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A Heuristic Approach Using Intelligent Transportation System for The Detection of Vehicles for Effectively Road Traffic Management

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***Abstract* –** Research explored VDC (vehicle detections) and compared the current classifier to new design classifiers like RTM (real-time traffic flow monitoring). It has considerable financial value, but it is also an important tool for maintaining public safety. In view of the current situation, where the accuracy of existing traffic flow statistics algorithms is poor and it is easy to generate false detections, a multi-lane traffic flow statistics algorithm based on a novel design classifier is proposed. Our suggested framework includes input data type, vehicle type, scale, scope, dynamicity, vehicle detection method, vehicle classification method, application, and assessment method. Following that, we use the offered framework to investigate the history of VDC approaches and highlight several open challenges that have evolved in the field. This article is intended to serve as a guide for researchers who want to utilize or build dependable VDC systems that satisfy their needs.

1. INTRODUCTION

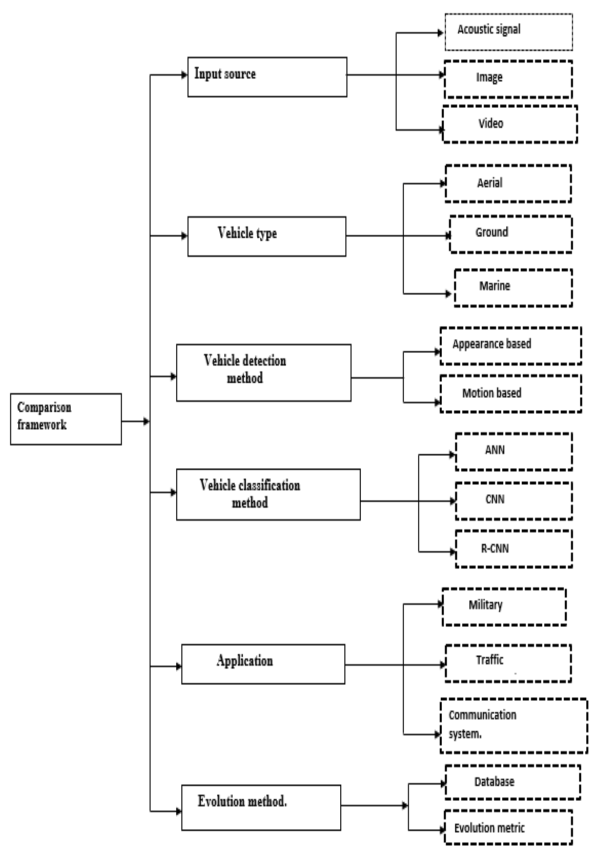
The scale of cities is always expanding as the economy develops and urbanization accelerates. As a result of this As a result of this process, urban traffic congestion is increasing. severe, posing a variety of significant difficulties for city planners and administrators. The most successful technique in order to reduce traffic congestion is to widen city roadways, but this method has some drawbacks, including the use of rare land resources, high construction costs, and a protracted building cycle, among others. As a result, effective tracking of traffic flow and acceptable diversion are effective approaches to alleviate traffic congestion.

Researchers have explored a wide range of machine-learning algorithms for the VDC problem in recent years. This report does a literature assessment of neural networks (NNs)-primarily based fully VDC solutions from January 2018 to December 2021 as part of research in the VDC field. The search was conducted using the keyword indices for paper abstracts containing the phrase "neural networks-based fully automobile detection and classification," as well as related subjects such as "automobile detection," "automobile classification," and "neural networks." The ACM virtual library, Elsevier Scopus, MDPI AG, Taylor, IEEE Xplore, Springer, Wiley Inter Science's net database, and exceptional PhD these are the search results. In addition, judicial cases from top gatherings in the disciplines of image processing and ITS are considered.

ICTDX, WACV, ICIGP, SIU, ITSC, CIS, CISP-BMEI, IV, and AIPR are among them. In addition, we used closely related works that had been published in several extraordinary meetings and journals. We sort through the papers after they've been gathered to find the ones that are solely about NNs-based fully VDC. The courses discussed in this paper have generated a lot of interest in recent years. From 2018 to 2021, the frequency of papers posted is shown in Figure 2.1. IEEE Xplore, Springer, MDPI AG, and ACM are the top four publishers, according to the large variety of publications.

