gaussian Mixture Model (GMM) is one of the ways to get rid of the background. GMM models the time series of pixel values [23–25]. The accuracy of the Gaussian Mixture Models (GMM) method in separating the background and the tracked object can be evaluated using several metrics, such as:

a. Intersection over Union (IoU): This metric measures the overlap between the predicted object bounding box and the ground truth bounding box, divided by their union. A higher IoU value indicates a better separation between the object and the background.
b. Precision-Recall (PR) curve: This metric plots the precision (the ratio of true positive detections to all positive detections) against the recall (the ratio of true positive detections to all actual positive instances) as the threshold for detection is varied. A higher area under the PR curve indicates a better separation between the object and the background.
c. Mean Average Precision (MAP): This metric is the mean of the average precision (AP) across all classes. AP is defined as the area under the PR curve.
d. F1-score: This is a measure of a test's accuracy. It considers both the precision and the recall of the test to compute the score. The F1 score can be interpreted as a weighted average of the precision and recall, where an F1 score reaches its best value at 1 and worst at 0.
e. Pixel-wise accuracy: This measures the percentage of pixels in the predicted object mask that match the pixels in the ground truth object mask.

Additionally, GMM method can also be evaluated by comparing the results with other motion tracking methodologies. It is important to note that the accuracy of the GMM method can also be affected by the quality of the training data and the initialization of the model.

3. Results and Discussion

Several test scenarios were conducted in this study to evaluate the performance of the system under construction. Utilizing the confusion matrix measurement from GMM parameter testing, a system performance study is conducted. The performance gained by a comparison of actual automobiles and application detection. The larger the Accuracy value, the greater the performance that results.

3.1. Test scenario 1

The test utilizes test data in the form of a movie lasting 5 minutes and 6 seconds, with a seamless density level analysis. Video specs based on test data are as follows:

a) Dimensions: 15.735 KB;
b) Length: 5 minutes and 6 seconds;
c) Number of passing vehicles: 58.

The following are the outcomes of testing the video scenario:

Figure 3. Detected cars of scenario 1

Table 1. Results of Scenario 1

Total Real Vehicles	58 unit
Total Vehicle System	54 unit
Accuracy	93,10%
Error Rate	6,9%

3.2. Test scenario 2

The test utilizes test data in the form of a movie lasting 2 minutes and 3 seconds, with a seamless density level analysis. Video specs based on test data are as follows:

a) Dimensions: 5.656 KB;
b) Length: 2 minutes and 3 seconds;
c) Number of passing vehicles: 29.

The following are the outcomes of testing the video scenario:

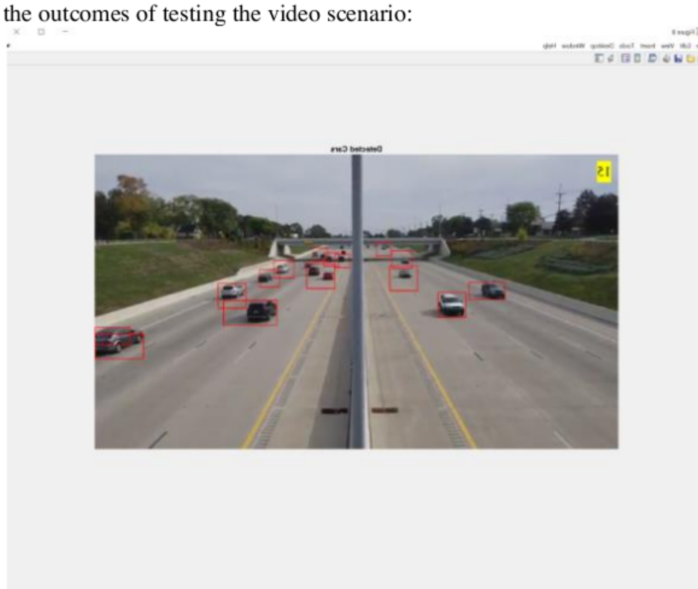

Figure 4. Detected cars of scenario 2

Table 2. Results of Scenario 2

Total Real Vehicles	29 unit
Total Vehicle System	26 unit
Accuracy	89,66%%
Error Rate	10,34%%

3.3. Test scenario 3

The test utilizes test data in the form of a movie lasting 14 minutes, with a seamless density level analysis. Video specs based on test data are as follows:

a) Dimensions: 51.302 KB;
b) Length: 14 minutes;
c) Number of passing vehicles: 131.

