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Indicator of Highway Conditions on Traffic Density Levels

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ABSTRACT

Traffic problems, especially congestion which is the impact of high levels of traffic density, are problems that have not been properly resolved, especially in big cities in Indonesia. In this article, 7 features of road conditions are proposed on the level of traffic density. These features include the number of vehicles, the average speed of the vehicle, the area of the main road, the length of traffic that has been determined, the duration of traffic congestion, and the time of traffic congestion. Determining the level of traffic density can be determined by utilizing the MCDM hybrid technique to produce information that can be used to support decision-making in traffic management or other policies such as formulating policies on the buying and selling of private vehicles. The number of indicators related to computer vision for presenting information on the level of traffic density requires a large amount of time and memory. Besides that, the perception of a decision maker in determining priority weights also influences the results of the information on the level of traffic density.

Keywords : computer vision, decisions, rankings, traffic jams.

1. INTRODUCTION

Generally, a smooth flow of traffic is expected by many road users without congestion. This traffic jam has a negative impact on road users' time to work or study, psychologically, vehicle operating costs (Sitanggang & Saribanon, 2018), and even causes increased air pollution (Sulistiyono, 2022). The ease with which the Indonesian people purchase vehicles on credit has led to an increasing number of vehicles and they prefer private vehicles compared to public transportation. This is one of the triggers for traffic jams, especially when activities start and end activities outside the home. Attempts to deal with traffic congestion have carried out many studies on the topic of traffic management (Gomides et al., 2020). Several things must be considered in managing congestion, such as the need to know the number of vehicles, detect the type of vehicle, track the vehicle, and estimate the speed of the vehicle. Vehicle detection uses the YOLO framework (Gomaa et al., 2022; Neupane et al., 2022; Perafan-Villota et al., 2022). This frame underwent framework innovation to improve its performance in object detection such as YOLOv2, YOLOv3, YOLOv4, and YOLO5 and of course, YOLOv5 has the best performance compared to others in the YOLO Family (Y. W. Chen & Shiu, 2022). It is not enough just to detect vehicles, other studies have also observed vehicle tracking using (Y. Chen & Hu, 2020; Perafan-Villota et al., 2022). Vehicle tracking is intended to find out the level of road congestion based on the average vehicle speed and type of highway which is divided into 3 types, namely highways (expressways), main roads, and secondary roads (branches) (Xing et al., 2019). Furthermore, the type of vehicle also affects road capacity. Trucks and buses are vehicles that have outside areas that can cause a greater level of congestion (Alfani et al., 2020). And visually, the average speed of the vehicle indicates the smoothness of the traffic. The slower the vehicle speed, the more indications that there is congestion in certain road areas, but it is possible that in certain areas regulations are enforced to reduce vehicle speed to a certain maximum limit. This research was conducted to support decision-making in managing traffic

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flow. The relevant field of knowledge for this is the decision support system (DSS). In this problem, DSS is based on several parameters known as Multi-Criteria Decision-Making (MCDM) which have (Jayady et al., 2021).

2. RESEARCH METHOD

Traffic management especially dealing with traffic jams depends on several influencing factors. In this study, 4 indicators are categorized in determining the level of traffic density which is divided into 6 types of density levels (Kholik et al., 2020) which are presented in table 1.

Table 1 Traffic Density Level

Level	Conditions
A	With free traffic flow, low traffic volume, and high speed, the user can choose the desired speed
B	Steady traffic flow and slightly limited speed due to increased traffic volume
C	Steady traffic flow and speed controlled by traffic volume
D	Unstable traffic flow and low speed
E	Unstable traffic flow, low speed, and traffic volume approaching capacity
F	Traffic flows are severely obstructed, very low speed, many vehicles stop, and traffic volume overcapacity

2.1 The Traffic Density Indicator

The traffic density indicator has 7 features, namely the number of vehicles, their type, the average of the average speed of each vehicle, road area, road length, duration, and time.

- Number of Vehicles
  Information on the number of vehicles on the road is very helpful for traffic officers to manage traffic flow. Identification of the number of vehicles using the Gaussian Mixture Model (GMM) method. This method can process background extraction. In GMM, each pixel in the frame is modeled into a Gaussian distribution. Its intensity distinguishes each pixel in RGB (Red, Green, Blue). Then each pixel is calculated as a foreground or background value using the following equation (Lahinta et al., 2019):

$$P(X_t) = \sum_{i=1}^{k} \omega_{i,t} . n(X_t, \mu_k, \Sigma_{i,t}) \quad (1)$$

Notation:
P(Xt) = probability for pixel (x, y) at time t.
K = the most used component or model.
ωi,t = weight to be distributed to K in frame t.
μk = mean of distribution to K in frame t.
Σi,t = covariance matrix.

