Detection and Classification of Vehicles in Smart City using Traditional to Emerging Technologies: A Review

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Abstract

A Smart City is a technologically superior metropolitan area that uses electrical technologies to collect data in order to improve operational capabilities, communicate information to the public, and provide better governmental services and public welfare. As a result of the lack of decision support systems, the problem that arises in these smart cities is traffic congestion for accurately identifying vehicle information. As a result, the focus of this paper is on in-depth writing that focuses on current strategies for vehicle detection in a smart city. It combines the state of their specialty's performance measurement and quantitative evaluation of leading strategies. Surveillance is the close observation of a situation. When discussing the smart city context, surveillance becomes an important concept because it primarily improves human living comfort. The last ten years of publications by various specialists (2012-2022) clearly describe various methods for vehicle detection. The goal of this document is to examine the strategic achievements encapsulated in the success indicators for detecting measures in the targeted field of research. This document thoroughly covers the applicable emerging methods in vehicle recognition and classification, as well as providing feedback on the benefits and drawbacks of traditional approaches. This study also investigated the most important findings and reasons for identifying lessons learned for the future roadmap.

Keywords: Deep learning, Machine learning, Internet of Things, Smart City, Smart Intelligence, Surveillance System, Vehicle detection.

1. Introduction

The Smart city system differs per region, depending on technological advancements, lifestyles, geography, and environment. Humanity could be benefited to a greater extent, thanks to the smart city system. As a result, human life has become easier.[1] The smart city is being built to digitalize the nation and improve people's living standards. The primary aim of the smart city is to contribute to the quality of life of future generations. Individuals, energy, resources, commodities, safety, and funding, among other things, would all flow via this ecosystem. As a result, smart city management [2] is concerned with the growth of the urban population using innovative technology to replace old technologies. The goal of the smart city is to make human existence safe, effective, and as convenient as possible. In essence, smart cities require a steady supply of power, water, as well as non-congested transportation and other necessities generated with the use of resources, electronic equipment, and other sensor devices, and maintained using computerized network technology. Everyone has been drawn to the phrase "smart city" [4].

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Internet and intranet collaborate to overcome a variety of issues that emerge in present approaches [5],[6]. In the 1990s, the smart city concept was at its peak, with more creative technology being used to start or realize it [7]. Intelligent cities rely on mobile wireless networks that are connected using software and interface technologies, such as digital, cyber, and intelligence [8]. Sensors are included in smart city technologies to develop safe innovative solutions using web-based services [9]. The fundamental issue with Wireless Sensor Networks (WSNs) is that they are difficult to maintain and are adaptable for policy changes. The goal of this study is to find a workable solution to the tough WSN difficulties. The primary part of this technology is a sensor open flow, which is built by software. The notion of software-defined networking and WSN [10] is expanded with this technology. Human life has become more difficult as a result of technological advancements, as has global warming. However, several new solutions have been developed to address these issues. Wireless Sensor Networks (WSNs) could be able to solve the problem by providing sophisticated computational capabilities [11]. WLANs and other cellular networks are simple networks. Ad-hoc wireless networks, however, require more sophisticated networks than WLANs and other cellular networks. Adaptive and programmable wireless sensor networks have brought about undesired changes to the environment as a result of ICT development in information technology. The cloud-based deployment of sensor networks has established an environment that is simple to administer and maintain, which benefits a large number of users. Networking costs are also lowered [13]. Figure 1 shows an example of vehicle detection process with bounding box with different colours for different types of vehicles.

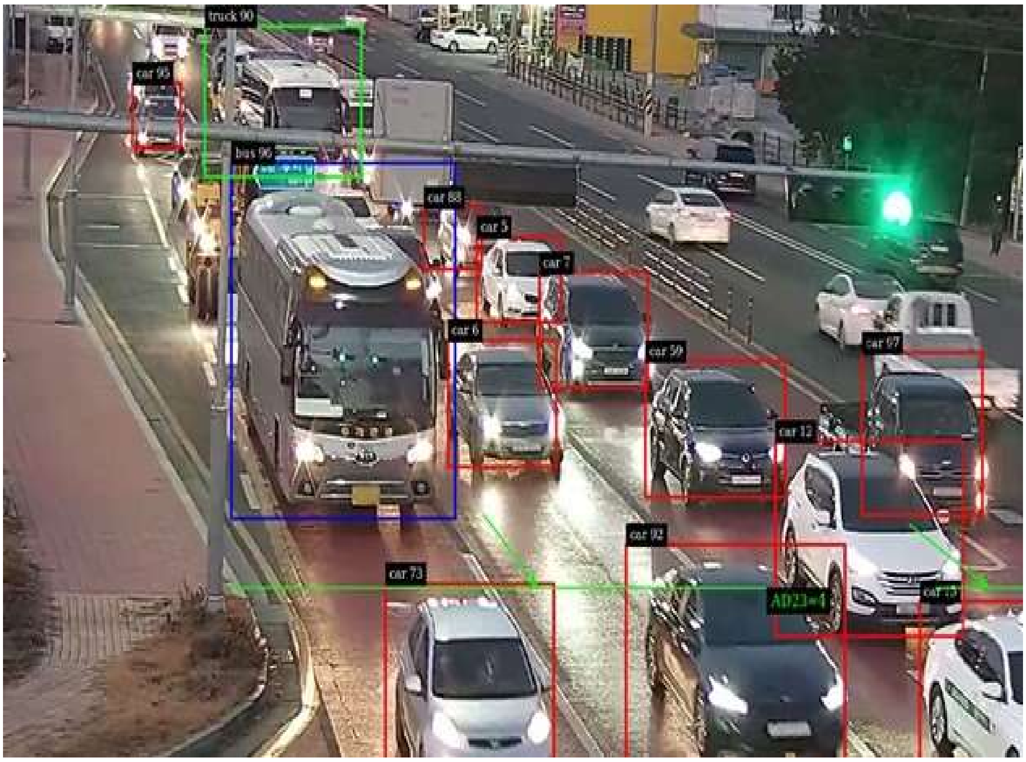

Fig. 1. Vehicle detection in smart city view [14]

1.1. Bibliometric Analysis

An overview of various papers published over the past decade is presented in this paper using bibliometric analysis of 10 databases, including Springer, MDPI, Science Direct, IEEE Xplore, ASCE library, Science press, Oxford Academic Press, Copernicus, Scopus, AAS, as well as state-of-the-art models. Data are extracted from these databases by using keywords such as "vehicle detection in a smart city" and "review of vehicle detection schemes for smart city surveillance". It is possible that this particular search has impacted directly or indirectly. Approximately 4000 documents are obtained from these ten databases, each categorizing documents into certain groups over the past decade. Articles (60 %), Book Chapters (13 %), Conference Papers (8 %), Case report (4 %), News (4 %), Encyclopaedia (3 %), Abstract (2 %), Mini review (2 %), Short communication (2 %), Editorial (2 %), were discovered when analysing each database. In conclusion, it occurs to us that there is a certain weighting for every section within each database that we examined, and when Science Direct is compared, it reveals the highest number of publications. Figure 2a depicts percentage-wise cluster in 10 databases over Keyword- "Vehicle detection in the smart city". Figure 2b depicts percentage-wise cluster in 10 databases over Keyword - "Review: vehicle detection scheme for smart city surveillance".

1.2. Key Highlights

This review paper focuses on bringing a theoretical aspect of detection vehicle in a smart city in which the following are the objectives;

a. Brings a detailed review of vehicle detection in the smart city using various technologies.
b. In this review, we present detection schemes utilizing Artificial Intelligence, Machine Learning, Deep Learning, and the Internet of Things.
c. The viability and propriety of ongoing plans can be quantified by means of various measurements.
d. Mostly, this work will give researchers to get inspired and move on a new path for creating new models that could potentially help detection vehicles in smart cities.

This paper will be useful for the researchers and also for the ministry of development in urban areas with help of these emerging technology to bring effective vehicle detection systems and also for researchers who can dig deep to bring new aspects or integrative aspects to these developments.

The paper has the following structure:
Section 1 depicts the introductory part of smart cities; Section 2 depict an overview of vehicle detection and classification. Section 3 explains the traditional approaches used for vehicle detection. Section 4 gives the overview to emerging technology-based vehicle detection. The evaluation of performance metrics used for evaluation of the emerging technologies are addressed in Section 5, and finally, the conclusion is summarised in Section 6.

2. An overview of vehicle detection and classification

Surveillance means the close observation of the scene. Surveillance becomes a crucial idea when we talk about the smart city context, as it mainly increases the living ease of human beings. Due to the rapid changes in technology, the number of vehicles being produced is increasing in an exponential manner.[15] These vehicles assist the public in a variety of ways, including transportation for officials or family members. The pathways in many countries are still not widened because of economic reasons, and sometimes widening leads to deforestation. Traffic management is a crucial idea in smart cities to make the environment viable for the public. Not all sorts of vehicles are allowed in smart cities. Vehicle tracking is one of the important sections in traffic monitoring, and it will help to make the lives of commuters easier. The growth of vehicle traffic has resulted in traffic accidents, congestion, and air pollution. Traffic accidents are one of the most difficult issues to address. It’s critical to have automated techniques for checking suspected automobiles while conducting criminal investigations related to traffic accidents [16].