The following are the outcomes of testing the video scenario:

Figure 5. Detected cars of scenario 3

Table 3. Results of Scenario 3

Total Real Vehicles	131 unit
Total Vehicle System	119 unit
Accuracy	90,84%%
Error Rate	9,16%%

3.4. Test scenario 4

The test utilizes test data in the form of a movie lasting 5 minutes and 6 seconds, with a seamless density level analysis. Video specs based on test data are as follows:

a) Dimensions: 71.465 KB;
b) Length: 5 minutes and 6 seconds;
c) Number of passing vehicles: 58.

The following are the outcomes of testing the video scenario:

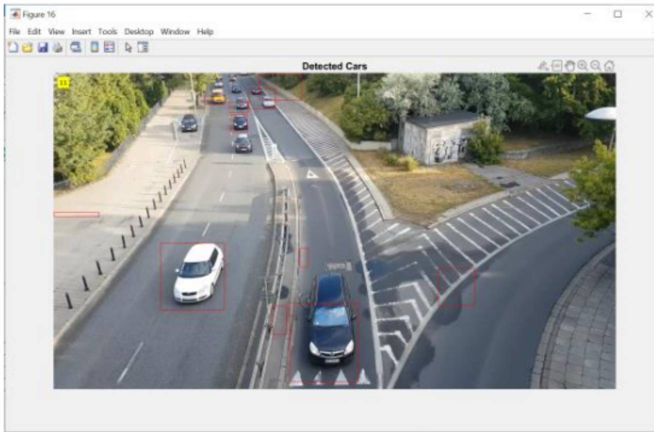

Figure 6. Detected cars of scenario 4

Table 4. Results of Scenario 4

Total Real Vehicles	58 unit
Total Vehicle System	55 unit
Accuracy	94,83%
Error Rate	5,17%

According to the application's output and the examination of visible test results, a comparison is made between data density and test results (actual). The following are examples of the possibilities that were considered:

Table 5. Results of analysis of error rate and accuracy

Scenario Movie	**Density Level System**	**Density Level Actual**	**Data Difference**
Results of Scenario 1	54	58	4
Results of Scenario 2	26	29	3
Results of Scenario 3	119	131	12
Results of Scenario 4	55	58	3
Jumlah	254	276	22
Error rate		**7.89%**	
Accuracy		**92.11%**	

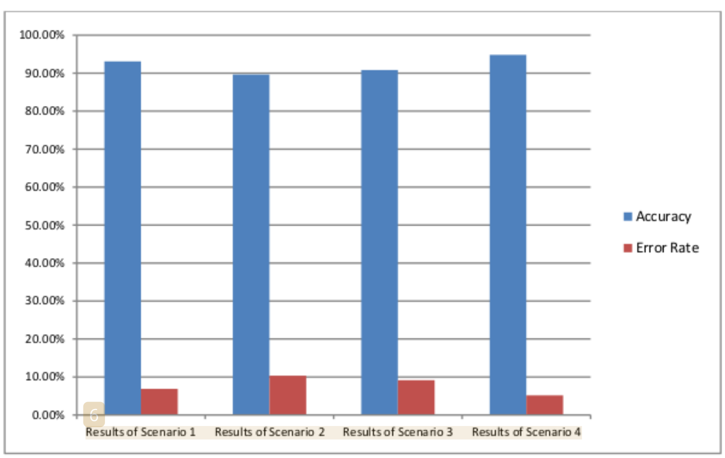

Figure 7. Graph results of analysis of error rate and accuracy

Based on the analysis of the table above, we know that the application has a 7.89% error rate and a 92.1% accuracy rate.

