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Navigating Traffic: A Survey of Techniques and Challenges in Congestion Detection

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ABSTRACT

Traffic congestion is a pervasive problem in urban areas due to the increasing number of people owning vehicles each year. The consequences of congestion include air pollution, increased fuel consumption, and wasted time and money. Therefore, traffic congestion detection is vital for effectively monitoring and managing traffic flow. Moreover, congestion detection can aid in the development of several applications, including Intelligent Transportation Systems (ITS), traffic management, emergency services, and environmental management. Researchers have utilized various approaches in the past to alleviate or resolve congestion. This paper highlights several recently proposed techniques for detecting traffic congestion. Additionally, it discusses five potential challenges that may arise for further improvement in the future: traffic features, congestion levels, traffic scene factors, real-time detection, and location scalability.

Keywords:
Traffic congestion detection; intelligent transportation systems; congestion detection technique

1. Introduction

Road transport is the most common form of long-distance mobility in this era. With the development of urbanization in various regions, the number of people owning vehicles is increasing year by year. According to a report from the New Straits Times in 2022, since 2019, the number of registered vehicles has exceeded the total population, with a growth of at least 1 million vehicles per year in Malaysia [1]. The rise in the number of vehicles on the road increases the occurrence of road traffic accidents, which in turn exacerbates traffic congestion [2]. Consequently, under the traffic congestion situation, the traffic accident rates will grow owing to increased traffic volume [3]. Apart from the increase in the number of registered vehicles, other factors such as weather conditions, physical road conditions, traffic control management, driving behaviour, and construction activities also contribute to the emergence of traffic congestion [4, 5].

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Traffic congestion is commonly defined as a situation where travel demand exceeds road capacity in the state of traffic flow [6]. It is typically divided into two types: recurrent and non-recurrent congestion. Recurrent congestion is a pattern of traffic that occurs consistently during the same peak travel period, usually during the morning and evening rush hour, which coincides with the peak time for school and work. On the other hand, non-recurrent congestion is an unexpected event that occurs without a consistent pattern. Examples of non-recurrent congestion include vehicle breakdowns, adverse weather events, vehicular crashes, and roadway construction.

The existence of traffic congestion brings about several issues, including air pollution, fuel consumption, as well as wasted time and money [5]. When traffic congestion occurs, the movement of vehicles changes frequently in line with the traffic queue. More gasoline or diesel fuel is consumed due to constant changes in vehicle motion. The higher the fuel consumption, the more air pollution gases are emitted, especially particulate matter (PM_{10}) and carbon dioxide (CO_2). A study conducted in 2020 showed that PM_{10} emissions are the main pollutant of traffic congestion [7]. Furthermore, more money must be spent refilling the vehicle with gasoline or diesel due to the increased fuel consumption. When motorists are stuck on a stretch of road because of congestion, their expected arrival time at their destination is delayed, preventing a lot of work from being completed in advance.

To alleviate traffic congestion, ITS have been developed by integrating information and communication technologies with transportation systems to efficiently manage and monitor traffic and transportation in terms of mobility, safety, and the environment. Some examples of current emerging technologies focused on ITS are vehicular ad hoc networks (VANETs), deep learning, sensing, Global Positioning System (GPS), data fusion, route planning, Internet of Things (IoT), and video cameras [8].

In past literature, numerous novel approaches and improvements have been proposed to detect traffic congestion more efficiently, with the aim of developing ITS. However, several challenges or issues also exist in these proposed methodologies. In this review study, we will discuss the recently proposed methodologies and their challenges. It is worth emphasizing that we focus on both traffic congestion estimation and detection as the field of interest in this paper. Hence, we conducted our search using three phrases and Boolean operators: 'traffic congestion detection' and 'traffic congestion estimation', without 'prediction', using the Scopus database. By restricting the search to journal papers published between 2018 and 2022, we identified 133 documents that met our criteria. We then manually filtered and selected appropriate papers for reviewing.