- Vehicle Type
  Each vehicle has a different size so a busy road does not only depend on the number of vehicles but the type of vehicle also affects the level of road density. Determination of the type of vehicle can be obtained by the classification method. Previous research stated that in classifying vehicle types, the Gaussian Mixture Model (GMM) method can also be used to classify motorcycles, minibusses/mini trucks, and buses/trucks (Putra et al., 2018). The calcification concept is divided into 3 stages after video extraction, namely the process of framing, frame binary, and identification of vehicle types. In the framing process, GMM is used to get the background in the form of a grayscale image. Next is smoothing and shadow removal. The binary frame stage is carried out to find the foreground pixels and foreground pixels then add up the pixel values to be classified based on the number of foreground pixels. In the final stage identification of the type of vehicle through labeling.

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- Estimation of Average Vehicle Speed
  The higher the volume of vehicles on a road section, the slower or lower the average speed of traffic vehicles (Agustina et al., 2022). The estimated average speed of the vehicle can be known from the number of frames needed to enter and exit objects labeled with the distance traveled. The Euclidean distance from the centroid of the nth frame and (n − 1) gives the distance traveled by each object (vehicle). The video frame rate is multiplied by the total number of frames. From this total time and distance, speed can be measured and mapped in real-time through equation 2 (Moazzam et al., 2019).

$$Speed = \frac{\propto \times distance}{(Frame(n) - Frame(n-1)) \times FrameRate} \qquad (2)$$

  The value ∝ is a calibration coefficient that maps the image to the object's movement and can be calculated by comparing the actual height of the vehicle with the height of the vehicle in the image.

- Road Area
  This indicator also has a role in the level of traffic density which influences decision-making in traffic management. The width of the road sections that are wide or large does not rule out the possibility of traffic congestion because it is possible to be filled with vehicles that are classified as large vehicles such as buses, trucks, and the like. Vice versa, the small road area does not rule out the possibility of traffic congestion because it is only passed by vehicles with small types of vehicles such as motorbikes and cars. The area of this road section aims to determine the ratio of road volume or capacity which correlates with other indicators, namely the number of vehicles, the speed of each vehicle, and other types of vehicles.

- Length
  The longer the road where traffic congestion occurs, the more severe the traffic density will be (Haramaini et al, 2018) because it is possible that traffic management has not yet been handled.

- Duration
  Traffic density also depends on how long traffic congestion occurs (Tasliyah Haramaini et al., 2018). The stopping of vehicles on roads can be due to traffic jams or being stopped as a result of traffic lights or priority factors for road users.

- Time of Traffic Flow
  In general, road users start their activities on the highway in the morning and end in the afternoon (work hours) so high traffic density can occur (Satoinong et al., 2019). But when it's not working hours, the highway will be quiet. This also affects traffic management decision-making regarding the handling of traffic flow. At any time other than working hours if there is traffic congestion, traffic accidents, natural disasters, or other factors can occur.

Giving a value to each traffic density indicator can be done in a way as presented in table 2.

Table 2 Traffic Density Indicator

No.	Indicators	Description	Unit
1.	Number of vehicles	The presence of vehicles in the designated traffic area. The value is a positive integer.	items
2.	Vehicle types	Types of vehicles such as trucks, buses, cars, motorbikes, and others. This indicator can be connected to the number of vehicles indicator so that the number of vehicles is more specific according to the type. This means that the vehicle type indicator can be split according to the total type of vehicle and	-

		equipped with the number of vehicles according to their type.	
3.	Average of vehicle speed	The average of average speed of each vehicle is obtained from the results of the comparison of the distance traveled in a certain time.	m/s
4.	Area	The traffic area defined in the identification of the level of traffic density	m^2
5.	Length	Predefined traffic length. This indicator has relevance to broad indicators.	m
6.	Duration	Duration of traffic jam	jam
7.	Time	When there is a traffic density that can be categorized to be quantified so that it is easier to do calculations. For example, 24 hours are categorized into 8 categories: a. At 00-03.00 AM with a value 0.2 b. At 03-06.00 AM with a value 1 c. At 06-09.00 AM with a value 0.8 d. At 09-12.00 AM with a value 0.6, etc.	-

2.2 Multi-Criteria Decision-Making (MCDM) Technique

The MCDM technique is widely used for optimal decision-making with several parameters that are more than 1. The MCDM technique utilization must also measure the level of algorithm performance such as the algorithm's ability to solve problems, the level of optimization of the solution of the algorithm used, and the calculation time and memory space required in the use of algorithms (Patel & Pathak, 2018). The stages in using the MCDM technique include:

- Data normalization
  The amount of data affects the use of database storage, besides that it causes calculations in the algorithm to become more complex and heavy. The data normalization process is used to minimize storage usage and calculations in the algorithm. The normalization process depends on the type of attribute used which is divided into 2 types, namely costs and benefits. The type of cost attribute is an attribute that has an impact that can be realized in nominal value, while the type of benefit attribute is an attribute that has an impact that can be realized with a benefit value. Previous research stated that there are 8 types of data normalization techniques in DSS (Jahan & Edwards, 2015) which are presented in table 3.