In the Gaussian Mixture Models (GMM) method for motion tracking, the pixel data is grouped by assuming that the pixel values in the video frames follow a Gaussian distribution. The GMM method models the background as a mixture of several Gaussian distributions, each representing a different part of the background. The Gaussian distributions can be represented by their mean and covariance, and the pixel values in each video frame are assigned to the Gaussian distribution that best fits the pixel values. The criteria used to determine the most common distribution as the background can vary depending on the implementation of the GMM method.

The GMM method also uses an algorithm called Expectation-Maximization (EM) algorithm to find the most probable values for the parameters of the Gaussian distributions that best fit the pixel data. The algorithm iteratively updates the parameters of the Gaussian distributions until it reaches a converged state, where the parameters of the Gaussian distributions are optimized to fit the pixel data.

It is important to note that the GMM method can be sensitive to the initialization of the model and the quality of the training data, so it is important to carefully select the initial parameters and the training data to obtain accurate results.

4. Conclusion

It is possible to use the proposed method to determine the number of vehicles in the video sequence. The datasets come from a variety of sources on the internet, including YouTube and public dataset archives. There are around 20 videos with a runtime of 10-30 seconds that were tagged with the keywords "traffic" and "traffic camera video". Implementation of the proposed method is done in MATLAB 2019B language. Vehicle detection's accuracy was tested in an experiment. Furthermore, the suggested method's detection of cars will be shown and compared to the number of vehicles counted manually when the input video is inserted into the method (truth in the field). A laptop with an Intel Core i7 processor (1.7-2.4 GHz) and 16 GB of RAM was used for the experiment. Car count accuracy ranges from 90% to 95%, depending on the video being used as an input for the suggested technique. On the other hand, this illustrates that the proposed approach works well on any video it is applied to. In total, 254 of the 276 vehicles in the video input were spotted, resulting in an accuracy of 92,1 percent.

References

[1] Knura, M.; Kluger, F.; Zahtila, M.; Schiewe, J.; Rosenhahn, B.; Burghardt, D. (2021). Using object detection on social media images for urban bicycle infrastructure planning: A case study of dresden, *ISPRS International Journal of Geo-Information*, Vol. 10, No. 11. doi:10.3390/ijgi10110733

[2] Gengeç, N.; Eker, O.; ÇeviKalp, H.; Yazici, A.; Yavuz, H. S. (2021). Visual object detection for autonomous transport vehicles in smart factories, *Turkish Journal of Electrical Engineering and Computer Sciences*, Vol. 29, No. 4, 2101–2115. doi:10.3906/ELK-2008-62

[3] Iswanto, I.; Raharja, N. M.; Maarif, A.; Shomad, M. A.; Nurjanah, A.; Rijalusalam, D. U.; Atmoko, R. A.; Ahmad, I.; Al-Barazanchi, I.; Mishra, S. (2021). Empowerment of mushroom farming communities with iot-based monitoring in Karang Kepanjen, Sleman, *Jurnal Pengabdian Dan Pemberdayaan Masyarakat Indonesia*, Vol. 1, No. 5, 198–208

[4] Zhang, W.; Gao, X. zhong; Yang, C. fu; Jiang, F.; Chen, Z. yuan. (2022). A object detection and tracking method for security in intelligence of unmanned surface vehicles, *Journal of Ambient Intelligence and Humanized Computing*, Vol. 13, No. 3, 1279–1291. doi:10.1007/s12652-020-02573-z