To overcome the drawbacks of typical vehicle identification methods, this study uses the deep learning target detection method and a novel design algorithm to properly recognize the vehicle, acquire vehicle position information, and use the vehicle location information to further track the vehicle. Using the relationship between vehicle location and traffic flow detection line, it obtains multi-lane around the same time, traffic flow statistics.

Existing VDC systems range significantly in terms of input source, vehicle type, scale, scope, vehicle detection technology, vehicle categorization approach, dynamicity, application, and assessment method. These dimensions make up our proposed comparison framework. Figure 4.1 depicts the proposed comparison structure. In the illustration, dimensions are represented by solid rectangles, while sample values are represented by dotted round rectangles. For a variety of reasons, each dimension is taken into account. For example, the vehicle type dimension is used to evaluate a VDC technique's capacity to recognize various cars from the input data source. As a result, a VDC system that can distinguish various vehicle types with greater precision and less processing complexity is preferred.



JOURNAL OF ALGEBRAIC STATISTICS
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Figure 1.1 Shows our proposed framework for comparison.

Pros and cons of ANN, CNN, AND R-CNN architectures:

CLASSIFIER	Pros	Cons
ANN	Information is stored across the whole network. Ability to work with limited information. Having the ability to tolerate mistakes. Having a memory that is spread.	Hardware is required. The network's behavior is unexplained. The correct network structure must be determined.
CNN	Image recognition challenges require a high level of precision. There is no need for human intervention, automatically detects the relevant features. Weight distribution.	CNN does not encode an object's location or orientation. Inability to be spatially invariant when dealing with incoming data. A huge amount of training data must be collected.
RNN	Every piece of information is remembered by an RNN over time. It can only be used to predict time series because it remembers previous inputs. Long Short Term Memory is the term for this type of memory (LSTM) Even convolutional layers are employed with RNN to broaden the effective pixel neighborhood.	Problems with gradient vanishing and exploding. It is quite tough to train an RNN. When utilizing tanh or relu as an activation function, it won't be able to handle very long sequences.

2. Literature review

Madhusri Maity et al. classified the incorporating existing vehicle detection algorithms distinct categories in this survey based on the architecture (Faster R-CNN/YOLO) that was employed as the backbone of these newly created approaches. We structured the full survey in chronological order to show the interrelationships between the proposed methods. In this review, we offer detailed descriptions of the architectures of Faster R-CNN, YOLO, and their proposed modifications, in addition to completing in-depth studies of the existing approaches [1]. Sajjad Hashemi et al. In this research, nine comparison dimensions are proposed: input data type; vehicle type; scale, scope, dynamicity; vehicle detection method; vehicle classification method; application; and evaluation method. Following that, we explore the history of VDC techniques and identify various open concerns that have arisen in the area by utilising the provided framework. [2]

Apeksha P Kulkarni et.al In this work, the author discusses As a result of the intense traffic flow, the number of road accidents rises. The traffic flow is monitored in this research utilising a computer vision paradigm, in which images or sequences of images improve the road perspective. This research project uses the Ardunio Microcontroller camera module coupled with the The Pi 3 is used to detect vehicles, monitor traffic, and estimate flow. utilizing low-cost electronic devices. [3] In this paper, Yongmei Zhang et al. The proposed method recovers vehicles based on video attributes and distinguishes between moving and non-moving vehicles based on pixel sizes and positions [4].

Feng Peng et.al The most effective way to achieve traffic flow monitoring is to use video recognition technology, as outlined in this paper. A multi-lane traffic flow statistics method based on YOLOv3 has been developed in light of the current scenario, in which the Existing traffic flow statistics algorithms aren't very accurate. weak and it is easy to induce false detection and false detection.[5] Amrita Vishwa et.al Taking its importance into account, an effective approach for detecting cars in an image making use of image processing is developed. The shot was taken from the vehicles' front view. As a result, this algorithm uses the front view to detect automobiles. [6].