The rest of this paper is structured as follows: In Section 2, various congestion detection techniques are described. The challenges of these proposed methods are discussed in Section 3, while the conclusion is presented in Section 4.

2. Detection Techniques

2.1 Image Processing

Traffic congestion can be estimated or detected using images or video recordings from surveillance cameras on roads in accordance with image processing methods. Nonetheless, bad weather, such as rain or fog, can potentially affect the accuracy of existing automatic traffic congestion detection methods. To address this issue, Cheng *et al.,* [9] used two algorithms: the discrete-frame difference and histogram equalization. The discrete-frame difference algorithm analysed vehicle motion features to extract vehicle images by comparing the grey level differences between frames. The purpose of using the histogram equalization algorithm was to enhance the contrast of the vehicle images. This was achieved by applying Eq. (1), which represents the grey mapping relationship of the traditional histogram equalization algorithm. In the analysis of processing time, histogram equalization had a shorter processing time compared to other methods, including conversion based on retinex, median fuzzy filter, readjust brightness method, dark channel prior, and neighbourhood average. By using discrete-time difference in the congestion detection, the computation time, resource consumption, and accuracy were improved by 37%, 11%, and 74%, respectively compared to background subtraction.

$$s_i = (L-1)\sum_{k=0}^{i}\frac{n_k}{N} \tag{1}$$

In Eq. (1), L is the number of grey levels in the original image, i is the greyscale value of the pixel, n_k is the number of pixels with the k^{th} greyscale value, N is the total number of pixels, and s_i is the new greyscale value of the pixel in the enhanced vehicle image.

Some traditional methods for detecting traffic congestion can be difficult and costly to implement. Ke *et al.,* [10] addressed these challenges by employing the grey level co-occurrence matrix (GLCM) and pyramid Lucas-Kanade optical flow to extract traffic density and traffic velocity, respectively. The GLCM describes the spatial relationship between pairs of pixels in an $M \times N$ image based on the greyscale value of the pixels I (x, y), the relative distance between the pixel pair d, and the relative direction θ, which can be represented by Eq. (2). In their work, instead of using the whole GLCM feature, the contrast characteristic of GLCM *Con* was extracted by applying Eq. (3) to increase the calculation speed for traffic density.

$$P_{d,\theta}(i,j) = \sum_{x=1}^{M}\sum_{y=1}^{N}[I(x,y)=i][I(x+d\cos\theta, y+d\sin\theta)=j] \tag{2}$$

$$Con = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}(i-j)^2 P_{d,\theta}(i,j) \tag{3}$$

where [ ] denotes the Iverson bracket, N_g represents the number of grey levels in the original image, and $P_{d,\theta}(i,j)$ is the GLCM value at position (i, j).

The pyramid Lucas-Kanade optical flow method constructs an image pyramid by repeatedly downsampling the original image. The method computes traffic velocity v within a sliding window of size $n \times n$ in the region of interest (ROI) at each pyramid level starting from the coarsest level to the finest level. Nevertheless, including all image pixels in the computation would reduce the computation speed. To alleviate this problem, corner pixels were the only ones tracked in their work.

Li *et al.,* [11] proposed a method to detect traffic congestion by treating it as a dynamic process and accumulating short-term congestion states from three region levels: segment, lane, and cell. They utilized the pyramid Lucas-Kanade optical flow method to eliminate speed calculation errors caused by tracking ID switching and combined it with a frame bounding box smooth (FBBS) module to group and smooth the bounding box of five consecutive frames, thus solving wide speed fluctuations caused by small intervals between two selected frames.

In summary, various image processing methods, such as histogram equalization, discrete-frame difference, and pyramid Lucas-Kanade optical flow, have been applied in traffic congestion detection for feature extraction, vehicle identification, or performance improvement. Table 1 lists a summary of the image processing methods discussed.