[5] Kim, Y. Y.; Kim, H.; Lee, W.; Choi, H. L.; Moon, I. C. (2021). Black-box expectation–maximization algorithm for estimating latent states of high-speed vehicles, *Journal of Aerospace Information Systems*, Vol. 18, No. 4, 175–192. doi:10.2514/1.I010831

[6] Iswanto, I.; Maseleno, A.; Raharja, N. M.; Maarif, A.; Zulfiar, M. H.; Rijalusalam, D. U.; Alayi, R.; Ansari, M. D.; Atmoko, R. A.; Ahmad, I. (2021). Empowerment of energy communities in minggir II village yogyakarta with iot-based biodigeser, *Jurnal Pengabdian Dan Pemberdayaan Masyarakat Indonesia*, Vol. 1, No. 6, 241–248

[7] Nasution, S. M.; Husni, E.; Kuspriyanto, K.; Yusuf, R.; Mulyawan, R. (2020). Road information collector using smartphone for measuring road width based on object and lane detection, *International Journal of Interactive Mobile Technologies*, Vol. 14, No. 2, 42–61. doi:10.3991/ijim.v14i02.11530

[8] Ng, S. C.; Kwok, C. P. (2020). An intelligent traffic light system using object detection and evolutionary algorithm for alleviating traffic congestion in hong kong, *International Journal of Computational Intelligence Systems*, Vol. 13, No. 1, 802–809. doi:10.2991/ijcis.d.200522.001

[9] Chen, X.; Chen, Y.; Zhang, G. (2021). A computer vision algorithm for locating and recognizing traffic signal control light status and countdown time, *Journal of Intelligent Transportation Systems: Technology, Planning, and*

Operations, Vol. 25, No. 5, 533–546. doi:10.1080/15472450.2021.1871611

[10] Li, Q.; Min, G.; Chen, P.; Liu, Y.; Tian, S.; Zhang, D.; Zhang, W. (2020). Computer vision-based techniques and path planning strategy in a slope monitoring system using unmanned aerial vehicle, *International Journal of Advanced Robotic Systems*, Vol. 17, No. 2, 1–14. doi:10.1177/1729881420904303

[11] Rahmawati, N. D.; Buchori, A.; Ghoffar, M. H. A. (2022). Design of virtual reality-based mathematics learning media on trigonometry material in senior high school, *AIP Conference Proceedings*, Vol. 2577. doi:10.1063/5.0096111

[12] Putra, R. G.; Pribadi, W.; Yuwono, I.; Sudirman, D. E. J.; Winarno, B. (2021). Adaptive Traffic Light Controller Based on Congestion Detection Using Computer Vision, *Journal of Physics: Conference Series*, Vol. 1845, No. 1. doi:10.1088/1742-6596/1845/1/012047

[13] Cazzato, D.; Cimarelli, C.; Sanchez-Lopez, J. L.; Voos, H.; Leo, M. (2020). A survey of computer vision methods for 2d object detection from unmanned aerial vehicles, *Journal of Imaging*, Vol. 6, No. 8. doi:10.3390/JIMAGING6080078

[14] Hammoudeh, M. A. A.; Alsaykhan, M.; Alsalameh, R.; Althwaibi, N. (2022). Computer Vision: A Review of Detecting Objects in Videos – Challenges and Techniques, *International Journal of Online and Biomedical Engineering*, Vol. 18, No. 1, 15–27. doi:10.3991/ijoe.v18i01.27577

[15] Wang, X.; Luo, B.; Zhang, Z. (2021). Application of UAV Target Tracking Based on Computer Vision, *Journal of Physics: Conference Series*, Vol. 1881, No. 4. doi:10.1088/1742-6596/1881/4/042053

[16] Karolina, R.; Syahrizal; Bahri, N. (2018). Optimization of fly ash and bottom ash substitution against paving block manufacture according to SNI 03-0691-1996, *IOP Conference Series: Materials Science and Engineering*, Vol. 309, 012134. doi:10.1088/1757-899X/309/1/012134