Shulin Li te.al For optimization and fast detection speed, the suggested technique combines detecting and tracking. Experiments on a self-created UAV traffic video dataset show that the proposed strategy produces better and higher [7] results. Ganchimeg. G et.al This research offers a review of vision-based vehicle identification and tracking systems for intersection monitoring. Vehicle surveillance systems face a number of challenges, particularly in urban traffic scenarios like road sections and intersections, where congested traffic, vehicle occlusion, posture and orientation fluctuation, and camera location all have a significant impact on their performance. [8]

R. Roopa Chandrika et.al Using image processing techniques, the study shows how to detect, count, and classify automobiles. Despite the fact that there has been a significant increase in amount of research on this topic, there is always room for improvement. The task of detecting and counting vehicles is divided into six steps: 1) Image capture, 2) Image analysis, 3) Object detection, 4) Counting, 5) Classification, and 6) Display of Results.[9] Rui Xu et.al In this research, we build and implement a deep learning-based vehicle infraction detection system that comprises vehicle detection, tracking, and recognition.[10].

According to the National Crime Record Bureau's Accidental Death and Suicides in India report, hundreds of people died in 2014 owing to accidents caused by low visibility during inclement weather conditions, primarily in two Indian states (Andhra Pradesh and Telangana).[11]. Another report [2] According to a report published on the website of the United States Department of Transportation, Federal Highway Administration, based on data collected over a ten-year period (2007–2016), approximately 21% of total annual accidental crashes in the United States occurred occurred as a result of poor visibility during bad weather.[12].

According to records filed in [13], almost 90% of street injuries in India are caused by driving irresponsibility. These records and data, which have been published in various large publications, clearly demonstrate the importance of executing accurate car detection in the real world. Mu et.al. [14]: The authors created a faster R-CNN based completely deep neural network in order to recognize cars in aerial photographs. Initially, the authors accomplished data enrichment with their proposed oversampling and sewing-based full data augmentation techniques, which allows you to correct disparities caused by short vehicle lengths in aerial pictures as well as the issue of favorable and unfavorable sample imbalance.

The authors of [15] mostly changed the connections between the up-sampling and down-sampling layers in order to preserve more top-level information and accurately detect small vehicles.

Ghoreyshi et. al. [16]: On this painting, the writers have created one-of-a-kind car identification networks in order to locate autos whose photographs were gathered from Iranian websites. The photographs of autos that can be employed for teaching and network checking out in this work share a lot of commonalities.

Zhou et. al. [17] has typically built this strategy to recognize automobiles in satellite tv for pc images. In order to do automobile detection using satellite television for computer images, the authors chose a modified YOLO model three network for this study. The modifications were made to the YOLO model three network because the motors in satellite tv for pc pictures are quite little, and the history of satellite tv for pc pictures causes interference in appearing correct automobile detection.

Doan et. al. [18] This method uses the YOLO model four network to do automobile detection and counting. With the rapid increase in population and vehicle numbers, traffic safety is becoming increasingly crucial, and precise video traffic flow monitoring is critical [19].

The deep learning method can accurately detect the vehicle, and the detection procedure takes less time, but it takes too long to train the model, and it's impossible to match the real-time needs of video-based traffic flow monitoring [20].

To ensure the algorithm's performance level, the three-frame difference method [8] is used to identify moving vehicles; calculate the vehicle's speed using its moving

JOURNAL OF ALGEBRAIC STATISTICS
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distance; combine it with traffic flow to evaluate road conditions; and use pixel position and size to effectively distinguish the motor vehicle from the non-motor vehicle.

Because the gathered video may contain a lot of noise, this work uses median clear out [22] and Gaussian clear out [23] to denoise it. The median clear out is used to remove discrete tiny salt and pepper noise from within the image, whereas Gaussian clean out is used to remove Gaussian noise. Corrosion growth is used to put off the discontinuous spaces that appear in the video. The three-body distinction technique has particular advantages in automotive contour segmentation [24], as previously mentioned.

Non-motor vehicles have a narrower contour width than motor vehicles, and they are unable to enter.

The method calculates the car's centroid coordinates and contour length, then checks if the contour length is greater than a certain threshold. If that's the case, check to see if the centroid function is in the modern lane's hobby position. Ajay S. Ladkat et al. used the GPU for image preprocessing to improve the image [25]. S. L. Bangare et al. [26-28] worked in IoT domain with P. S. Bangare et al. [29] feature extraction and K. Gulati et al [30] for emotion detection methods.