Table 1
Summary of image processing methods

Reference	Image processing methods
[9]	Discrete-frame difference, histogram equalization
[10]	GLCM, pyramid Lucas-Kanade optical flow
[11]	Pyramid Lucas-Kanade optical flow, FBBS module

2.2 Deep Learning

In addition to image processing techniques, deep learning methods have recently gained attention from academics in various fields due to their excellent processing speed and accuracy [12]. Among various types of deep neural networks, the convolutional neural network (CNN) is the most commonly used. The most representative object detection algorithm that uses CNN is the You Only Look Once (YOLO) algorithm [13].

In a study conducted by Chakraborty *et al.*, [14] the entire traffic images were used as input for YOLO and CNN to classify congestion, rather than determining the number of vehicles. Both YOLO and CNN achieved an improved accuracy of about 5% compared to the support vector machine (SVM), which had an accuracy of 85%. YOLO achieved a slightly higher accuracy of 1.2% compared to CNN, which had a structure of four convolution layers and two max pooling layers with dropout and data augmentation for overfitting prevention. Despite this, several limitations still need to be addressed in the future, such as binary classification, traffic scenes at nighttime, congested areas far from the camera, and glare issues.

In a recent study by Ribeiro *et al.*, [15] YOLOv2 and Faster-CNN were used for vehicle detection in traffic classification. ResNet-101 was adopted as the backbone model for feature extraction in Faster-CNN. Two vehicle monitoring combinations, YOLOv2 with Kalman filter and Faster-CNN with DeepSort, were tested for classifying congestion. The proposed method involved three steps: vehicle monitoring, feature extraction, and classification, as shown in Figure 1. The study found that both methods achieved 98% accuracy using a random forest (RF) classifier.

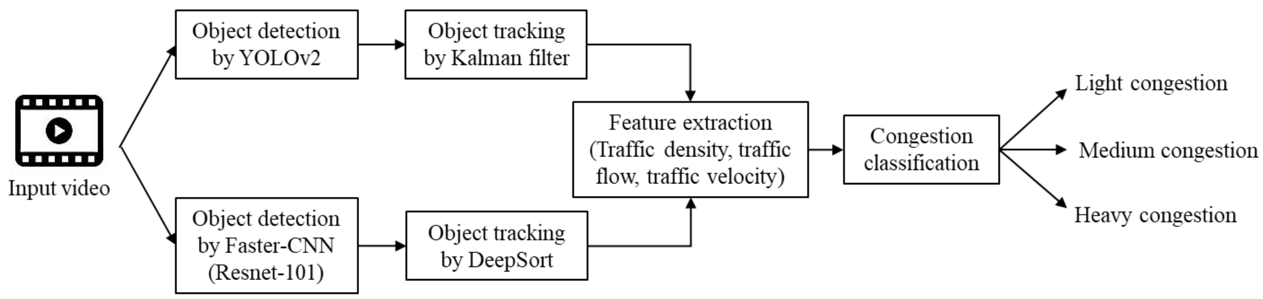

Fig. 1. Flow of the method proposed by Ribeiro *et al.,* [15]

On the other hand, Faster-CNN was also utilized by Gao *et al.,* [16] and Roess *et al.,* [17] as the main framework to estimate traffic congestion by treating it as a regression problem based on Level of Service (LOS). The VGG-16 backbone model was used to extract feature maps from input traffic images. To improve accuracy, traffic density and occupancy were respectively applied as input to reflect spatial and temporal congestion. While the model achieved a precision, recall, and F-measure of about 99%, it did not account for traffic scenes captured from various camera angles and did not consider additional vehicle features such as driving behaviour and traffic velocity.

YOLOv4 was adopted by Li *et al.*, [11] along with Simple Online and Realtime Tracking (SORT), to detect the sequence of vehicle positions in image frames before estimating traffic flow, average speed, and occupancy rate. With the help of the pyramid Lucas-Kanade optical flow and the FBBS module (discussed in Section 2.1), the accuracy and speed of YOLOv4 with SORT were improved, and it performed slightly better than YOLOv3 with SORT. However, the study did not explore congestion prediction or different camera data fusion, even though YOLOv4 with SORT achieved a precision rate of approximately 97%.