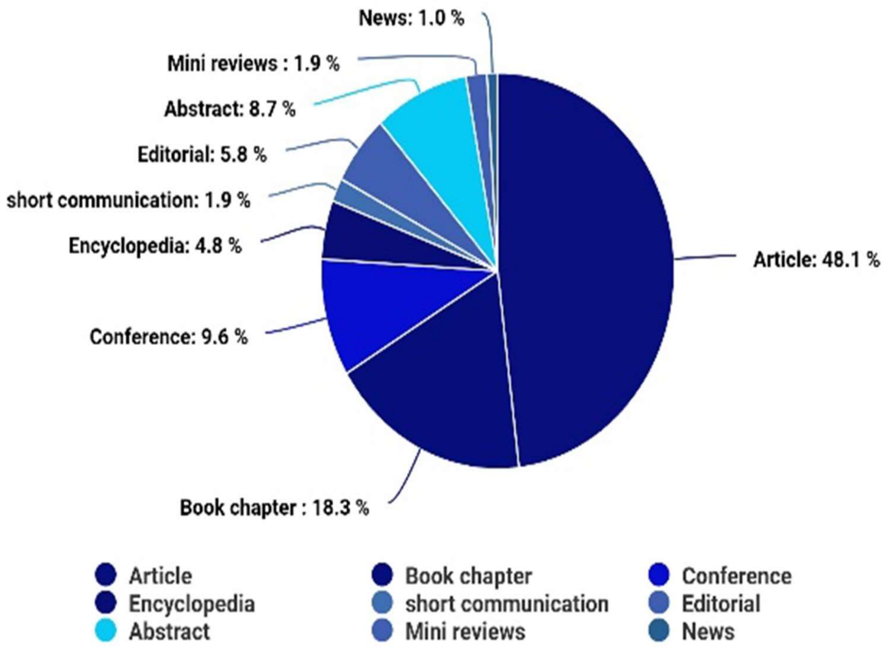

Fig. 2. depicts percentage-wise cluster in 10 databases over Keyword- "Vehicle detection in the smart city"

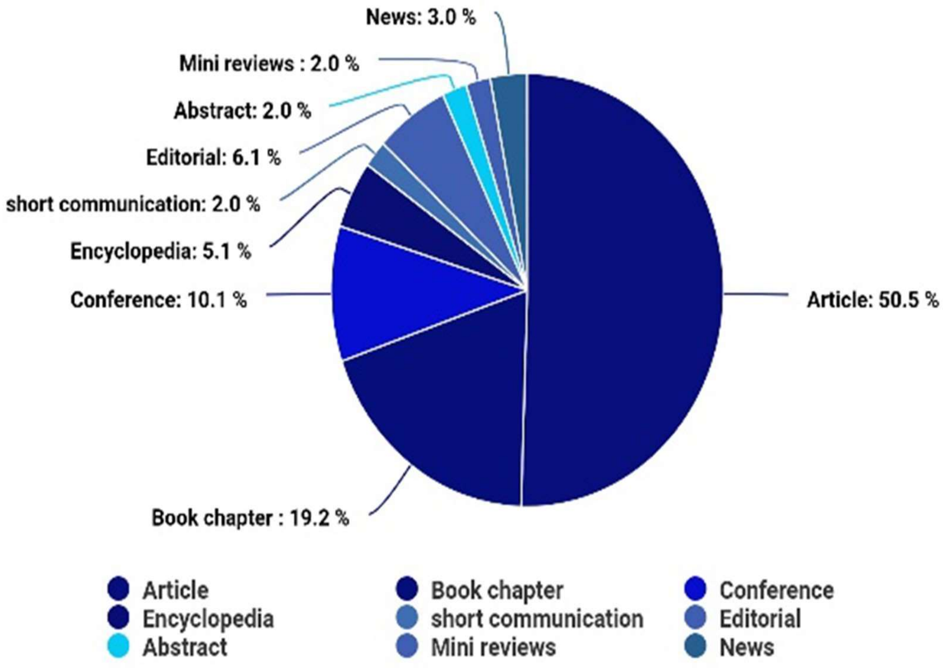

Fig. 3. depicts percentage-wise cluster in 10 databases over Keyword - "Review: vehicle detection scheme for smart city surveillance".

Proper knowledge of the surroundings is needed to detect the cars in the scene. Normally, the intrusion of moving vehicles causes many disturbances in the surroundings like optical, chemical, magnetic, acoustic, thermal, electrical, and seismic changes [17]. These disturbances can be captured by different sensing techniques whereby the system can sense the presence of vehicles in road surface [18]. Sensors mainly used for vehicle detection can be classified into three Categories: transducers, signal processing devices, and data processing devices. Transducers mainly detect the movement or the presence of vehicles in the scene. Signal processing devices mainly process the electrical properties of the vehicles from the information collected by transducers. Data processing devices include several hardware and software components which work mainly on the information collected by the transducers [19]. The parameters like count, speed, and presence of the vehicles are mainly considered by the management system for detection. The sensors used for vehicle detection are mainly classified into in-roadway sensors and over-roadway sensors. Sensors for roadways must be installed on, implanted, or installed beneath pavement. Pneumatic road tube, magnetic sensors, piezoelectric cable, inductive loop detector, and weigh-in-motion sensors like piezoelectric, bending plate, and load cell are such examples. In-road way sensors are also called intrusive sensors because it needs pavement cutting for installation. Overhead roadway detectors do not have to be installed directly onto, into, or under the pavement. They are installed in the centre or on either side of the road. Over-the-roadway sensors use technologies such as video image processors, active and passive infrared, microwave radar, ultrasonic, and passive acoustics. Over-road way sensors are also called non-intrusive sensors because it doesn’t need pavement cutting for installation [20].

Loops are the simple form used for detection and have been in use for decades. Slight changes in the inductance are used for the detection of vehicles. Several shapes of loops are in application with varying degrees of accuracy in detection. Inductive loops are very sensitive to other electrical fields in their proximity, even those underground and overhead power lines. Loops are also affected by the presence of metallic holes. Proper care in installation is needed for the effective use of loops for a long time. Installation costs are low, and only minimal maintenance is needed if properly installed. Inductive loops can be used to calculate various parameters such as volume, presence, occupancy, speed, headway, and gap related to vehicle detection.[21]. Loops are applicable in all weather conditions because they are insensitive to rain, fog, and snow. The installation process requires pavement cutting and leads to a decrease in the life of the road surface. Lane closure is needed for installation and for maintenance too. Detection accuracy is less with an inductive loop. Furthermore, road resurfacing and regular repairs may demand the reinstallation of the sensors. Magnetic sensors detect changes in the magnetic flux of the earth when a car crosses over a detection region. Magnetic devices used for sensing are not influenced by snow, fog and rain and have application in all weather conditions. It also decreases pavement life and requires a greater number of sensors for proper detection [22]. The cost of installation is very high and requires lane closure for installation and maintenance. Magnetic sensors are not suitable for parking occupancy measurement as they will not detect stopped vehicles. Cable and wiring problems are inevitable with roadway sensors. Loops cannot be applied to bridge decks and railroad crossings as they are affected by metallic plates. A pneumatic road tube sensor sends a huge air pressure through the tube when a car or any vehicle moves across it. This will close a switch, resulting in an electrical pulse to the detection module. Pneumatic road tubes are low cost and easy to install, but the accuracy of detection may be affected by the presence of large volumes of buses and trucks. Sometimes the weather conditions influence the detection ability [23].

Active infrared devices are designed and use the radar principle for detection. The presence is identified by checking the time required to reflect the low infrared beam from the road surface. Passive infrared devices collect the radiation energy difference on the road surface for presence detection [24]. Active infrared devices can provide the speed of the vehicle, while passive devices provide traffic parameters like count, presence, vehicle length, and the queue length in the traffic signal. Weather conditions like rain and fog may affect the reflection of the infrared beam and lead to errors in the detection accuracy. Doppler microwave devices mainly radiate low-energy beams to the pavement surface and, based on the reflection, detect the speed and volume of vehicles. Microwave radars are mainly used for parking and occupancy measurement by using the range-finding ability of radar technology. They are capable of detecting vehicles in multiple lanes and are insensitive to all weather conditions, but the pavement structure may affect the traffic parameter measurement [25].

Acoustic devices used in vehicle detection are passive and seek the sound energy of moving vehicles. Based on the parameters of sound, they can determine the volume, speed, occupancy, or parking of vehicles. Depending upon the characteristics of the sound energy, classification of vehicles is also possible [26]. Snowy and low temperature conditions deteriorate the measurement accuracy. Ultrasonic sounds are also used for vehicle detection and use radar principles for measurement. The reflection of the ultrasonic energy from the target is used for the speed and volume measurement [27]. Surveillance of multiple lanes is possible, but the efficiency of such devices is influenced by climatic changes and air turbulence.

Images and videos captured from the scene are a fine source for vehicle detection and identification. Video-based surveillance has many uses in many fields, like remote location security, home security, and military applications. The microprocessor and its variants are mainly used for the verification of images and videos from the scene. Compared to other vehicle detection algorithms, Video detection algorithms can provide more information about the scene [28]. The data provided is suitable for finding the volume, speed, presence, density, and occupancy like other algorithms used for detection purposes. Apart from this, data can be utilized to identify vehicles, classify them, and to detect incidents. Video-based detection procedures are highly reliable, but the increase of vehicles in urban areas, detection has become a crucial task in surveillance systems.

Performance of the image and video-based detection algorithms is influenced by environmental factors like wind, lightning, and precipitation. Weather conditions, increased number of lanes, shadows, occlusion by heavy vehicles, day or night light illumination, movement of the overhead camera, resolution of the camera, and limited depth of field of the imager can affect the measurement accuracy of detection. When compared to traditional approaches, the amount of data provided is huge and requires large storage devices. Installation and maintenance costs are very high, but the multimodal and multi-exposure data are very useful in the identification of vehicles. Images are another source of information which gives a close observation of the scene under consideration [29]. Proper knowledge of the surroundings is needed to develop the detection of the targets present in the scene. In order to detect vehicles, it is necessary to know what differentiates them from the rest of the image or from the surroundings in the scene. Pixel values, colours, and gradients can be used as differentiators for vehicle detection. The features of the vehicles mainly depend on their appearance in the image.