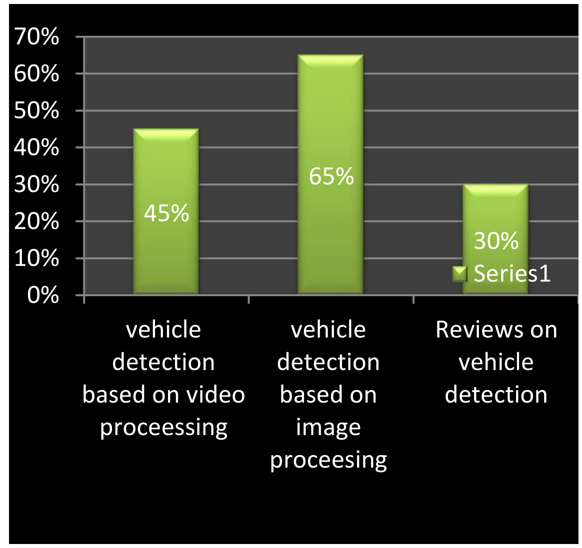

Fig 2.1 Performance of literature review

1. Introduction approximately graphical illustration of normal literature evaluate wherein is offers records (VD) automobile detection primarily based totally on video processing as giving video as in positioned to set of rules that's improves overall performance of set of rules there's offers category statistics base characteristic extracted, preprocessing and primarily based totally there a way to will increase Accuracy of classifier.

2. VD (automobile detection) primarily based totally on photo processing which mentioned on primarily based totally their literature survey that's offers their strategies how, primarily based totally on photo processing improves accuracy of algorithms which offers categorized or statistics characteristic extractions, preprocessing strategies which improves overall performance of classifier. in graphs displays Has their offers how tons initiatives are layout primarily based totally on photo processing has mentioned on literature survey.

JOURNAL OF ALGEBRAIC STATISTICS
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3. Reviews primarily based totally on VD (automobile detections) which has offers records approximately comparatives look at of classifier and theirs offers accuracy of classifier, and the way classifier we've got layout of our challenge layout.

1.2 COMPARATIVES STUDY OF VEHICLE DETECTIONS:

In comparatives have a look at we studied [1 -10] reference paper their evaluate Methodology, set of rules associated accuracy in comparative have a look at which has given their associated operating in addition to accuracy their database, classifications of database, preprocessing characteristic extraction, and the way improves gaining knowledge of overall performance of classifier.

Table 1. Comparative study of Algorithms and their Accuracy.

Sr.no	**Author**	**Method**	**Algorithm**	**Accuracy**
1	Madhusri Maity et.al	A review	R-CNN, YOLO	-
2	Sajjad Hashemi et.al	A review	R-CNN	-
3	Apeksha P Kulkarni	This research project aims to use reduced electronic gadgets to detect automobiles, monitor, and estimate traffic flow. utilizes Including the Raspberry Pi 3, there is a camera module for the Raspberry Pi.	-	According to the data, the image recognition accuracy rate is 97.1 percent.
4	Yongmei Zhang et.al	The proposed approach recovers autos using video attributes and uses pixel sizes and locations to distinguish between moving and non-moving vehicles.	This algorithm utilizes moving cars using the three-frame difference technique and displays the number of vehicles, speed information, and the number of vehicles per lane in a direct visual manner to ensure real performance.	The average vehicle speed detection rate in this study is 86%.
5	Feng Peng et.al	To achieve the aim of tracking, the same vehicle is judged by whether the center point of the vehicle marker box in the	YOLO V3	Accuracy rate of traffic flow detection is 87.7%.

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p.2211-2230
https://publishoa.com
ISSN: 1309-3452

		adjacent two frames is at the same point.		
6	Seelam Shanmukha Kalyan1 et.al	The shot was taken from the vehicles' front view. As a result, this algorithm uses the front view to detect automobiles.	Fuzzy logic	Accuracy rate is 80%
7	Shulin Li et .al	Unmanned Aerial Vehicles (UAVs) appear to have a number of advantages over fixed cameras, including greater flexibility, broader vision, and faster speeds, all of which make vehicle detection more difficult.	RCNN	86.7%
8	Ganchimeg. G et.al	For intersection monitoring, a review of vision-based vehicle detection and tracking systems is conducted.	-	87%
9	R.Roopa Chandrika et al.	Using image processing techniques, the study shows how to detect, count, and classify automobiles.	Machine learning	86%
10	Rui Xu et.al	In this research, we build and implement a deep learning-based vehicle infraction detection system that comprises vehicle detection, tracking, and recognition.	Deep Learning	87%

Table -2 The map and detection speed of the proposed Network with or without tracking.