A CNN model was utilized by Jilani *et al.,* [18] to classify traffic congestion, with the assistance of Generative Adversarial Networks (GAN)-based data augmentation. The model comprised five convolution layers, three max pooling layers, and a fully connected layer, with incorporated dropout layers to prevent overfitting. The input and output of the model were greyscale traffic images and congestion states (congested or non-congested), respectively. Due to the low-quality images in the collected dataset, the GAN model proposed in a previous study [19] was used for synthetic augmentation followed by common techniques such as horizontal and vertical flipping. The GAN-CNN method achieved over 97% in terms of precision, recall, precision, and F1-score. However, further exploration is required for multiclass classification and nighttime traffic scenes to enhance reliability.

Another CNN model was developed by Chakraborty *et al.,* [20] to assess traffic congestion using remote sensing satellite images. The model consisted of a convolutional layer, two max pooling layers, and five fully connected layers to identify and measure vehicle area. The optimal number of fully connected layers was determined based on the highest F1-score. Vehicles were detected and masked within a moving window from the extracted satellite road image. The CNN model calculated the total vehicle area to compute the traffic density for binary congestion classification. Compared to ResNet-18 [21] and CNN [22], the proposed model had a higher accuracy (99%) and shorter processing time. However, it was only applicable to highways and main roads, making it less scalable for rural areas.

Several studies have used CNNs as a feature extractor instead of using them for the entire congestion detection process. For instance, the traffic occupancy and traffic flow features were extracted by Ke *et al.,* [10] using a GMM-CNN model. Furthermore, the VGG-19, GoogleNet, Inceptionv3, and ResNet-101 were adopted by Abdelwahab *et al.,* [23] to extract local texture features with the LTR method. Among these models, ResNet-101 achieved the highest accuracy (95%) when extracting texture features from a batch of five frames.

A deeply supervised inception network (DSIN) with an attention proposal module (APM) was introduced by Sun *et al.,* [24] to mitigate environmental factors in traffic congestion detection. The APM cropped the ROI by analysing binary edge density in images. The DSIN used Inception-v3 as the backbone model and received the cropped images as input, outputting binary congestion states. The DSIN consisted mainly of three inception modules and two grid size reduction modules. The number of parameters in the DSIN was reduced by replacing large convolutions with smaller factorized convolutions in inception modules. With several modifications to the original Inception-v3 and affine transformation of the dataset, the accuracy of DSIN with APM achieved up to 99% compared to standalone DSIN, modified AlexNet, and modified VGGNet. The proposed model is applicable for real-time detection due to its short mean time detection, but future work can integrate ROI extraction with deep features.

In short, different types of YOLOs, Faster-CNNs, and CNNs were applied to enhance the accuracy and processing time of the congestion detection system. Deep learning methods not only played the role of the main detection framework but were also used as feature extractors. Table 2 provides a summary of the deep learning methods discussed.

Table 2
Summary of deep learning methods

Reference	Deep learning methods
[14]	YOLO, CNN (4 convolution layers, 2 max pooling layers)
[15]	YOLOv2, Faster-CNN (ResNet-101)
[16]	Faster-CNN (VGG-16)
[11]	YOLOv4
[18]	CNN (5 convolution layers, 3 max pooling layers, 1 fully connected layer)
[20]	CNN (1 convolution layer, 2 max pooling layers, 5 fully connected layer)
[10]	GMM-CNN
[23]	VGG-19, GoogleNet, Inceptionv3, ResNet-101
[24]	DSIN

2.3 Machine Learning

Machine learning is a subfield of artificial intelligence that enables computer systems to learn patterns, relationships, and insights from data without explicit programming. This capability enhances the performance of machines on various tasks by learning from the provided data. The process involves training a model on a dataset to identify patterns and relationships and using the model to make predictions or decisions on new data. Machine learning methods have been used in recent years to study traffic congestion detection, addressing related problems, and demonstrating the feasibility of respective techniques.

