## Vehicle Detection Using Machine Learning Model with the Gaussian Mixture Model (GMM)

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#### Table of Contents Review:

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- 2. Keputusan Editor : 04 Oktober 2022 : [JoWUA] Thank you for your submitting Paper and submission id is: 9925227.
- Keputusan Editor : 07 Oktober 2022 : [JoWUA] Editor Decision- Submission Confirmation Paper ID - 9925227
- 4. Keputusan Editor : 11 November 2022 : [JoWUA] Revisions requested Paper ID 9925227
- 5. Submit Revisi : 30 November 2022 : [JoWUA] Send Revisions Paper
- 6. Keputusan Editor : 19 Desember 2022 : [JoWUA] Editor Decision Accepted Paper.
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1. Submit Paper : 04 Oktober 2022 : [JoWUA] Acknowledgement of a new manuscript submission.



#### **Submitting Paper**

1 pesan

Rika Rosnelly <rikarosnelly@gmail.com>

04 Oktober 2022 12.16

Kepada: Jowua editor@jowua.com

Dear Journals Editorial Office,

Here I attach my research article in the field of computer science entitled: "Vehicle Detection Using Machine Learning Model with the Gaussian Mixture Model (GMM)" to the Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA). Hopefully my article can be published, thank you

Regards, Rika Rosnelly

Full Paper Rika Rosnelly.docx 3690K

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*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. 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.





(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].

#### 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%	

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:

Error Rate



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.



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:

|--|

Scenario	Density	/ Level	Data Difference
Movie	System	Actual	
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		92.1	1%



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.

#### 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.

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2. Keputusan Editor : 04 Oktober 2022 : [JoWUA] - Thank you for your submitting Paper



#### Thank you for your submitting Paper

1 pesan

Jowua <editor@jowua.com> Kepada: rikarosnelly@gmail.com 04 Oktober 2022 19.05

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

Thank you for submitting your manuscript,

"Vehicle detection using machine learning model with the Gaussian Mixture Model (GMM)" to Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA)!

The submission id is: 9925227 Please refer to this number in any future correspondence.

During the review process, you can keep track of the status of your manuscript by accessing the journal web site <a href="https://jowua.com/article-status/">https://jowua.com/article-status/</a>.

If you forgot your password, you can click the Forget Password link on the Login page at <u>https://jowua.com/forgot-password</u>.

With kind regards,

Journals Editorial Office Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA)!

3. Keputusan Editor : 07 Oktober 2022 : [JoWUA] Editor Decision-Submission Confirmation - Paper ID - 9925227



#### Submission Confirmation - Paper ID - 9925227

1 pesan

Jowua <editor@jowua.com> Kepada: rikarosnelly@gmail.com 07 Oktober 2022 11.45

Dear Rika Rosnelly,

We are writing to inform you that your manuscript "Vehicle detection using machine learning model with the Gaussian Mixture Model (GMM)" is currently in the peer review process at Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA)!

We have received your submission and are excited to consider it for publication. Our team of reviewers will be carefully evaluating the content and research presented in your paper to determine its suitability for our journal.

Please be aware that this process can take several weeks or even months, depending on the complexity of the paper and the availability of reviewers. We will do our best to keep you updated on the progress of your manuscript and will notify you as soon as we have reached a decision.

Thank you for considering Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA)! for your research. We look forward to the opportunity to review your work.

Sincerely, Journals Editorial Office Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA)! 4. Keputusan Editor : 11 November 2022 : [JoWUA] Revisions requested Paper ID - 9925227.



#### **Revisions requested Paper ID - 9925227**

1 pesan

#### JoWUA <editor@jowua.com>

Kepada: rikarosnelly@gmail.com

11 November 2022 16.37

Dear Rika Rosnelly,

We are writing to inform you that the peer review process for your manuscript, "Vehicle detection using machine learning model with the Gaussian Mixture Model (GMM)" has been completed.

Overall, the reviewers were impressed with the quality of your work and the potential impact of your research. However, they also provided a number of suggestions for improvement and further clarification, which are detailed in the attached review report.

We encourage you to carefully consider all of the comments and recommendations made by the reviewers and make any necessary revisions to your manuscript. Once you have made the requested changes, please submit a revised version of your manuscript for further consideration.

We appreciate your attention to these matters and look forward to receiving your revised manuscript. Sincerely, Editor

Reviewer A:

1. What other motion tracking methods were considered before settling on the Gaussian Mixture Models (GMM) method?

2. How was the accuracy of the GMM method in separating the background and the tracked object evaluated?3. How were the pixel data grouped in the GMM method and what criteria were used to determine the most common distribution as the background?

4. Are there any limitations to the GMM method in motion tracking, and if so, how were they addressed in the study?

5. Can you provide more information about the conditions under which the GMM method was tested, such as the type of traffic, lighting conditions, and camera placement?

Reviewer B:

How does the GMM method compare to other methods in terms of computational cost and processing time
 Can you provide more information on the dataset used in the study, including the source and the number of videos used?
 How does the proposed method compare to the state of the art on motion tracking
 Are there any further experiments that you recommend to validate the performance of the proposed method?

5. Are there any applications in the real-world using this method for traffic monitoring or other use cases?

5. Submit Revisi : 30 November 2022 : [JoWUA] - Send Revisions Paper



#### **Send Revisions Paper**

1 pesan

Rika Rosnelly <rikarosnelly@gmail.com>

30 November 2022 13.24

Kepada: JoWUA <editor@jowua.com>

Dear Editor,

Here I send a revision article for my paper ID 9925227 with title "Vehicle Detection Using Machine Learning Model with the Gaussian Mixture Model (GMM)". Thank you.

**Best Regards** 

**Rika Rosnelly** 

Full Paper Rika Rosnelly-Revision.docx

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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.





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.





Figure 3. Detected cars of scenario 1

Table	1. I	Results	of S	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.



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.



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:

Scenario	Density Level		Data Difference
Movie	System	Actual	
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		92.1	1%



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 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.

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

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*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.





(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.



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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.
- 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;
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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;
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The following are the outcomes of testing the video scenario:





Table 3. Results of Scenario 3		
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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;
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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	Density Level		Data Difference
Movie	System	Actual	
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.

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