Communications	**Map**	**Detection speed**
YOLOV3	61%	5fps
Fuzzy logic	61.4 %	3fps

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p.2211-2230
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ISSN: 1309-3452

RCNN	61.8 %	8bs
Faster-RCNN + tracking	67.9 %	10fbs

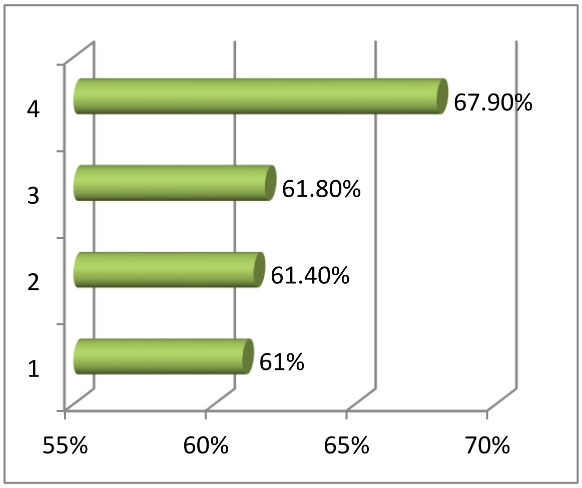

Fig 2.2 Vehicle categorization systems based on neural networks have statistics.

As shown in Tab. II, the detection effects of the -RCNN and other classifiers, as well as the proposed community, have all improved following the tracking mixture. Although the detecting speeds are much slower than those of networks without tracking, they are still faster than real-time and will suffice for most practical applications.

1.3 INPUT SOURCE:

This dimension is designed to answer the query, "What is the VDC system's input supply?" Image, video, and auditory signals are examples of different types of input data. Sixty six Because of the large range of autos that produce numerous challenging situations in traffic control structures, as shown in Figure 2.3, the primary focus is on tourist photography. The second place goes to videos uploaded by site visitors. Within the following positions are aerial images and acoustic alarms. Surveillance cameras, roadside microphones, cameras mounted on unmanned aircraft, movement detection sensors, and other types of sensors are among the continuous or cellular equipment used to collect information about automobiles. Seventy-seven A huge representation of information series and processing media is depicted in Figure 2.3. Intrusive, nonintrusive, and off-roadway data series approaches, as well as aggregate media, fall into four categories. s7. At the surface, intrusive sensors are installed. Intrusive information series gear such as a strain gauge, magnetic tube, and magnetic sensor are well known. Nonintrusive sensors are usually installed alongside or above roads. Cameras, radar, infrared sensors, ultrasonic sensors, mild detection and ranging (LiDAR) sensors, and acoustic sensors are examples of nonintrusive information devices. Both nonintrusive and intrusive sensors are environmentally conscious, costly renovation, and more money to spend Non-invasive information creditors, on the other hand, are easier to set up and maintain than intrusive equipment. 7.

Hazards in the atmosphere, noise, and a lack of communication among intrusive sensors all contribute to poor tracking data. Off-roadway sensors are cellular sensors that can be installed in vehicles equipped with GPS receivers, satellites, and planes. In VANET localization structures, GPS receivers are often used to extract mobility data such as position, travelling lane speed, acceleration, and deceleration. 48–50 Combination processing mediums collect information for VDC construction by combining invasive, non-intrusive, and off-roadway gear.

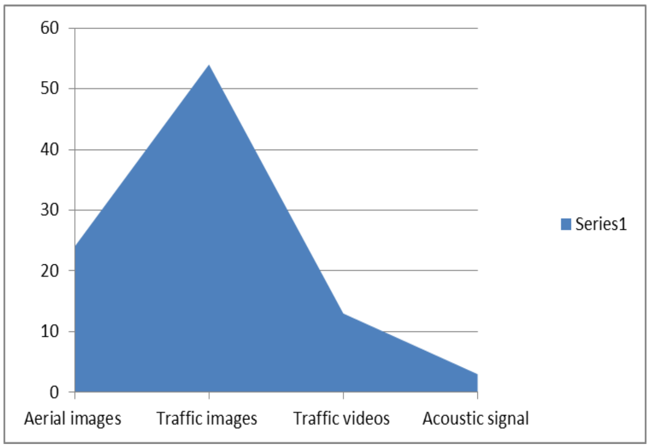

Fig 2.3 In this work, the distribution of VDC systems is examined in terms of input data type.