The proposed congestion detection methodology by Sony *et al.,* [25] addressed the limitations of existing methods in handling large datasets by normalizing the collected data and optimizing it using the Whale Optimization Algorithm (WOA) to obtain optimal feature values. A Multi-SVM (MSVM) was used instead of SVM, which is limited to binary classification, to classify congestion into four types. It was found through qualitative analysis that the accuracy, precision, and recall were slightly improved by the WOA-MSVM method compared to MSVM, and slightly better accuracy and recall were exhibited than the McMaster with gradient descent-based particle swarm optimization (GPSO) method. Further studies can explore the integration of other optimization algorithms with MSVM to improve its performance.

Two traditional SVM classifiers, SVM-1 and SVM-2, were applied by Abdelwahab *et al.,* [23] to classify traffic congestion based on texture and motion features, respectively. During training, each classifier was trained separately using their corresponding features. In the testing phase, the output from each classifier was combined using the kernel trick technique. The aggregation process employed a linear kernel and a radial basis function (RBF) kernel for texture and motion features, respectively, and the result was classified into one of three congestion classes. The proposed method achieved a high accuracy of approximately 97%. Future research can explore other aggregation techniques and test the method on other traffic scenes to improve scalability verification.

An audio-based RF classifier was proposed by Gatto *et al.,* [26] for distinguishing between congested and non-congested traffic by segmenting video footage, extracting and filtering audio, and generating feature vectors based on Mel Frequency Cepstral Coefficient (MFCC) analysis. The process of generating training and testing sets for the RF classifier is displayed in Figure 2. The RF classifier achieved over 90% accuracy, but recording sources on different highway lanes must be placed far apart to prevent sound interference.

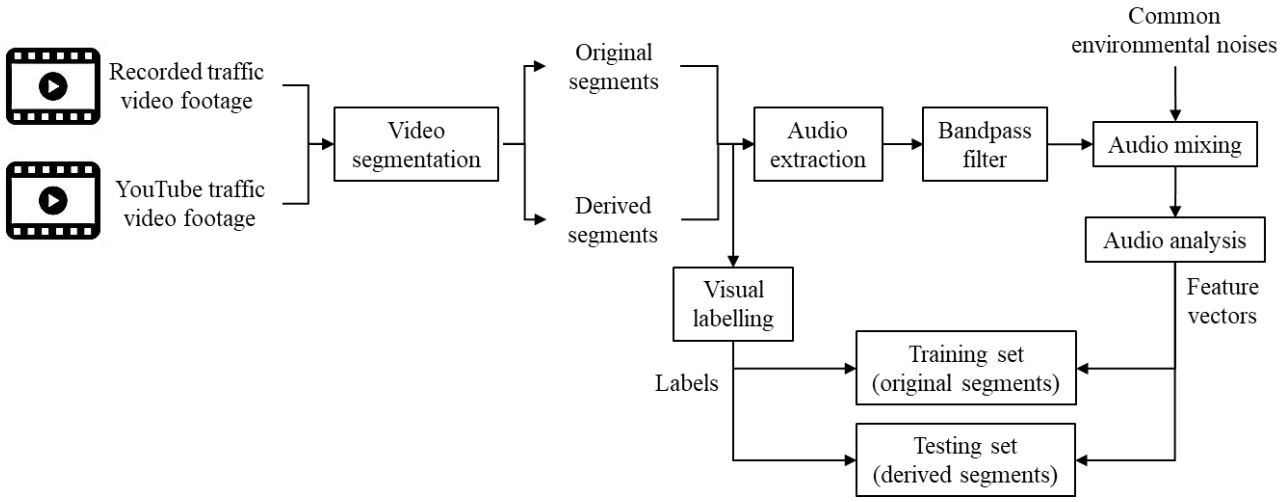

Fig. 2. Process of generating training and testing sets for the RF classifier [26]

Classifiers are crucial for detecting congestion and supporting various frameworks. In a study by Ribeiro *et al.,* [15] SVM, multi-layer perceptron (MLP), and RF classifiers were used to enhance the classification process of YOLOv2 and Faster-RCNN models. The RF classifier demonstrated the highest accuracy, indicating its potential for improving object detection models. This study emphasizes the importance of using different classifiers to improve accuracy and efficiency in object detection frameworks.