Table 1

Technologies used in traditional system for vehicle detection

Roadway Sensors	Advantages	Disadvantages
Inductive loop detector	• Well-developed and Flexible design • Easy to install • Low cost of installation and maintenance • Accurate and reliable • Provides basic traffic parameters • Insensitive to weather conditions	• Pavement cutting is needed for installation • installation shortens the life of the pavement. • Lane closure required for installation and maintenance • Mounting on metallic bridge decks is not Recommended
Magnetic sensors	• Less sensitive to traffic stresses than loops • Few models send data via a wireless link • No need of pavement cut for some models • Accurate and reliable • Some models useful in bridge decks	• Some models have small detection zones • More time needed to install • Pavement cutting is needed for installation of few models • Cannot detect stopped vehicles • Closure of lanes for installation of some models

Piezoelectric cable	• Accurate and reliable • Provides basic traffic parameters • Pavement cutting is needed	• Regular and constant inspections to check heavy traffic loads • Large scale application leads to error in accuracy • Typical piezoelectric systems are less accurate
Pneumatic Road tubes	• Cheap and self-contained • Easy to install • Well recognized technology with acceptable accuracy • Axle-based classification appears attractive	• The possibility of counting two vehicles as one • Tube installations are not durable • Tube sensors are not suitable for high-traffic and high-speed roads.
Active and Passive Infrared sensors	• Precise measurement of vehicle presence, speed, and type • Multizone passive sensors are effective for speed • Multiple lane coverage is possible • Lane closure is not required for installation and maintenance	• Rain and fog influence the passive sensor's sensitivity and leads to error in vehicle detection • High cost installation • Active sensors are influenced by fog and snow
Microwave Radar	• Weather Conditions have no impact • Speed measurement is easy • Lane closure is not requireed for installation and maintenance • Multiple lane operation available	• Antenna beam bandwidth restrictions • Doppler sensors fail in stopped vehicle detection • High cost installation
Ultrasonic sensors	• Precise measurement of vehicle presence, speed, and type • Can cover Multiple lanes • Lane closure is not required for installation and maintenance	• Accuracy of sensors are influenced by climatic changes and air turbulence. • Performance is inacceptable in moderate to high speeds • Occupancy measurement is degraded large pulse repetition periods • Temperature compensation is available in few models
Acoustic sensors	• Detection by Passive sensors • Precipitation is not influenced • Can cover Multiple lanes • Lane closure is not required for installation and maintenance	• Low temperatures influence detection accuracy • Slow traffic results in poor performance. • Errors in measurement due to interference
Video & image	• Monitors multiple lanes • Multiple detection zones/lanes • Useful in wide-area detection and monitoring • Rich array of data available • Changing and adding detection zones is easy • Multi-media and multi modal data is available • Generally cost-effective	• Periodic lens cleaning is required • Day-to-night transition, Occlusion, and vehicle/road contrast can all have an impact on performance. • Susceptible to camera motion caused by strong winds • Highway lighting is essential for night time sensor actuation • Detection is influenced by vehicle projections, shadows, and weather conditions such as fog, rain, and snow

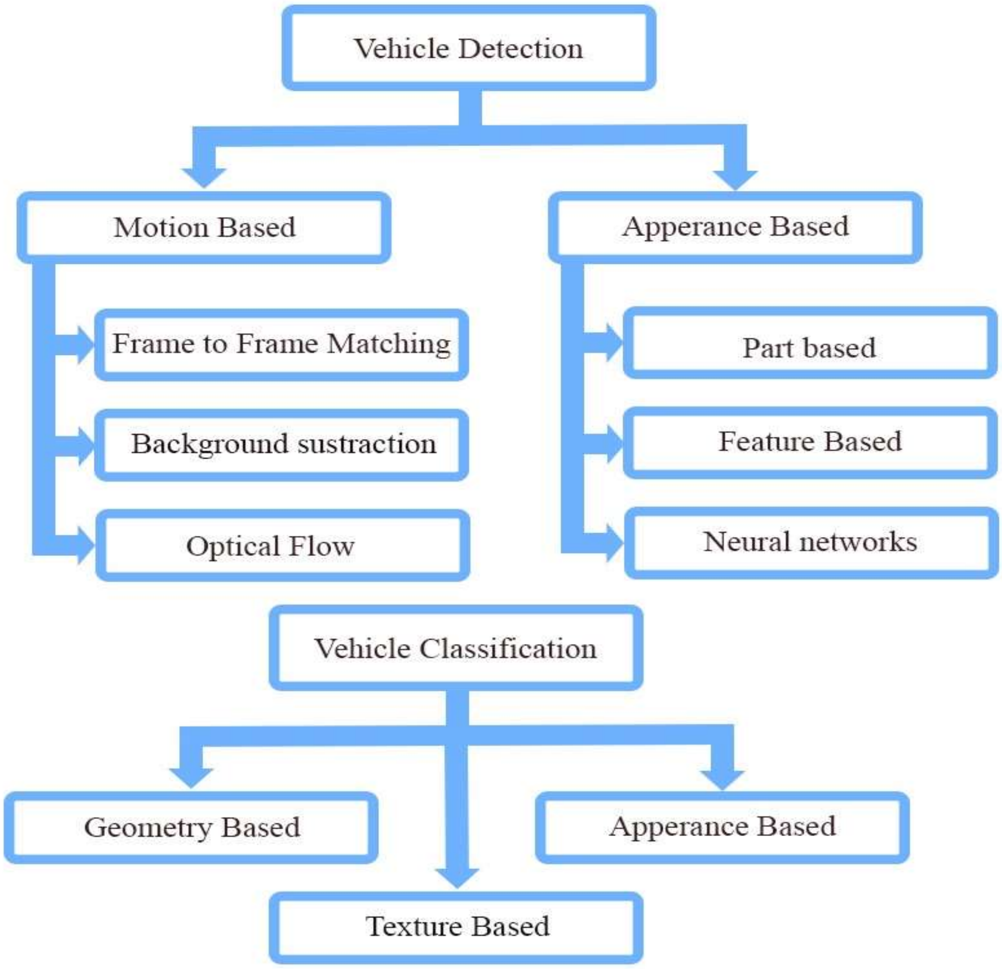

Fig. 4. Vehicle detection & classification methods

Vehicle detection promises to bring several benefits to society, including the prevention of road accidents. Nowadays, cameras are installed on the vehicles themselves to detect obstacles in front and behind them. Dash cam cameras can help the driver to take necessary steps to prevent accidents within a small time. The image processing algorithms act on the data obtained from the dash camera and alert the driver to control the speed of the car so that pedestrians or nearby vehicles will be in safe condition [30]. The driver-less cars work only with the video processing algorithms. Artificial intelligence and machine learning methods play a big role in the implementation of driverless cars. The appearance of the vehicle in the image is evident in the features extracted for the detection purpose. Feature extraction is done mainly in two domains. Spatial domain-based methods collect the vehicle information from the image and use it for the purpose of detection. Frequency domain methods collect the vehicle data, then apply Fourier transform and analyse the spectrum for classification and identification [31].

Image pre-processing is considered a vital step in vehicle detection algorithms. Vehicle detection covers movement extraction, tracking, and behaviour analysis and acts as a prerequisite to improving the classification process. Vehicle detection approaches are classified into motion-based and appearance-based. The appearance-based method considers the vehicle's shape, color, and texture, whereas motion-based approaches consider the moving attributes of pixels in the image. In motion-based approaches, the background is considered as static to analyse the motion of vehicles. In motion detection technique, moving foreground objects are separated from an image's still background [32]. The motion indications-based models are classified as follows: a spatial frame differencing method that evaluates the prior two or three successive frames, a background subtraction method that uses frame history to build a background model, and an optical flow method that uses the image surface's pixel movement. The Blob evaluation algorithm utilises frames of video recorded from an over-head video camera and performs some mathematical operations on each fixed frame obtained from the moving frames to count the number of cars displayed in a frame. The set of changes in pixels in consecutive frames gives information on the presence of vehicles in the image.

Background modelling approaches are used along with blob detection to improve the effectiveness of the blob detection methods [33]. Gaussian Mixture Model (GMM) is a density-based method consists of components of Gaussian functions and can be used to model the background and can improve the detection performance of blob detection procedures. The GMM methods are insensitive to illumination changes, and the object detection accuracy is improved considerably. GMM based methods are highly reliable for background processing and can produce high accuracy in some aspects of background design [34]. Shu et al. use a comparison with Symmetric difference and single-mode background concepts using Gaussian distribution as a parameter to update background models. GMM optimisation using Blob Evaluation modification techniques combined with ROI adjustment in high traffic conditions could improve accuracy of vehicle process. GMM methods also suffers from errors include a shadow vehicle being detected as an object and two adjacent vehicles being treated as a single object [35].

A decision tree is a search algorithm that aims to search for the targets in the video by using vehicle characteristics. These methods are useful in the classification of vehicles, which uses the type or colour of vehicles as the key for classification [36]. Typically, the type or colour of the vehicles in DT classifiers classifies the vehicles into 4 types, like small, medium, large, and unknown. The colour-based method classifies vehicles into 7 colours, like green, yellow, red, black, white, blue, and unknown. Human fatigue is eliminated by using DT in classification problems. ID3, C4.5 and CART are other sources of DT classifiers that play improved roles in vehicle classification [37].

Decision tree-based algorithms are greedy but its computational capabilities are used for vehicle detection in many algorithms. Phan et al proposed a novel algorithm in which motion vehicles are identified and examined using a Convolutional Decision Tree with feature extraction to classify cars and a Single Shot Detector to manage occlusion when the inter-vehicle area between vehicles significantly decreases.