Table 3. Input data types discussed their pros and cons.

INPUT DATA TYPE	PROS	CONS
Acoustic	Rain doesn't bother me. Detection that is passive Installation is simple.	The precision of detection is impacted by the cold temperature. Sluggish traffic results in poor overall performance. Has limits to get informed of the wide range of autos available in the field.
Image	Processing is simple. Cost-effective Quick and simple.	Image noises can take many different shapes. The appearances of several autos are comparable to the static background. Various types of vehicles A vehicle obstruct the view. In the backdrop, there is a lot of traffic.
Videos	Directly and immediately determine the quantity of moving autos. Multiple highways and zones are under surveillance. Adding and changing detection zones is straightforward. When data from one camera position can be linked to another, wide-area detection is conceivable. Only if numerous detection zones must be in the camera's range of vision is it cost-effective.	Field of view is restricted. The image quality is harmed by bad weather, shadows, vehicle projection into adjacent lanes, occlusion, day-to-night transition, and vehicle/road contrast. On camera lenses, water, salt dirt, icicles, and cobwebs can degrade detection performance. For optimal presence detection and speed measurement, the camera must be mounted at a height of 50 to 60 feet (in a side mounting configuration). Video noises come in a variety of shapes and sizes. In the foreground, there is a traffic

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p.2211-2230
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ISSN: 1309-3452

		gridlock. The field of vision of the camera is shaky.

VEHICLE DETECTION METHOD:

One of the most important duties in any VDC machine is to understand and locate automobiles with inside the enter sources. The bulk of VDC buildings use device studying approaches for automotive detection. Feature extraction is the most important task in device-based fully automated vehicle detection approaches. The main goal is to reduce the number of records in the input supply by extracting the most important ones.

Eighty-eight Some of the function extraction approaches include the histogram of oriented gradient (HOG), 39 Haar-like features, 29 adjacent binary patterns (LBP), 10 accelerated strong features (SURF), fifty four, and scale-invariant function transform (SIFT). fifty-ninth After removing features, they used to construct device studying styles such as choice trees, K-nearest neighbors (KNN), and help vector machines (SVM). 60 There are two types of methods for identifying automobiles: movement-based and look-based strategies.

MOTION-BASED METHOD:

In motion-based fully techniques, the detection of motors are mostly reliant on their utilizing behavior. Furthermore, in order to locate motors, those techniques require a series of photos. 23 The basic goal is to use the entry sources to differentiate the moving foreground items from the history. 2 Motion-based totally approaches are ideal for real-time applications such as traffic analysis. Because most transferring locations are easily identifiable, the detection cost of motion-based completely techniques are typically expensive. The number is 66. Those processes, on the other hand, do not account for motor motion, do not account for the varying capacities of motors, and are subject to minor changes.

3. PROPOSED METHODOLOGY:

Proposed framework mainly consists of 4 blocks, viz. input, backbone, neck and dense prediction. Depend on the frame rate of the camera the images are extracted and after preprocessing these images are feed as input to the input block as shown in figure 3.1.

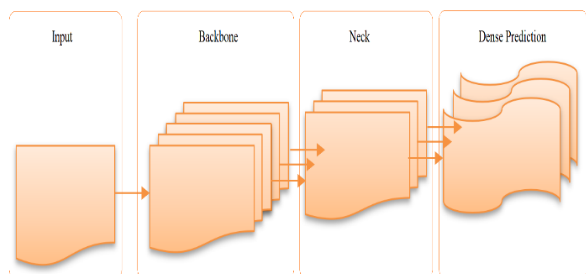

Figure 3.1 System architecture for detection of vehicle

DenseNet, which is utilised to extract the features from the image, serves as the framework of the architecture. As the network goes deeper, this block produces multiple tiers of the features with increasing meanings. The neck, which consists of the additional layers between the backbone and the head, is the following block. They are employed to extract various feature maps from various backbone stages. Everything about it is from the feature pyramid network. The network in charge of carrying out the detection portion of bounding boxes is called

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p.2211-2230
https://publishoa.com
ISSN: 1309-3452

dense prediction.