Locality constraint distance metric learning (LCML), a novel approach that integrates locality constraint with distance metric learning to minimize the influence among different traffic scenes, was proposed by Wang *et al.,* [27]. LCML enhanced metric learning performance by considering only the neighbours of testing samples. Local Binary Pattern (LBP) was used for low-level features and kernel regression (KR) was used for classification. LCML outperformed linear regression (LR), KR, local linear embedding (LLE), robust principal component analysis (RPCA), and metric learning for kernel regression (MLKR), in terms of mean absolute error (MAE) and mean squared error (MSE). However, incorporating density-based features and hierarchical models may further improve congestion classification precision.

Several clustering methods have been employed for traffic congestion detection. Mohanty *et al.,* [28] compared K-means clustering, Fuzzy C-means (FCM) clustering, and Fuzzy K-means (FKM) clustering in VANET using the Simulation of Urban Mobility (SUMO) simulator. These methods clustered speed, fuel consumption, and CO_2 emission data collected from onboard units (OBUs) in vehicles. K-means clustering had the shortest computation time as it did not use fuzzy logic, while FCM and FKM clustering took longer to produce similar results to K-means clustering. FKM clustering had the lowest inter-cluster distance and the highest potential for congestion detection. However, future research shall also consider brake frequency and weather as factors.

Clustering methods combined with fuzzy logic have been used to identify traffic congestion. Rui *et al.,* [29] conducted a study where vehicles within communication range of roadside units (RSUs) were clustered, and a cluster head (CH) was selected. Information collected from the cluster heads was used to assess average speed, traffic density, and average stop delay in a fuzzy assessment process.

Self-organizing map (SOM) was applied by Gu *et al.,* [30] to cluster and classify road segments between bus stops (RSBs) based on three traffic parameters: bus dwell time (BWT), average travel speed (ATS), and travel efficiency (TE). The cluster with the highest congestion index was identified as the congested RSBs. Correlations between the ATS of taxis and buses and the average operation speed of buses were used to validate the reliability of the congested RSBs. This study could be expanded to evaluate other public transport options and assess performance using multiple metrics.

Machine learning has emerged as a promising solution for traffic congestion detection. Classifiers and clustering methods are the predominant approaches used in this domain, regardless of whether the problem is treated as a classification or regression task. These methods have been proposed individually or in combination with other techniques to improve performance. The discussed machine learning methods are listed in Table 3.

Table 3
Summary of machine learning methods

Reference	Machine learning methods
[25]	WOA-MSVM
[23]	SVM
[26]	RF
[15]	SVM, MLP, RF
[27]	LCML
[28]	K-means, FCM, FKM clustering
[29]	Vehicle clustering
[30]	SOM

2.4 Fuzzy Logic

Fuzzy logic deals with uncertainty and imprecision in data, allowing for values between 0 and 1 to represent degrees of truth, making it useful for complex systems such as traffic congestion detection. Variables are assigned membership functions that describe their degree of belonging to a set, which can be used for fuzzy inference and control. Fuzzy inference involves decision-making based on fuzzy system rules, whereas fuzzy control uses fuzzy logic to regulate the output of a system.

A comprehensive fuzzy assessment method was developed by Rui *et al.,* [29] after the implementation of vehicle clustering. Each evaluation factor had a trapezoidal membership function assigned based on the clustered data. Congestion degrees were categorized into four levels (free-flow, slight, moderate, severe) according to driver acceptance and the traffic evaluation index system in China. The weight of factors was determined by linearly combining the analytic hierarchy process (AHP) and entropy method (EM). The fuzzy result was obtained by multiplying the weight set with a single factor evaluation set and was decided based on the maximum membership degree principle. The method had high stability compared to a single factor and provided accurate congestion determination aligned with the actual traffic situation. The prerequisite for these advantages is that each vehicle must have GPS for data communication.