[17] Yi, Z. (2021). Application of computer vision in 3D film, *Journal of Physics: Conference Series*, Vol. 1915, No. 2. doi:10.1088/1742-6596/1915/2/022026

[18] Belén, F.; Vallese, F. D.; Leist, L. G. T.; Ferrão, M. F.; Gomes, A. de A.; Pistonesi, M. F. (2020). Computer-vision based second-order (kinetic-color) data generation: arsenic quantitation in natural waters, *Microchemical Journal*, Vol. 157, No. March, 104916. doi:10.1016/j.microc.2020.104916

[19] Kavya, T. S.; Jang, Y. M.; Peng, T.; Cho, S. B. (2020). Vehicle detection and tracking from a video captured by moving host, *Indian Journal of Computer Science and Engineering*, Vol. 11, No. 3, 226–235. doi:10.21817/indjcse/2020/v11i3/201103187

[20] Pan, Q.; Zhang, H. (2020). Key Algorithms of Video Target Detection and Recognition in Intelligent Transportation Systems, *International Journal of Pattern Recognition and Artificial Intelligence*, Vol. 34, No. 9, 1–17. doi:10.1142/S0218001420550162

[21] Marzouk, M. A.; El Azeem, A. A. (2022). Vehicles detection and counting based on internet of things technology and video processing techniques, *IAES International Journal of Artificial Intelligence*, Vol. 11, No. 2, 405–413. doi:10.11591/ijai.v11.i2.pp405-413

[22] Saygılı, A. (2022). Computer-Aided Detection of COVID-19 from CT Images Based on Gaussian Mixture Model and Kernel Support Vector Machines Classifier, *Arabian Journal for Science and Engineering*, Vol. 47, No. 2, 2435–2453. doi:10.1007/s13369-021-06240-z

[23] Luo, X.; Wang, Y.; Cai, B.; Li, Z. (2021). Moving object detection in traffic surveillance video: New mod-at method based on adaptive threshold, *ISPRS International Journal of Geo-Information*, Vol. 10, No. 11. doi:10.3390/ijgi10110742

[24] Gardner, P.; Bull, L. A.; Dervilis, N.; Worden, K. (2022). Domain-adapted Gaussian mixture models for population-based structural health monitoring, *Journal of Civil Structural Health Monitoring*. doi:10.1007/s13349-022-00565-5

[25] Soeleman, M. A. (2019). *Deteksi Objek Bergerak Pada Video Dan Penerapan Metode Gaussian Mixture Model*

 Rika Rosnelly	Email:rikarosnelly@gmail.com; rika@potensi-utama.ac.id Orcid: 0000-0002-0407-5160	Profil Author : Dr. Rika Rosnelly, S.Kom, M.Kom was born in Medan, North Sumatra on September 19, 1975. As for my Educational History, S1 at the STMIK Logika Medan graduated in 2005. S2 at Putera Indonesia University YPTK Padang graduated in 2008. S3 Computer Science, at Gadjah Mada University Yogyakarta graduated in 2017. Currently I am serving as a Permanent Lecturer at Universitas Potensi Utama. My research study in the field of Image Processing, Artificial Intelligence, Decision Support System.
 Bob Subhan Riza	Email: bob.potensi@gmail.com Orcid: 0000-0001-6358-9412	Profil Author : Bob Subhan Riza, ST, M.Kom was born in Medan, North Sumatra on August 5, 1970. As for my Educational History, - D3 at USU Medan Polytechnic graduated in 1993 - S1 at the University of North Sumatra, Medan graduated in 2000 - S2 at Putera Indonesia University YPTK Padang graduated in 2014. Currently I am serving as a Permanent Lecturer at Universitas Potensi Utama. My research study in the field of Image Processing.
 Linda Wahyuni	Email: lindawahyuni391@gmail.com Orcid: 0000-0003-2027-7616	Profil Author : Linda Wahyuni, M.Kom was born in Pasar V Kebun Kelapa, Beringin District, Deliserdang Regency, on May 7, 1983. As for my educational history, - S1 at STMIK Potensi Utama Medan graduated in 2007 - S2 at Putera Indonesia University YPTK Padang graduated in 2009. I am currently serving as a Permanent Lecturer at the Main Potential University. My research studies are in the areas of DSS, Expert Systems, Information Systems.
 Edy Victor Haryanto	Email: edyvictor@gmail.com Orcid: 0000-0001-8317-3545	Profil Author : Edy Victor Haryanto, S. M.Kom was born in Medan, North Sumatra on October 30, 1977. As for my Educational History, - S1 at the STMIK Potensi Utama, Medan graduated in 2007 - S2 at Putera Indonesia University YPTK Padang graduated in 2009. Currently I am serving as a Permanent Lecturer at Universitas Potensi Utama. My research study in the field of Image Processing, Artificial Intelligence, DSS.