The stereo vision or the appearance of a target can be analysed in terms of colour, texture, and shape. Vehicle detection is a procedure in which three-dimensional natural features are modelled into two-dimensional images and the pixels are identified for detection purposes [38]. For improved detection, the images can be divided into several parts. The spatial difference of the individual part is utilised to identify the vehicles in the image. The vehicles in the images are divided into front, side and rear view. Occlusion produces by large vehicles can be resolved by part based comparison approaches. The encoder uses the feature representation algorithms to determine the appearance of vehicles on the road. Properties such as edges, corners, lines are considered for the detection and the illumination may change its appearance. Edge-based histogram, Oriented Gradient Dimension Histogram [39], Scale Invariant Feature Transformation and Haar Transform Features are methods used to classify vehicles.

3. Traditional approaches for vehicle detection

The traditional approaches mainly use frame to frame matching, background extraction, and optical flow-based models. A series of frames are used to detect the moving vehicles in the scene. The changes in the pixel values corresponds to presence of a moving target in the scene. We suppose the following when choosing a background foreground method: (1) pixel-level parsing, (2) frame-level data tracking and decision, and (3) the use of a few methods to decrease computation costs, such as reduced features and pixel processing in specific areas of greater variations. Such difficulties are critical for feature recognition of algorithms and parallel processing [40].

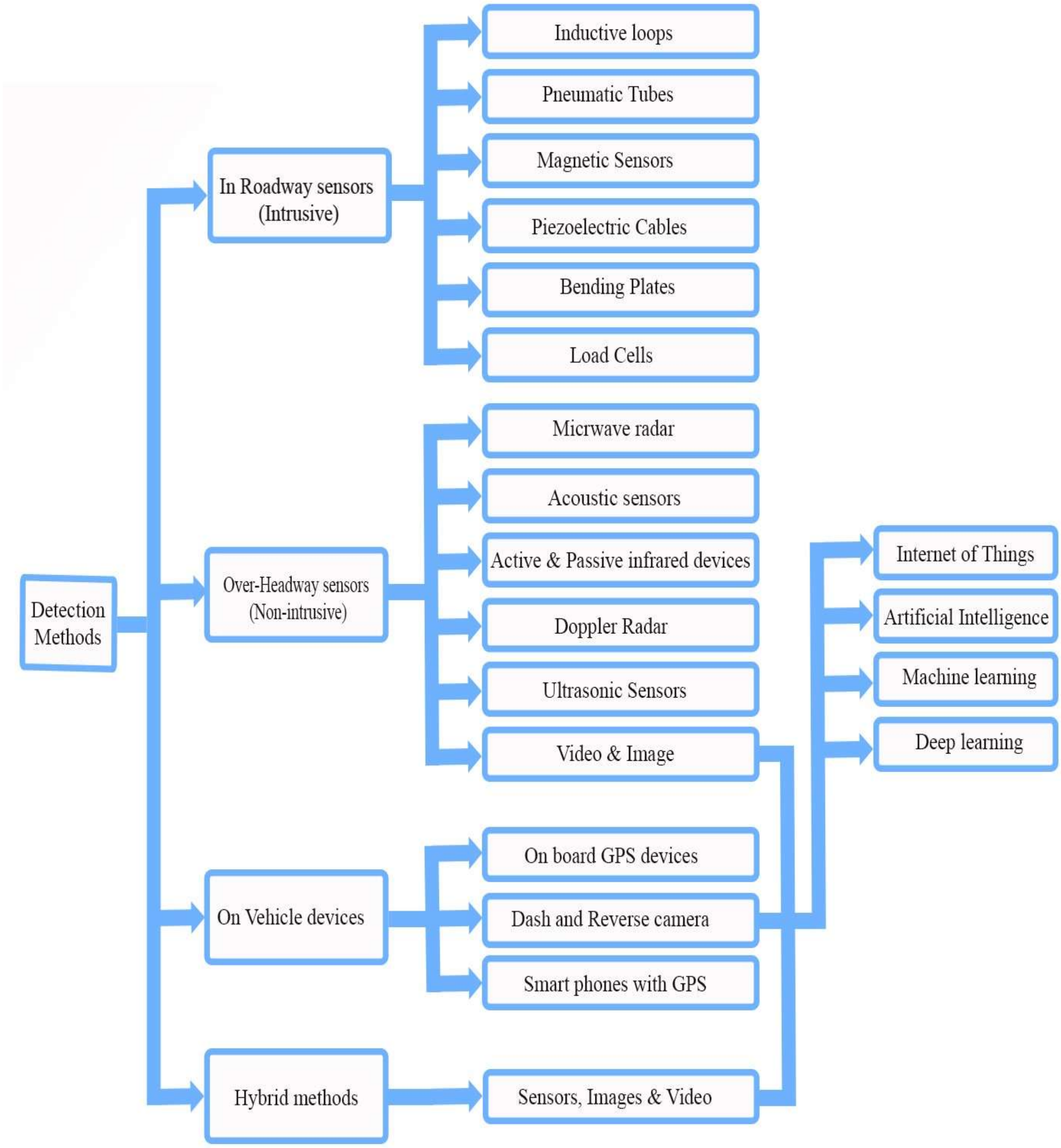

Fig. 5. Road map of technologies used in vehicle detection

Image parsing is one of the best analysis methods of natural scenes in which each pixel is marked with properties of the objects or portion of the scene. Detailed scene understanding algorithms have applications in keyword-based image search, sentence-based image or video depictions, and in self-driving vehicles or robots. Image parsing can be used as key for vehicle detection purpose. This is utilised in frame to frame matching method of vehicle detection [41].

Algorithms used in the blob analysis explained in the Section 2 is depicted as follows. Allow $V(\tau)$ to be a video with M ground truth vehicles that has a timeframe τ. It's a succession of K pictures or frames with indices of 1, 2, 3..., K. Consequently, every frame during time k may be viewed as a matrix, I_k of order m x n, whose elements represent pixels, $x_k(i,j)$, where, for a grey-space $x_k(i,j) \in R_G^1$ and $R_G^1 \subset R^1$, and a 3D colour-space $x(i,j) \in R_C^3$ and $R_C^3 \subset R^3$, for $(1 \leq i \leq m, 1 \leq j \leq n)$ [42]. We only utilize grayscale in this project, and the image at frame k is represented as follows:

$$I_k = x_k(i, j) \mid x_k(i, j) \in R_G^1 \text{ and} \tag{1}$$

the background as:

$$BG_k = x_k(i, j) \mid x_k(i, j) \in R_G^1 \tag{2}$$

In frame-to-frame matching, differences in each frame or correlation between the frames are evaluated for change detection or for the presence of vehicles in the scene. Hence, each pixel is checked for intensity changes, thereby enabling correlation to easily identify and consider it as the presence of vehicles or automobiles. In the background modelling method, correlation method is used to check the presence of a target in the observed scene. If an image includes L potential vehicle or blob units within a frame k, then it can be represented as $blob^k_l$:

$blob^k_l = x_k(i, j) \parallel pixel\ (i, j)$ is connected to pixel (r, s), and

$blob^k_l \subset B_k$ for $l = 1, 2..., L$

Using a correlated elements evaluation, individual pixels that mimic hypothetical automobiles contained in the input video are grouped into blobs. Similar pixels in the detection frame's foreground and background are possible in frame-to-frame approaches. This will create many holes in the binary mask of the moving vehicle. This leads to wrong detection and affects the accuracy of measurement. To remove the unwanted holes, morphological operations like erosion and dilation are applied. These applications can reduce the presence of holes and can reduce the noise present in the binary mask. This approach can generate a full mask with a normal aspect ratio and is able to improve the detection capability of the algorithm [43]. Morphological operations can also generate the shape or form of moving vehicles in an efficient manner. The extraction of aspect ratio is important for the bounding box creation in the blob analysis method as it affects the length prediction of vehicles. Blob evaluation is then utilized to derive geometrical properties such as the encompassing box's area (the total of linked pixels or space occupation), height, breadth, and centroid. Occlusion occurs as a result of the camera's location and altitude, and various mistakes are formed during the detection phase [44], [45]. Typically, in such cases, by reducing occlusion-related impacts from huge vehicles, which change their attribute values significantly, any occlusion-handling method is required. As a result, occlusion is a hot topic in this area. Certain publications divide it into full and partial categories, and some area estimates are provided. To provide an accurate vehicle traffic monitoring system, it is vital to know how frequently the algorithm detects occlusions and through what effectiveness it fulfils its function. Because occlusion happens in brief periods, readings must be taken at the same intervals [46]-[48]. The detection step sends the entire area of tracked items to the categorization stage, such as observed automobiles or moving objects. In addition, all objects tracking sequences, Ts(x), are part of the classification stage's input space. The geometric, cinematic, and temporal elements in a sequence Ts(x) must be specified as well as the time at which each instance will be classified. In addition, $Ts(x) = x_1, x_2, \ldots, x_c, \ldots, x_k$ corresponds to each moving vehicle x, where xc is a well-defined instance of its type. There is quite a bit of variation in the characteristics, as these mobile objects or automobiles were located at more than one spot in the ROI, and one of the most important geometrical features in the area was insufficient for meaningful classification.