A fuzzy controller was developed to improve vehicle detection accuracy in congested traffic by using vehicle speed and density data collected via vehicle-to-vehicle communication [31]. The controller utilized speed and density membership functions to calculate local congestion levels and generate a four-level congestion rating. A total of 16 fuzzy rule relations were generated to improve congestion detection accuracy. The local congestion level was determined based on the output value of the congestion level, and the regional congestion level was identified using hypothesis testing based on adjacent vehicle response messages. The method was found to have higher accuracy than other methods and lower back-off time slots and network overhead than cooperative traffic congestion detection (CoTEC), but was limited by a single hop of dedicated short-range communications (DSRC) communication for long road segments. Figure 3 illustrates the process flow of the method.

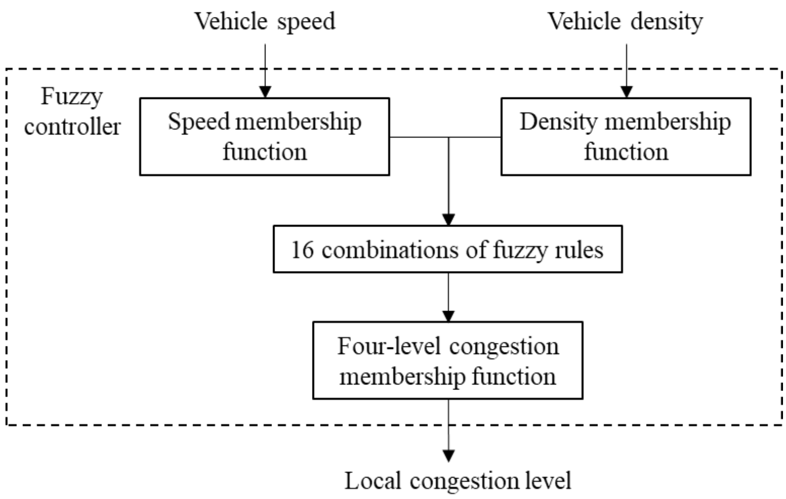

Fig. 3. Method applied by Wang *et al.,* [25]

A fuzzy inference model was introduced by Kalinic and Jukka [32] with linguistic rules as a foundation to overcome limitations of the conventional mathematical approach for evaluating traffic conditions, which cannot account for unexpected traffic situations and individual driver behaviour, resulting in inaccuracies and uncertainties. The model utilized two traffic parameters, traffic flow and density, and assigned seven level triangular membership functions to fuzzify both input and output parameters. The inputs were combined using if-then fuzzy rules with an AND operator, and a Mamdani implication operator was applied to truncate the output fuzzy set. The maximum aggregation operator was employed to combine the outputs of each rule, and the aggregated output was de-fuzzified using the centroid method. Although the proposed model could detect congestion levels of road segments and lanes, it lacked a performance evaluation and assigned identical weights to flow and density without considering road conditions.

After reviewing various fuzzy logic approaches, different fuzzy membership functions, such as trapezoidal, speed, and density, were utilized to fuzzify the input and output variables. The relationship between the input and output variables was described by creating a set of fuzzy rules using “if-then” statements. The Mamdani implication and maximum aggregation method were used during the fuzzy inference process to obtain a single crisp output value.

2.5 Summary of Traffic Congestion Detection Techniques

This section aims to analyse and discuss the different techniques employed in prior research to detect or estimate traffic congestion. These techniques can be classified into four categories: image processing, deep learning, machine learning, and fuzzy logic. Notably, most of the approaches used for traffic congestion detection are based on deep learning, suggesting its immense potential in the coming years. Furthermore, the deep learning techniques demonstrate superior performance when compared to other methods. Nonetheless, despite the advantages of each method, there are still several limitations and challenges that need to be addressed.

3. Challenges

Research in the field of traffic congestion detection can be implemented using a variety of methods, ranging from simple camera-based solutions to complex machine learning algorithms. However, to ensure the effectiveness of these methods, it is important to consider the limitations and challenges from multiple angles. In this section, challenges related to traffic features, congestion levels, traffic scene factors, real-time detection, and location scalability are discussed.