Image processing based on a vehicle recognition system is used to characterize the environment in this article, which means that autos are recognized as points in space R3. vt R3 depicts the position of vehicle v in this environment at time t. A vehicle is a machine that carries people or things by land, sea, or air. Bicycles, autos, rail vehicles, ships, and aeroplanes are just a few kinds of vehicles. 17–26 Each vehicle is described in the VDC literature as a set of features f 1, f 2,..., f K, with f I being the dominant feature. The most difficult task for VDC systems is accurately separating features in order to appropriately recognize and categories vehicles.

Vehicle identification is an important machine vision problem that tries to accurately identify automobiles. 15,20 Vehicle detection systems are available in a range of configurations, the most prevalent of which being appearance-based and motion-based systems. By eliminating the background and emphasizing the vehicle, appearance-based approaches identify a source of worry in a given image (or part of it). 27,28 Vehicles are classified based on aesthetic features such as edge and slope. The goal of motion-based approaches is to identify moving foreground objects. Figure 3.2 shown the fundamental block of the vehicle detection system

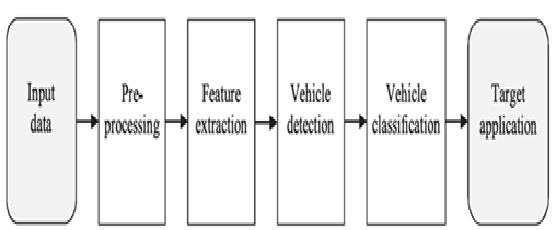

Fig 3.2 fundamental components of the vehicle detection system

Preprocessing phase requires the videos or images from the cars as input and converts them to the system's preferred format using image processing software. Noise removal, filtering, dimension reduction, and segmentation are the four main preprocessing methods. The quality of feature extraction and image analysis results is significantly improved by preprocessing.

Feature extraction stage takes the preprocessed data as input, analyses it with feature extraction algorithms, and uses feature extraction algorithms to extract relevant features from a digital image or video, such as forms, edges, or movements. By minimizing the amount of redundant data in the learning process, feature extraction enables for faster learning and generalization. 1,32 The collected features can be grouped according to their importance.

Vehicle detection step extracts a set of feature vectors relevant to vehicles from the input stream. The method entails analyzing feature vectors to determine the type of vehicle, with the outcome being the detected cars and their types, which are generally positioned within a bounding box.

The next stage, **Vehicle classification**, is to organize the cars into a collection of homogenous classes, with items within each class being more similar than those in other classes. After all, the classified vehicles can be used in a variety of domains and applications, including VANETs, the Internet of Things, intelligent transportation, traffic congestion avoidance, navigation systems, traffic/vehicular surveillance, accident prevention, insurance (rating),2 unmanned aerial vehicle control, and communication systems.

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p.2211-2230
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4. RESULTS AND DISCUSSION

Proposed System Architecture (PSA) is tested various videos of the vehicles with different light intensity on the road. The performance parameters are calculated by using confusion matrix.

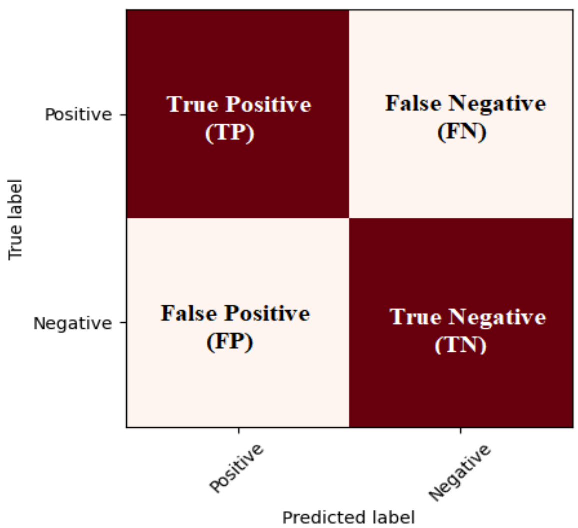

Figure 4.1 Confusion matrix

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}$$

…equation (4.1)

$$Precision = \frac{\text{TP}}{\text{TP+FP}}$$

…equation (4.2)

$$Recall = \frac{\text{TP}}{\text{TP+FN}}$$

…equation (4.3)

$$F1\ score = \frac{\text{2TP}}{\text{2TP+FP+FN}}$$

…equation (4.4)