 Annas Prasetio	Email: annasprasetio45@gmail.com Orcid: 0000-0002-1734-928X	Profil Author : Annas Prasetio, M.Kom was born in Medan. Worked as an instructor and computer teacher. Master of Computer Science at Potensi Utama University.

Vehicle detection using machine learning model with the Gaussian Mixture Model (GMM)

ORIGINALITY REPORT

11%	6%	7%	6%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	www.scikit-yb.org Internet Source	2%
2	Submitted to Queen Mary and Westfield College Student Paper	1%
3	Rika Rosnelly, Bob Subhan Riza, Linda Wahyuni, Suparni Suparni, Annas Prasetio, Robbi Rahim. "Improvement of Hybrid Image Enhancement for Detection and Classification of Malaria Disease Types and Stages with Artificial Intelligence", TEM Journal, 2022 Publication	1%
4	Submitted to Abdullah Gul University Student Paper	1%
5	dokumen.dinus.ac.id Internet Source	1%
6	Submitted to Colorado Technical University Online Student Paper	1%

7	Ruiyang Hao, Bingyu Lu, Ying Cheng, Xiu Li, Biqing Huang. "A steel surface defect inspection approach towards smart industrial monitoring", Journal of Intelligent Manufacturing, 2020 Publication	1 %
8	docplayer.net Internet Source	1 %
9	Submitted to Bahcesehir University Student Paper	<1 %
10	Mohammad. Al-Fawa'Reh, Alaa Hawamdeh, Rana Alrawashdeh, Mousa Tayseer Jafar. "Intelligent Methods for flood forecasting in Wadi al Wala, Jordan", 2021 International Congress of Advanced Technology and Engineering (ICOTEN), 2021 Publication	<1 %
11	essuir.sumdu.edu.ua Internet Source	<1 %
12	Ahmed Seif, Wassim Alexan. "A High Capacity Gray Code Based Security Scheme for Non-Redundant Data Embedding", 2020 International Conference on Innovative Trends in Communication and Computer Engineering (ITCE), 2020 Publication	<1 %

13	Jordina Torrents-Barrena, Domenec Puig, Jaime Melendez, Aida Valls. "Computer-aided diagnosis of breast cancer via Gabor wavelet bank and binary-class SVM in mammographic images", Journal of Experimental & Theoretical Artificial Intelligence, 2015 Publication	<1 %
14	ebin.pub Internet Source	<1 %
15	www.fao.org Internet Source	<1 %
16	www.researchgate.net Internet Source	<1 %

Exclude quotes	Off	Exclude matches	Off
Exclude bibliography	On		

Vehicle detection using machine learning model with the Gaussian Mixture Model (GMM)

GRADEMARK REPORT

FINAL GRADE

/0

GENERAL COMMENTS

Instructor

PAGE 1

PAGE 2

PAGE 3

PAGE 4

PAGE 5

PAGE 6

PAGE 7

PAGE 8

PAGE 9

PAGE 10