Table 3 Normalization Techniques

Model	Attribute Types	
	Cost	**Benefit**
Max-min	$n_{ij} = \frac{r_{max} - r_{ij}}{r_{max} - r_{min}}$	$n_{ij} = \frac{r_{ij} - r_{min}}{r_{max} - r_{min}}$
Vector	$n_{ij} = 1 - \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}}$	$n_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}}$
Linier	$n_{ij} = \frac{\frac{1}{r_{ij}}}{\sqrt{\sum_{i=1}^{m} \frac{1}{r_{ij}}}}$	$n_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}}}$
Logarithmic	$n_{ij} = \frac{1 - \frac{ln(r_{ij})}{ln \prod_{i=1}^{m} r_{ij}}}{m-1}$	$n_{ij} = \frac{ln(r_{ij})}{ln(\prod_{i=1}^{m} r_{ij})}$

- The weighting of the priority level of the attributes or decision support parameters.

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The weighting of the attribute priority level is the giving of the attribute priority value to the amount of contribution or impact on a decision. This weighting is scaled within the range of 0% -100% with the condition that all attribute weighting values add up to 100%. Conversely, you can equalize the weight values by comparing each attribute weight value to all weight values and then multiplying it by 100, or what is known as conversion (Rosita et al., 2019). Determination of attribute weights is carried out by decision makers based on their expertise or experience or the provisions of the MCDM technique which are hierarchical as in the AHP technique which has standard priority weights 1-9 (Thomas L. Saaty, 2008).

- Ranking alternative solutions

  The MCDM technique is divided into 7 types, including Analytical Hierarchy Process (AHP), Et Choice Translating Reality (ELECTRE), VIšekriterijumsko KOMpromisno Rangiranje (VIKOR), Weight Sum Model (WSM) or Sum Additive Weighting (SUM) & Weight Product Model (WPM), hybrid MCDM, aggregation methods, Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Decision Making Trial and Evaluation Laboratory (DEMATEAL) (Eltarabishi et al., 2020). However, the MCDM technique that is often used in 2015-2019 is Hybrid MCDM. This technique is a combination of MCDM techniques such as the combination of the AHP and TOPSIS methods for selecting outstanding librarians (Saputra, 2017). Weighting using the AHP method. The researcher stated that the use of AHP is considered effective in reducing the level of subjectivity of decision-makers. The weight value given by the decision maker on the attribute affects the decision result. While the ranking process using TOPSIS produces the final value in the form of a ranking according to predetermined attribute weighting.

3. RESULT AND DISCUSSION

In handling traffic to the level of traffic density, priority handling is needed. This requires priority weighting of traffic density indicators. The use of AHP technique is a method used for weighting the priority level of each of these indicators by comparing the priority level of each indicator to other indicators so that a comparison matrix between indicators is formed. This matrix measures the same number of rows and columns (square matrix) so that the diagonal value in this matrix is guaranteed to be 1. The resulting priority weight is the sum of the comparison values for each column, each of which has been normalized. In the AHP theory there, are 9 indicators used (Thomas L. Saaty, 2008), namely:

- Equal importance
- Weak or slight
- Moderate importance
- Moderate plus
- Strong importance
- Strong plus
- Very strong or demonstrated importance
- Extreme importance
- Absolute very important of The results of the obtained indicator priority weighting can be used to rank the level of traffic density using the TOPSIS technique. The stages are as follows:
- Each value resulting from normalized data is multiplied by the priority weight according to the indicator.
- Search for the maximum and minimum values for each column from the results of the first stage as positive ideal values (D+) and negative ideal values (D-).
- Finding the distance of each data to the positive ideal value and negative ideal value so that at this stage 2 solution tables (positive solution table and negative solution table) are obtained with the same matrix size as in the first stage.
- Search for the value of the final solution (V), namely by comparing the value of the negative solution with the sum of the value of the positive solution and the value of the negative solution. The highest V value is the result of the highest ranking or the highest level of density and vice versa.

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4. CONCLUSIONS

Features of road conditions on the level of traffic density consist of 7 indicators namely number, type, average speed, area, length, duration, and time. The large number of indicators that involve several methods related to computer vision requires a complex calculation process that requires considerable time and space. Meanwhile, priority weighting based on the perception or experience, or expertise of a decision-maker can affect the level of traffic density. Therefore we need a systematic priority weighting standard to produce an intelligent system with the concept of thinking humanely. The existence of information on the level of traffic density can be used as material for consideration in traffic management but it is possible that it can be used as a basis for the formulation of a policy on buying and selling of private vehicles by the government.

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