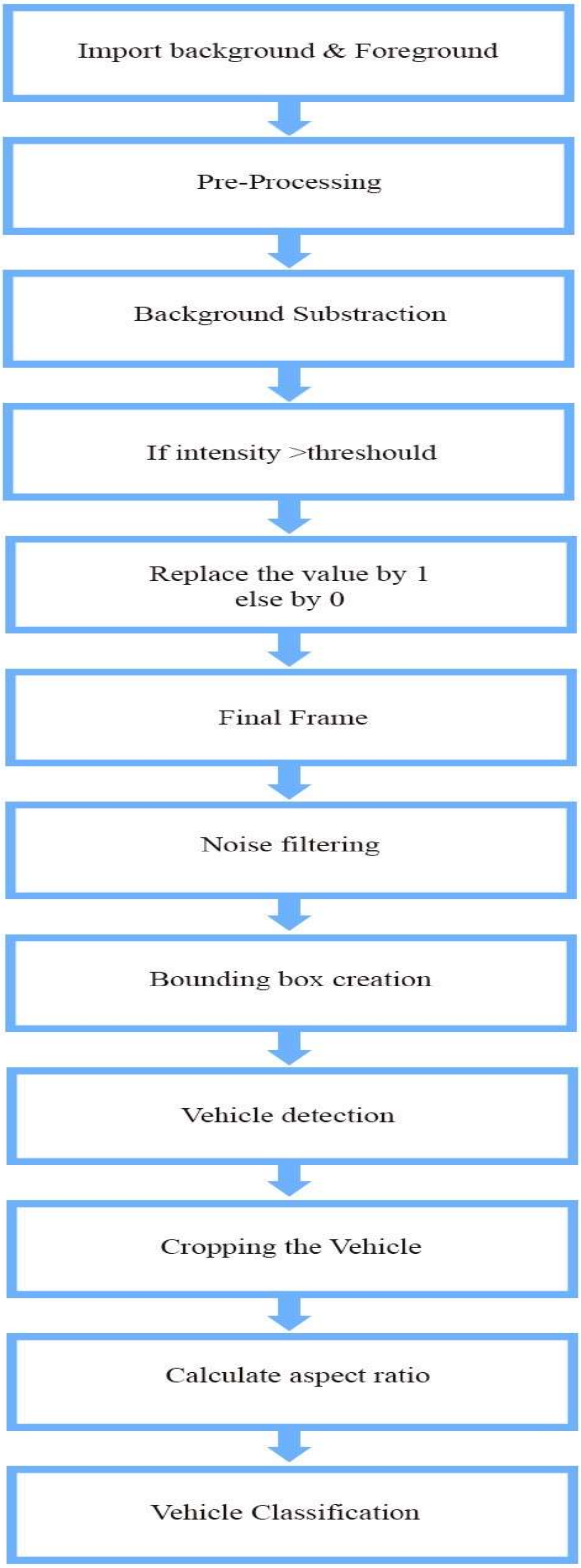

Fig. 6. Flowchart of traditional vehicle detection algorithm

3.1. Occlusion handling

Occlusion handling are one of the main concerns comes in traditional approaches.There are mainly two types of occlusion problems that arise in vehicle detection. A vehicle may be hidden by more than one type, which is referred to as intra-class occlusion, and if it is occluded by other vehicle, it is referred as inter-class occlusion [49]. Occlusion happens in indoor and in outdoor scenes. Occlusion removal is a challenging issue as the information on different viewing angles is unavailable in most cases. Visible region limitations increase regeneration issues with the removal of occlusion. Generative adversarial networks can be utilised to regenerate the occluded data in an effective way because they can generate the same class of data effectively [50]. Amodal perception can be used as a tool for processing this issue. By the comparison of amodal and modal segmentation, it can mask the existence, degree, contour and parts of occlusion. A partial completion-based scene de-occlusion procedure is proposed by Zhan et al. [51]. Partial completion networks (PCN) are used to recover the occluded region from different objects by taking one at a time with the help of two partial occluded networks, namely PCN-mask and PCN-content. Context-based generation of missing parts of the vehicle is suggested by Pathak et al. An unsupervised network is utilised to generate the sematic relationship and the missing portions of the image [52]

4. Vehicle Detection Using Emerging Technologies

As the world is rapidly revolutionized and emerged using emerging technologies like IoT, ML, AI and DL. These advanced techniques for detecting vehicles in smart cities bring an effective result from the traditional aspect. Section 3.1 depicts a brief explanation to deep learning-based vehicle detection concept. Because there is so much research being done in these areas, this section has been broken down into Four subsections: detecting vehicles in smart cities using Machine Learning, Detecting vehicles with Deep Learning techniques, Artificial intelligence based vehicle detection in smart cities and vehicle detection using IoT (sections 3.2, 3.3, 3.4, and 3.5).

4.1. Vehicle Detection Using Modern Approach

Video and image-based surveillance store the data captured from the scene and are useful for future use. The stored data is a source for the identification of vehicles in a crime scene. But overhead cameras produce large amounts of data, and processing or storing this raw data is a tough task. This data also requires a large bandwidth for transmission. The computation of large amounts of data creates problems in modern technology-based surveillance systems. The use of emerging technologies is a perfect solution to these problems. The Figure 8 shows the typical steps used in algorithms that use emerging technologies as a solution. The figure also depicts the generic vehicle detection in which the initial dataset is collected from the sensors which are IoT, where real-time data will continuously be fetched and given for further processing [53], [54]. Due to the rapid changes in imaging technology, the surveillance cameras provide a large amount of information from the observed scene, and the use of many overhead cameras for multiple lane coverage also increases complexity and redundancy in information. Neural networks are other sources for feature representation method that's comes under emerging technologies. Vehicle detection using neural networks has Five major stages. They are: 1) loading the data, 2) Developing the convolutional neural network (CNN), 3) Customising learning options, 4) Training the target detection model with CNN, and 5) evaluating the trained detection method [55]. The use of artificial intelligence-based methods is gaining attention because of its capability in extracting relevant information from huge amount of data. They mainly collect or extract the relevant information by using artificial neurons. Convolutional neural networks play an important role in relevant data extraction-based methods. Use of the internet of things in information collection helps to capture deep information from the scene by effective sensing strategies [56]. Deep learning-based methods are an emerging field that employs multiple CNN layers to extract extremely detailed information in video-based detection. The deep feature extraction models improve the vehicle detection process in an effective manner. Huge data is required to operate deep learning models for efficient detection accuracy. The data collected by many cameras and sometimes huge video and image datasets is given to the deep learning models for training. It is evident in the first block shown in figure 5. Several attributes like cost function and optimisation techniques are used to train the models [57].

In order to validate the accuracy of detection, the models are tested with known images or with the dataset taken for training. Proper selection of data improves the detection algorithm. Sometimes information content used for training leads to overfitting problems that create a reduction in detection accuracy. A properly validated model is used for vehicle detection and the deep features collected by the models are enough to detect small vehicles in different illumination areas. In addition to detection, these models can track the detected vehicles for surveillance purposes. Vehicle classification is another task in surveillance in smart cities, and this is also improved with the use of deep learning-based and IoT-based models. Patterns extracted during the training procedure are used in smart cities for car identification and classification [58],[59].

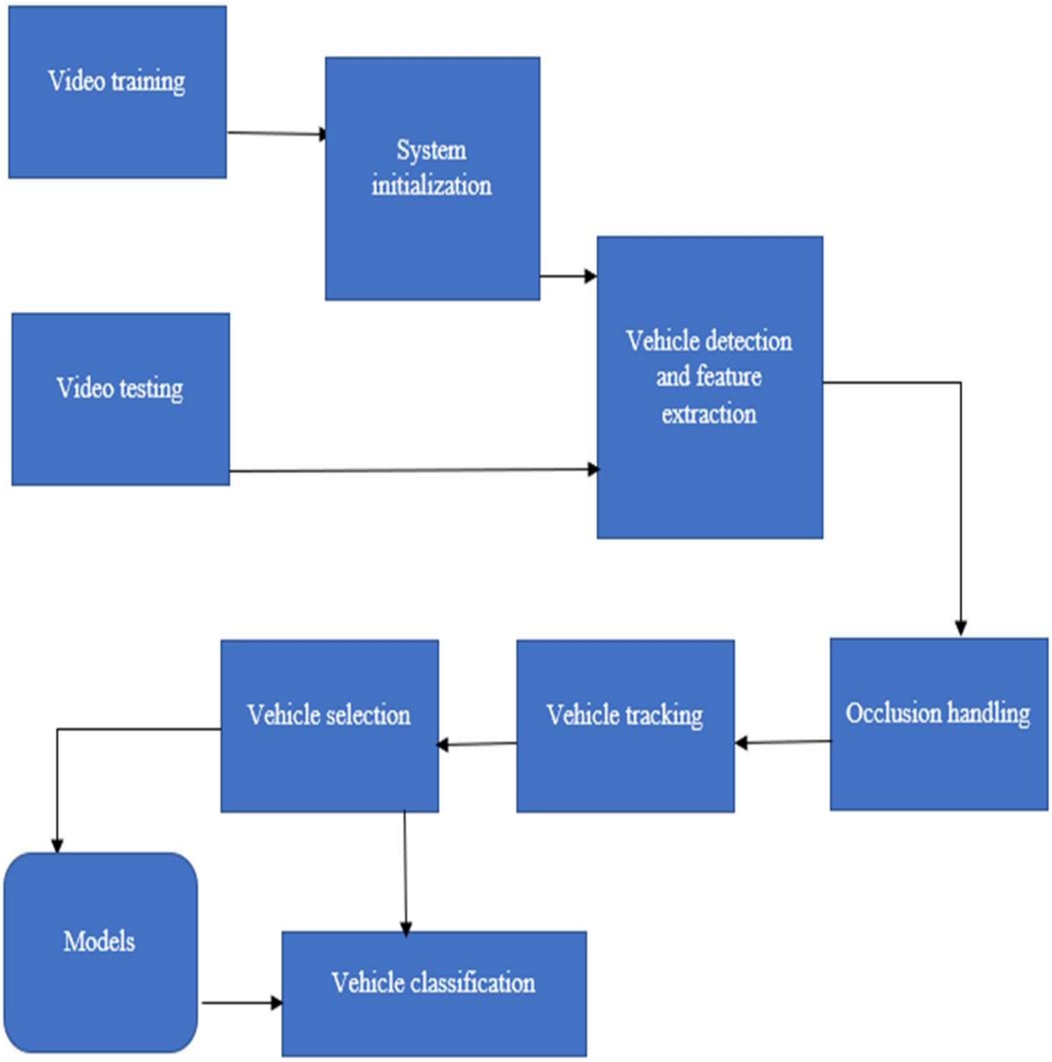

Fig. 7. Emerging technology-based vehicle detection

4.2. Vehicle detection using machine learning in smart cities

Dominguez et al. (2021) [60] demonstrate how to enhance vehicle identification in intelligent crosswalks using a variety of machine learning approaches. This method minimizes resetting labels in traditional fuzzy classifiers, which is often dependent on the system's site and traffic conditions. To solve this, information from real traffic on highways in Spain and Portugal was used to assess several AI algorithms. In addition to random forests, highly randomized forests (extra trees), Multi-Layer Perceptrons (MLPs), Deep Reinforcement Learning (DRLs), k-nearest neighbour algorithms (KNN), and logistic regression have also been employed. ROC analysis was performed to validate the results and generate good performance in the RF domain with an accuracy of 97.86 %, a True Positive Rate (TPR) of 96.83 %, and a False Positive Rate (FPR) of 1.72 %. DRL and TSF came in second and third, respectively, while MLP and LR had the lowest results.