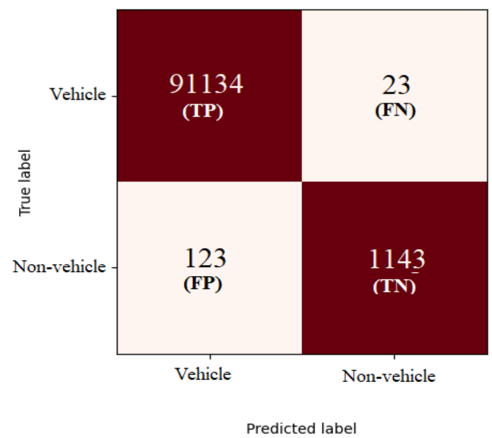

Figure 4.2 Confusion matrix of PSA

Performance parameters have been calculated from the confusion matrix as shown in figure 4.1 and figure 4.2 and it is tabulated in table 4.1.

Performance Parameter	Value
Accuracy	99.84
Precision	99.97
Recall	99.87
F1 score	99.92

Table 4.1 Performance parameters of the PSA applied on 92423 images

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 3, 2022, p.2211-2230
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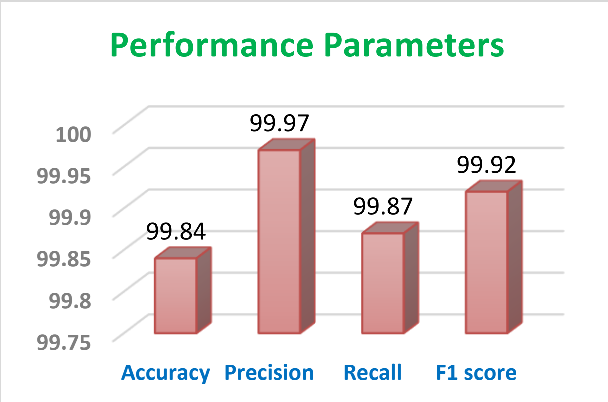

Figure 4.3 Graphical representations of the performance parameters of the PSA

From table 4.1 and figure 4.3 it is clear that values of every performance parameter is 99.8% which only shows that PSA is highly accurate and reliable.

PSA is compared with existing algorithms on the basis of accuracy and is tabulated in table 4.2 and for better visualization presented in figure 4.4.

Architecture for Vehicle Detection	**Accuracy (%)**
PSA	99.84
SVM	78.32
CNN	87.92
RCNN	92.31
Yolo V3	95.82
Yolo V4	97.29

Table 4.2 Comparison of accuracy of the PSA with existing architectures

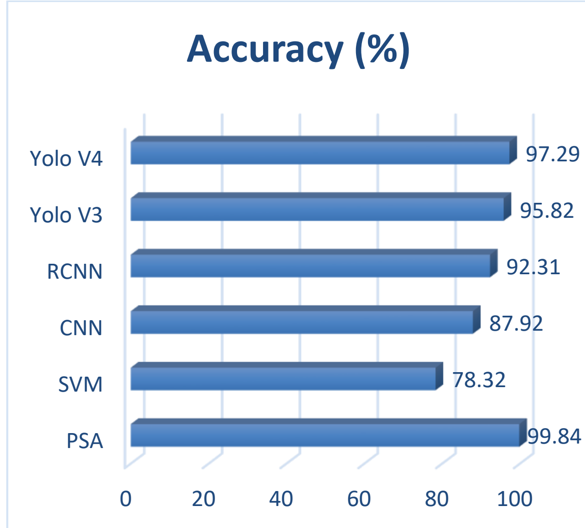

Figure 4.4 Comparison of accuracy of PSA with existing architectures

From figure 4.4 it is clear that the PSA is more accurate than that of the all-existing architectures. So, it is always good to used PSA for the monitoring of the road traffic to get good results.

5. CONCLUSION

Because of the importance of intelligent transportation, many methods for constructing automatic VDC systems have been proposed. Machine learning underpins the majority of these methods, particularly NNs. From 2018 to 2021, this article examines nine data structure input, entity type, size, and scope implementation, configurability, vehicle analytical method, vehicle classification method, and evaluation method parameters of NN-based

VDC approaches. These dimensions are used to compare and contrast the VDC approaches. The PSA presented in this article is tested on 92423 images and the accuracy for the vehicle detection is comes out to be 99.84% which is way higher than that of the existing algorithms.

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