Traffic features refer to the variables or attributes that are measured and analysed to determine the level of congestion on a road network. These features include data on traffic flow, traffic density, traffic occupancy, traffic velocity, and traffic volume, among others. Other variables associated with the vehicle itself, such as brake frequency, fuel consumption, and CO_2 emission, are also taken into consideration when designing a congestion detection system. It has been found that some works only use one or two features in detecting congestion, which can cause the obtained detection results to be biased toward those particular features [9, 16, 20, 24]. This can lead to incomplete or inaccurate analysis of the detection problem and may result in ineffective solutions. To obtain a more accurate and complete analysis of traffic congestion, it is important to use multiple traffic features rather than just one or two. Therefore, traffic congestion detection systems should be designed to incorporate various traffic features.

In traffic congestion detection, the congestion level or state refers to the severity of traffic congestion on a particular road or section. Typically, congestion levels are categorized from low to high congestion, depending on the objectives of the study. Unfortunately, some studies only use two congestion levels, which lack granularity [11, 18, 24, 26]. This limitation can cause the method to be unable to distinguish between multiple levels and types of congestion. Traffic congestion can occur for various reasons, either recurrent or non-recurrent. In addition, when the detection system is limited to binary classification, it cannot differentiate between types of congestion and may not provide sufficient information for effective decision-making by transportation authorities.

Moreover, one of the main limitations in traffic congestion detection is related to the external conditions and characteristics that affect the traffic scene and the quality of the image data captured by the camera. These factors include illumination conditions, weather conditions, camera position and angle, occlusions, image resolution, and image quality. Detection methods, particularly those based on image processing, deep learning, and machine learning, often rely on image sets during the detection process. However, these image sets may only take into account some factors [9, 14, 28]. For example, Gao *et al.,* [16] trained and tested Faster-CNN using image sets that did not consider camera angle and occlusions factors. The lack of consideration of additional factors in the detection system may lead to inaccurate detection and tracking of vehicles, resulting in false alarms and missed detections.

Real-time traffic congestion detection is also a challenging task as it requires a low-latency system to provide up-to-date and accurate information on traffic flow, congestion, and any incidents that may affect traffic flow as soon as they occur. Some proposed detection methods may not be able to detect congestion in real-time, or their real-time performance has not been evaluated [20, 25, 27]. If congestion detection is not in real-time, there will be a delay in detecting the congestion, which means that the response time to take action will be longer. This delay can cause further traffic build-up and increase overall congestion, making the situation worse.

Location scalability is crucial to ensure that a traffic congestion detection system can cover a large area and provide accurate and timely information about traffic congestion in various locations. Traffic congestion can occur due to various reasons, such as accidents, roadworks, special events, and rush hour traffic, in different areas. Therefore, a traffic congestion detection system must be capable of monitoring multiple locations simultaneously and providing real-time updates on traffic conditions. However, two studies do not consider location scalability [20]. To verify the flexibility of a method in multiple locations, traffic data from various locations is necessary.

4. Conclusions

In conclusion, the main goal of this study is to survey recent techniques applied in traffic congestion detection and discuss possible challenges. The investigation has shown that traffic congestion can be addressed by using image processing, deep learning, machine learning, and fuzzy logic. Five possible challenges, including traffic features, congestion levels, traffic scene factors, real-time detection, and location scalability, are discussed to emphasize their importance. The evidence from this study indicates that deep learning is the predominant method for detecting traffic congestion. Furthermore, there is still room for further improvement in the scalability and robustness of these methods. The insights gained from this study may assist in enhancing the establishment of traffic congestion systems and integrating other relevant functionalities.

Nonetheless, this study is limited by the absence of an analysis of traffic features and congestion levels to support the explanation of challenges. Despite its limitations, the study undoubtedly adds to our understanding of the current technology trend in traffic congestion detection, recent detection methods, and future method development. Further research needs to closely examine traffic features, congestion levels, and hardware implementation.

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