Balqafih et al. (2021) [61] created an IoT-based accident recognition and categorization system. The automatic categorization of vehicle accidents enables emergency responders to receive the necessary information about each accident, based on the severity. A Microprocessor, GPS and several sensors helps the model to detect different physical conditions related to vehicle speed and many classification algorithms were tested using the constructed system to see which one was the most efficient. A collection of classifiers (CART) includes Decision Tree (DT), Gaussian Mixture Models (GMM), Classification and Regression Trees and Naive Bayes Tree (NB). The CART and GMM models performed better after implementation. It was also discovered that the seriousness of accidents is mostly determined by the g-force value and the presence of flames.

According to Mohanata et al. (2021) [62], accident severity can be predicted using Logistic Regression, K-Nearest Neighbours, Decision Trees and Artificial Neural Networks. Additionally, the article included a model for a secure communication architecture that may be used to securely share information across all ITS components. All models have been evaluated, and the results indicate that they are very accurate models.

Minnikhanov et al. (2020) [63] employed a combination of machine learning approaches and computer vision to identify and classify traffic irregularities in real-time. We propose a technique for detecting vehicle/pedestrian violations of lawful trajectory anomalies as a consequence of this study, which we tested on real-time video in Kazan.

Among the most prominent delineation of multivariate outlier detection algorithms in Biazquez et al. (2018) [64] is their application to data collected from sensor vehicles to detect and identify various atypical driving circumstances, including traffic jams. Detecting outliers is a critical challenge in acquiring relevant and meaningful information, as several studies have been proven. Outlier detection algorithms and data classification approaches were combined in this study. To gauge the relationship between the multivariate outliers and traffic congestion, the output of the outlier identification phase will then go through a series of classifiers.

Outlier measurement approaches remove the anomalies present in the data that arise due to system failures, instrument errors, or human interventions. Some anomalies are beneficial as they provide useful information for identification purposes [64]. Univariate and multivariate analysis help to identify outliers. To detect multivariate outliers, statistical methods such as Mahalanobis distance and various covariance estimators can be used. Principal component analysis and projection pursuits, which are primarily used for covariance and mean analysis, are appealing methods for outlier detection. Distance-based algorithms, such as KNN, and density-based algorithms [65], such as Clustering, are also useful for outlier detection. An outlier detector is an unsupervised learning tool that can be used to train a deep learning network. The efficient feature extraction properties of stacked auto encoders are also useful in outlier detection. SVM is a kernel-based model used for supervised and unsupervised learning is also effective in outlier detection [66].

4.3. Vehicle detection using deep learning in smart cities

Lingani et al. (2019) [67] suggested a method for resolving traffic junction turning-vehicles counting that is less intrusive, does not involve road digging, and is less expensive to implement. Any cameras, including smartphones, may be used to see live or recorded videos from previously deployed cameras across the city. Their system used object detection techniques such as Neural Networks and Deep Learning, computer vision technologies and a variety of approaches and algorithms. Their method will identify, categorize, trace, and calculate mobile object's speed and acceleration using a convolution neural network on static images, recorded movies, and real-time live videos. A convolutional network is designed by utilising a computer system with an NVIDIA graphics card enabled GPU, CUDA and OpenCV algorithms. The developed model is styled to work similarly to the human brain.

Nayak et al. (2020) [68] suggested a deep learning, video-based Intrusion Detection System (IDS). With the You Only Look Once (YOLO) technique, item detection was achieved and intrusion detection was based on the displacement of the object's centre of mass. The invader was also tracked in real-time using the Simple Online and Real-time Tracking (SORT) method. The method utilises Jetson TX2 platform for implementation purpose. Jetson TX2 is the most powerful and energy-efficient embedded AI computing device [69]. With Jetson TX2 as the target edge device, detection models using darknet based deep learning algorithms are easily implemented and tested. Using the NVIDIA Jetson TX2 development platform, the proposed system was evaluated for live video streaming with 97 % accuracy and an average frame rate of 30 frames per second. The suggested IDS was a general one in which the user may choose any size and shape zone of interest (intrusion-free area) from the reference (beginning) frame and prospective invaders such as people, vehicles, and other objects from a list of learned object classes. As a result, it may be used for a variety of smart city applications, including no-entry zones, no-parking zones, smart home security, and so on [70].The As illustrated by Zhang et al. (2015) [71], they suggest a combined method for detecting and distinguishing vehicle types in traffic videos recorded with fixed mount cameras based on 3D differences and deep convolutional neural networks. This integrated technique may make use of the three-frame difference's real-time motion detection capability as well as DCNNs' image recognition capabilities [72]. They tested the suggested technique using road traffic footage for accuracy and performance, and the results were quite encouraging.

Wang F et al.'s (2020) [73] proposed a strategy to improve the objective function by enhancing the traditional Single Shot Detector (SSD)algorithm, which streamlines the search window selection and improves the algorithm's accuracy. It combines appearance depth features with depth features, resulting in an appearance depth feature-depth feature combination. Compared with previous SSD algorithms, this algorithm delivers better anti-blocking and detection accuracy as well as greater stability under varying conditions.

Wang Z et al. (2020) [74] designed a real-time vehicle recognition system based on a SqueezeNet (H-SqueezeNet) background subtraction model and a MOG2 (Mixture of Gaussian).SqueezeNet is a smaller CNN architecture with competitive accuracy that uses fewer parameters with selected bypass connections to make the model to produce fast convergence in training and vehicle detection[75]. To identify vehicle types with a high degree of certainty, we use the H-SqueezeNet model to obtain scale invariant Regions of Interest (ROIs) from video frames. A performance evaluation was conducted using CDnet2014 data, the UA-DETRAC dataset, and video frames. Based on the results of the experiment, the technique may be able to achieve 39.1 frames per second detection speed and remarkable detection accuracy in traffic surveillance systems. A vehicle perception model developed by Liu et al., 2021 [76] collect more deep features to represent small objects present in the road scene. The method uses an adaptive feature representation model to conquer the occlusion created by heavy vehicles and detect small sized vehicles in an efficient manner. Next, a layer-by-layer fusion of shallow information is used to address the issue of feature loss. YOLO-v5-based deep object identification model suggested by Carrasco et al. (2021) [77] is also lightweight, and can identify things that are very big, very small, and very microscopic. A multi-scale learning approach is used, and it will automatically determine the best scale to use for tracking objects in an image of road surface by learning deep feature representations at different scales. With this recommended multi-scale module, there are fewer parameters to train than in YOLO-v5.

Radhore et al. (2021) [78] created a smart traffic control model based on the detection of traffic offences on the road using vehicle cameras. To do so, the vehicle's camera watches all of the automobiles in front of it on the road, and the recordings are sent to the fog device connected to the car. A fog device analyses video footage to identify defiant activity and reports it to traffic authorities if it detects any violations. Initially, the SSD algorithm is used to locate the front vehicles and the Hough transform to detect the lanes. A violation detection algorithm is later used to identify the violations.

Using MOG2 with faster R-CNN Wei et al. (2021) [79] developed a powerful model with good detection performance but suffers from redundancy issues, complexity, and low speed in detection. Among the main state-of-the-art level-of-detail DL-based object detection techniques, Bisio et al. (2021) [80] did a detailed performance evaluation of one of them as well as an experimental analysis of vehicle detection on the VisDRonebenchmark dataset using the RetinaNet framework. Together with the results of VisDrone testing, the RetinaNet framework has been proven to be efficient.

Naufal et al. (2020) proposed utilising the trained Region-based Convolutional Neural Network (Mask R-CNN) for allotting a parking slot from the input image of a parking space. Utilizing the Exposure Fusion framework, the pre-process enhances contrast in open area images to overcome the problem of lighting variation. The second stage checks if the parking spot is occupied with mAlexNet. Convolutional Neural Network (CNN) is used to locate vehicles from roadway camera outputs and extract the desired information using video analysis techniques. Khalifa et.al suggested the use of YOLOv5s architecture together with the k-means algorithm to optimise bounding boxes under different illumination conditions. The proposed model achieved a mAP of 97.8 in the daytime dataset and 95.1 in the night-time dataset, according to the results of the simulated and evaluated algorithm.[55]

The YOLOv4 algorithm is used in Amrouche's research (2022) to design a real-time vehicle recognition and tracking framework. The model achieved an accuracy of 96.30 % for the data driven and an overall accuracy of 94.17 %. A set of images are utilised after removing the noise with SIFT operator. The use of regional CNN on this set images can detect more vehicles in an efficient manner. The model is tested with Boxy data and the produces increased performance in runtime and accuracy is also improved.[82]

4.4. Vehicle detection using artificial intelligence in smart cities

Sukhadia et al. (2020) [83] describes a smart traffic management system that employs ML approaches to start regulating and overseeing the course of transportation, with intelligent governance and application to have an impact on the worst traffic problems in major smart cities.

To improve first responder coordination in connected cars, Taherifard et al. (2019) [84] propose that sensory data in cars be used to gather contextual elements that may be gathered using various Convolutional Neural Networks (CNN) architectures to select the appropriate first responder group once an accident met. CNNs are trained and tested using real collision images from a large dataset. Based on the acquired images alone, they estimate that the ResNet-34 network can accurately predict the first responder(s) in event of an accident with 88.9% accuracy using hidden layer unfreezing and image augmentation techniques.

Constructing a data augmentation approach for object tracking is more difficult than image classification because there are more complexities introduced by distorting the image, bounding box positions, and the sizes of the components in detection datasets[85].Deep learning models usually use image or data augmentation to increase the volume of data. Proper training of models can improve the detection and classification purposes of them. Translations and flipping images at different angles are common forms of image augmentation. Boundary bax based annotations are also utilised in the augmentation process.

The suggested technique by Liu et al. (2021) [86] may collect information from a variety of sources, raise driver awareness, and predict potential crashes, therefore improving driving comfort, security, and performance. As a result of Industry 4.0, the real world and digital information are complemented with robust,high-speed,low latency networks and AI technologies. The article examines the economic, technological, and legal implications of 5G networks for Smart Cities and Smart Transportation (both semi and fully autonomous communications). Finally, remaining obstacles and issues in AI-V2X research must be addressed for AI to fully achieve its obligations to enhance V2X systems. Various analyses of the recognition of vehicles in 5G networks have produced the following results: With 5G, transportation will be improved by 84.3 %, traffic will be monitored by 88.2 %, V2X communication will be developed by 85.47 %, driving comfort will be improved by 82.25 %, and traffic congestion will be reduced by 91.74 %.

Tariq et al. (2020) created a 3-dimensional highway surveillance model for smart city monitoring [87]. The suggested method is capable of detecting vehicles and detecting strange actions on the road. Stacking is used to merge pre-trained deep neural network models for license plate recognition,automobile identification, and intrusion detection. It will minimize traffic control manpower, time, and complexity.

Trivedi et al. (2018) [88] conduct a study on the counting of cars in YouTube videos, or more specifically, on counting cars for available online video using- Adaptive thresholding, the calculation of centre position, frame differences, edge detection, morphology, Euclidean distance methods[89], and the calculation of change in position, gaussian blur and delta positions. To distinguish a car from another thing, they analyze size differences between automobile objects, such as four-wheelers, and pedestrians on the road, and static objects such as trees and roadside posters. Check out the simulation findings for traffic videos in Ahmedabad, Chennai, Bangalore, and Mumbai on YouTube, which are accessible in various resolutions. There's also the issue of traffic at night. Simulation results for the Ahmedabad Traffic video are validated using recall, accuracy, and the F1 parameter. Chen et al.(2020) [90] designed a convolutional architecture enabled fusion approach to detect size of the vehicles by considering various features. Validation by JiangSu Highway Dataset reveals its efficiency over the state of art Faster -RCNN based detection.

4.5. Vehicle detection using IoT in smart cities

The Internet of Things (IoT) is emerging as a ubiquitous, always-on universal computing network. It is a network of devices integrated with electronics, software, sensors, actuators, and communication facilities, capable of exchanging the collected data with each other and with the controlling framework.[91]. IoTs are developed to be sensed rapidly and remotely piloted across established infrastructure and are integrated into the natural environment with the control of software systems. They can provide improved adeptness, exactness, and economic profit, as well as reduce human involvement. These sensors gather useful data using existing technologies and then transfer it between devices [92].

An alternate low-power and cost-effective technique were presented by Solic et al. (2019) [93]. The research includes the development of two innovative vehicle proximity detectors, based on 868-MHz LoRa and 866-MHz UHF RFID technologies. One is battery-powered and uses LoRa technology, while the other is powered by solar cells and uses BAP technology. The research results show that the suggested technique is adequate since it achieves the same functionality as traditional devices at a cheaper cost and lower usage.

LoRa technology combines wireless sensor network technologies with several sensor nodes. The wireless sensor concept mainly aims to detect the presence of the vehicle at shorter distances with low signal transmission power [94]. The LoRaWAN algorithm utilises star topology for its implementation in smart roads. Short Lora is another form which utilises 5 sensor nodes in a star topology for vehicle or traffic flow detection in which one node controls the measurement operations. LoRa technology is very effective at detecting stopped vehicles and slow-moving traffic moving at less than 40km/h. LoRa and Short LoRa send radio signal strength indicators (RSSI) to sensors placed at small distances. A decrease in RSSI signal denotes the presence of a vehicle in the transmission line. The use of lasers in sensor detection can increase the detection efficiency of LoRa networks [95].

RFID sensors can improve the stability and security of vehicles and can integrate with the automobile industry for production and transportation of industrial goods. Smart cities employ RFID sensors for number plate identification and intelligent parking slot allotment. Integrated RFID sensors in vehicle tyres can provide tyre monitoring as well as useful vehicle detection. UHF RFID sensors work well with other emerging technologies [96].

A new method for detecting and reporting accidents was proposed by Bhatti et al. (2019)[97]. The proposed system uses the Internet of Things to develop and build a low-cost system that can be installed in current automobiles using increased technical specifications. A customized Android application is being built in this scenario to collect data on velocity, gravity pull, temperature, sound, and position. The speed of a vehicle is a factor that is used to aid in the detection of accidents. It occurs as a result of distinct changes in environmental variables (e.g., disturbance, deceleration rates) in low-speed accidents vs high-speed collisions. The data is then analyzed to see whether there have been any traffic accidents. As a part of the development of the navigation system, a hospital near the scene of the incident would be informed. Simulated and real-world data from the Road Safety Open Repository are used to check the developed method's accuracy, and the results show that it seems promising.

Alzubi et al. (2021) [98] proposed Responder-dependent Additive Information Fusion (RAIF) in which Sensor data collected by a linked device based on the IoT was used to determine the level of attainment of the recommendation for the guided vehicle. The data is gathered from multiple instances from a device that is connected to the Internet. The data from the timely responding sensors is compared to the prior history to improve the precision of guided vehicle navigation. As a part of the information fusion approach, classification machine learning is applied to detect occurrences that recur as well as those that do not recur according to correlation. This helps to identify and mitigate errors in data resulting from sensor failures, thereby increasing the precision of the test.

A Smart Traffic Management System for Real-Time Traffic Updates by Rizwan et al. (2016) [99] combines traffic indicators to update traffic data in real-time to improve traffic management. A low-cost vehicle detection sensor is embedded every 500 meters or 1000 meters on a road. The Internet of Things (IoT) can rapidly collect and supply traffic data for processing. For Big Data analytics, real-time streaming data is provided. A mobile application is developed to examine traffic density at various locations and to provide an alternate method for traffic control. Several analytical techniques can be used to measure traffic volume and offer solutions Using predictive analytics.

Li et al. (2020) [100] investigates the intelligent vehicle network system and smart city administration from the perspective of genetic algorithms and visual perception. Massive urban data can be swiftly saved, processed, and analyzed utilizing distributed and parallel computing and important information may be retrieved, allowing smart cities to make better decisions and enhance the efficiency of infrastructure and resource usage. The simulation results suggest that the proposed coordination technique may achieve the lowest energy usage schedule, increasing the data centre's advantages, successfully enhancing urban road traffic capacity and reducing congestion.

With the help of scattered servers, 6G technology-based edge intelligence enables newer vehicles to become part of effective transportation systems. The large amounts of data can be computed and can help the drivers and passengers make use of the transportation system in a reliable manner. The intelligent offloading scheme helps the intelligent transportation systems achieve and process all the functional services. The experimental results demonstrate the significance of a greedy and dynamic strategy for intelligent transportation [101]. With the help of IoTs, application programming interfaces can invoke many public services on a common platform. A collaborative, learning based IoT API has been created to address all the services and make them useful for the users. Implicit relationships between IoTs are improved by the matrix factorisation model. The real-world dataset-based experimentation gives the effectiveness and superiority of the given model [102]. VANETs are self-organized wireless multi-hop networks in which nodes collaborate with one another to support data transmission. To quantify node credibility by avoiding the allocation of malleable nodes is suggested by Gao et al. A trust management method is used for it, and direct and recommended trust models are utilised for the application. The trust management is dynamically computed by historical integration and a Bayesian algorithm [103].

VANETs have been widely used in intelligent transport system (ITSs) for applications such as unmanned aerial vehicle (UAV) control and direction prediction. Gao et al. proposed a dependable VANET routing decision scheme based on the Manhattan mobility model that considers the integration of roadside units (RSUs) into wireless and wired modes for the transmission of data. For different transmission distances, routing decision analysis is also carried out in compliance with the probabilistic model. When compared to other baseline procedure methods, the suggested technique can aid real-time planning and optimise system's performance [104]. The Polychromatic Sets (PS) model is developed into path planning analysis of multiple characteristics of the road. An effective trajectory planning scheme is presented based on the priority level, with priority given to the highest roadways in the target direction. The system can repeatedly procure real-time road details via mobile and keep updating it, and provide more users with more accurate road info and route planning, allowing users to avoid congested road segments while consuming less time. Test findings showed that the algorithm can provide customised trip planning services while minimising time and distance [105].

Tiny FCOS is a compact FCOS-based object tracking model with three distinguishing features: (1) a compact backbone system that efficiently reduces model weight. (2) a simplified dilated convolution group for constructing FP network (3) The FCN prediction branch utilse one convolution block for recognition analysis with PASCAL VOC datasets show that Tiny FCOS has a mAP of 62.4%, which is 4% higher than Tiny YOLOv3. Tiny FCOS outperforms conventional systems and offers a novel solution to real-time object tracking difficulties [106].

5. Performance evaluation

When it comes to the vehicle detection scheme that is about to perform, it should have a proper matrix to be chosen and evaluated. The choice of the matrix will influence the performance and evaluation of the framework. Most deep learning based classification models discuss the confusion matrix while implementing the model. It shows the effectiveness of the classification algorithm developed. The Confusion Matrix (CM) is a table that compares ground truth labels to model predictions. Every row of CM represents a predicted class, and each denotes an actual class. It is not a performance metric but it serves as a basis for other metrics to analyse results.[107]. Table 2 gives an idea of the members of the confusion matrix and other performance metrics mainly considered in the reviewed methods used for classification of the detected vehicles. Machine learning is simply a mathematical and probabilistic model that necessitates numerous computations. It is trivial for humans to perform those tasks, but computational machines can easily perform similar tasks. Normal hardware may be unable to perform extensive computations quickly, as a model may require calculating and updating millions of variables in run-time for a single incremental model, such as deep neural networks. Table 3 depict the general hardware and software specification used for detection system in smart cities using emerging technologies [108]-[110].

Several methods are considered for reviewing the vehicle detection scenario. Table 4 shows a comparison study of many relevant studies for vehicle identification in smart cities at various levels. Different stages of vehicle detection is classified into 4 stages. Pre-processing stage includes Noise removal, data cleaning, selection of proper data for training and testing of CNN model, pre-registration of images. Feature extraction and Feature selection are similar both collect relevant data from images in training. Selection of kernel size is crucial in feature representation. Vehicle detection covers the detection algorithms utilised to collect the traffic data includes presence, parking occupancy, Volume, speed, queue length, and vehicle length etc.

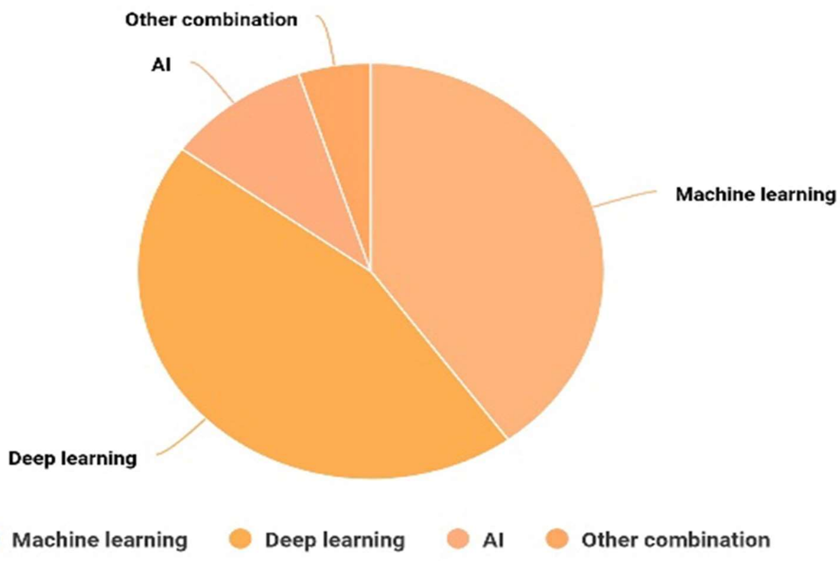

Fig. 8. Reviewed papers on vehicle detection using emerging technologies

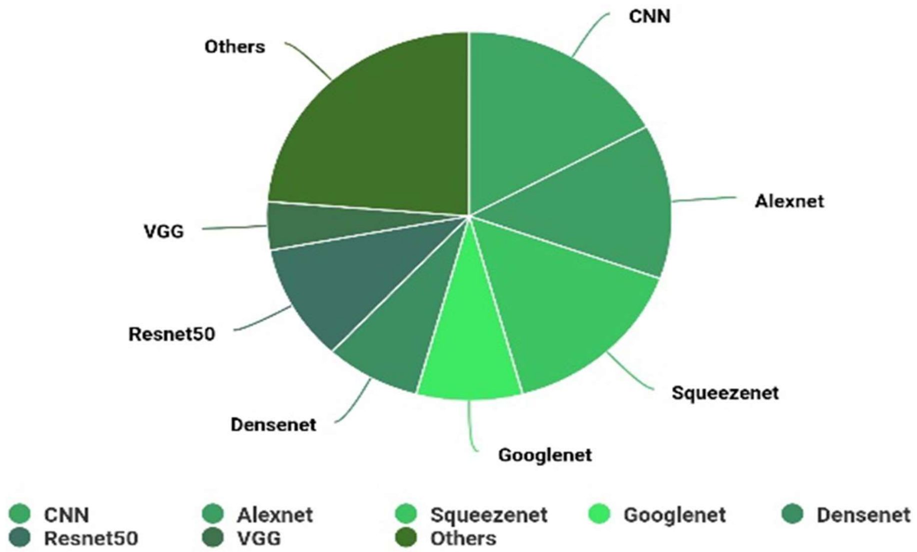

Fig. 9. Most used DL methods for vehicle detection.

Few methods evaluated its competence in real time and few used pre-processed and preregistered images for training the model. Most deep learning models with faster vehicle detection use CNN and residual networks for feature representation. Information collected by IoT models gives improved results with machine learning models. Spatial computation algorithms are mostly used in most of the emerging methods, which include R-CNN, fast RCNN, and faster RCNN algorithms. In figure 8, you will see the publications that were examined regarding the incidence of new technologies used in detecting vehicles, and in figure 9, you will see what technological approach is most widely applied in recognizing vehicles in smart cities.

Table 2 Performance matrices

Metrics of Performance Measure	**Mathematical Description**
True Positive Rate (Sensitivity)	$TPR = \frac{TP}{TP + FN)}$
Specificity(S)	$S = \frac{TN}{(FP + TN)}$
Positive Predictive Rate (Precision)	$PPR = \frac{TP}{(TP + FP)}$
Accuracy	$Accuracy = \frac{TP + TN}{(TP + TN + FP + FN)}$
F Score	$Fscore = \frac{2TP}{(2TP + FP + FN)}$
Recall	$Recall = \frac{TP}{(TP + FN)}$
False Rejection Rate (FER)	$FER = \frac{FN}{(TN + FN)}$
False Acceptance Rate (FAR)	$FAR = \frac{FP}{(FP + TN)}$
Negative Predictive Rate (NPR)	$NPR = \frac{TN}{(TN + FN)}$
Receiver Operating Characteristic (ROC)	$TPR\ Vs\ FPR$

Table 3 Overall software and hardware specification

Hardware Configuration	Configuration Parameter	Software Configuration	Configuration Parameter
OS	Windows 10	Development Environment	Google Colab
CPU	AMD A8,5600k	Programming Language	Python
RAM	64.0 GB	Image Algorithm Library	Open CV
Memory(video)	1000 MB	Deep Learning algorithm Library	Pytorch
CPU	I5 Processor 8th Gen	Programming Language	Python

Table 4 An overall analysis of stages by authors on vehicle detection in smart cities

Authors	Pre processing	Feature extraction	Feature selection	Vehicle detection	Improved efficiency
Dominguez et al. (2021)	✓	✓	✓	✓	✓
Balqafih et al. (2021)		✓		✓	✓
Kumar et al. (2021)		✓		✓	✓
Minnikhanov et al. (2020)		✓	✓	✓	✓
Lingani et al. (2019)			✓	✓	✓
Nayak et al. (2020)	✓		✓	✓	
Zhang et al. (2015)		✓	✓	✓	✓
Xu et al. (2020)		✓		✓	✓
Wang et al. (2020)		✓		✓	✓
Sukhadia et al. (2020)		✓		✓	
Liu et al. (2021)			✓		✓
Solic et al. (2019)				✓	✓
Rizwan et al. (2016)		✓	✓	✓	

6. Conclusion

This paper presents the overall review of vehicle detection along with its merits and demerits. The information covered will help the researchers working in the same area. The importance of emerging technologies, their use in vehicle detection and the steps behind such models are addressed. A detailed explanation of the working of the learning-based algorithm and the customising options is provided. Performance metrics and the need for sophisticated software for implementing emerging models were also presented. The study offers an overview of the techniques for detecting vehicles using real-time data. As a result, these approaches have been extensively explored in terms of conventional emerging strategies. Given the number of articles with bibliometric analyses on vehicle detection, this will be the first and best attempt to encompass studies on vehicle detection in smart cities utilising developing technologies throughout the last decade (2012-2022), including all possible methodologies. A study such as this will help the Ministry of Urban Development and the research community understand vehicle detection in smart cities in the last few years and better integrate and develop models for even more accurate theoretical and practical applications. Although deep learning and machine learning are the most advanced technologies, they have limitations in terms of detection that must be addressed. Improvements include the extreme volume of data to be fed, the quality of data for better processing, dealing with natural data, and perpetuality of the domain; additional features; encryption of data; privacy of the system that's about to emerge; leading DL in the right direction by incorporating expert knowledge; and developing DL systems that will be time-sensitive will improve DL. To process AI, a lot of computing power is necessary, and for IoT, upgrading the security architecture to prevent third-party attacks is a must.

Acknowledgements

I would like to thank Centre for Engineering Research and Development (CERD), Government of Kerala, College of Engineering Thalassery and APJ Abdul Kalam Technological University, Kerala for giving financial support for carrying out the research work. Thank you to the supervisor, who has provided many directions in conducting this research.

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