TEM Journal. Volume 13, Issue 1, pages 16-25, ISSN 2217-8309, DOI: 10.18421/TEM131-02, February 2024.

An Efficient Machine Learning Prediction Method for Vehicle Detection: Data Analytics Framework

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Abstract **- The availability of transportation is considered a significant hallmark of a developed society. Since the evolution of the human species, the imperative to relocate from one location to another has been a fundamental requirement. At present, there exists a plethora of transportation options in Indonesia. However, most individuals favor road transportation due to its ease and convenience. The rise in population has led to a corresponding increase in the number of vehicles on the roadways. Hence, it presents a challenge for security authorities and governmental bodies to oversee all automobiles' mobility across various locations effectively. The present study proposes a methodology for detecting and tracking vehicles using video-based techniques. The process's initial stages involve preprocessing, including frame conversion and background subtraction. Next, the process of detecting vehicles involves the utilization of change detection and a model of body shape. Subsequently, the next stage entails the feature extraction process, focusing on extracting energy features and directional cosine. Subsequently, a technique for optimizing data is employed on the vector comprising excessively extracted features.**

The methodology integrates a data mining technique based on association rules, which is subsequently complemented by a random forest classification algorithm. The approach generally integrates multiple methodologies to attain effective and precise identification of automobiles in video-derived datasets.

Keywords **- Artificial intelligence, machine learning, support vector machine, vehicle detection, transportation, data analytics.**

DOI: 10.18421/TEM131-02
https://doi.org/10.18421/TEM131-02

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Received: 28 June 2023.
Revised: 30 November 2023.
Accepted: 06 December 2023.
Published: 27 February 2024.

1. Introduction

Traffic disruption is a prevalent issue in Indonesia, particularly in the province of Special Capital District (DKI) Jakarta. The authorities have implemented multiple measures to mitigate traffic disruption in Jakarta.

One of these initiatives involves the establishment of the Jakarta Smart City information system. The Jakarta Smart City information system harnesses closed-circuit television (CCTV) data from multiple sources, such as the Transportation Agency (DisHub), Bali Tower, the Public Works Service (PU), and Transjakarta, among others. Around 6,000 CCTVs are distributed across the Jakarta region, with their real-time data being transmitted and displayed on the portal of the Jakarta Smart City system [1].

Quick detection of vehicles becomes necessary to provide inattentive drivers with sufficient time to avoid traveling conflicts and thus minimize the likelihood of rear-end collisions. Moreover, the current techniques for traffic surveillance that count automobiles using electric circuits on the road are costly [1], [2]. All of these factors necessitate the investigation of novel and favored techniques for the vehicle recognition task. Typically, the primary objective of detecting vehicles is to identify potential vehicle positions within an image and designate them as areas of interest (A.O.I.) for subsequent processing tasks. In contrast, computerized automobile identification is a complicated and intrinsically tricky task [2].

To detect moving vehicles on avenues, reliable systems and programs with efficient extraction methods are required. Real-time traffic inputs produce an enormous volume of data every day; to manage such a large quantity of data, artificial intelligence (A.I.) and computer vision methods are combined to improve the precision of the framework. This recent technological advancement has reduced human and labor needs. A robust video-based surveillance apparatus must be adaptable to the environment's behaviors. However, threats such as trembling cameras and noise interference still exist. Recognizing vehicles during the day is difficult because lengthy reflections cast by the sun can lead to misclassification or interference [3], [4].

In contrast, night vision detection presents difficulties due to the lack of adequate enlightenment, making it difficult for the classifier to identify effectively. Identifying target motion using artificial intelligence (A.I.) technology is one of the foundations of automobile environment sensing. Moving objects in conveyance typically refer to automobiles or individuals available in operating conditions. Additional immobile things, including transportation systems and vegetation, are typically called landscapes. To obtain the desired format, it is necessary to distinguish moving components from the background contemporaneously by examining the video input footage extensively [5].

Diverse strategies were employed to establish technologies capable of detecting, counting, and classifying automobiles for use in automated transport platforms' traffic tracking. This section addresses the subject matter of these kinds of systems and an understanding of the methodologies used in creating them. Naz *et al*. [6] presented a video-based actual time tracking of vehicles using the optimized simulated loop methodology. The researchers utilized real-time traffic monitoring equipment installed along roads to determine the number of vehicles that traveled on the road. In this approach, accounting is done in three stages by monitoring the vehicle's movements throughout an imaginary loop monitoring zone. Ukani *et al*. [7] presented an alternative video-based vehicle identification approach. In this approach, comparatively high-mounted observation cameras were employed for collecting a roadway video feed; the Adjustable framework estimating, and the Gaussian shadowing reduction consisted of the two primary techniques used.

The system's precision depends on the viewing angle and its capacity to eliminate shadowing and phantom effects.

The fundamental restriction of the algorithm is its incapacity to classify vehicle categories. Heety *et al.* [8] presented a video analysis approach to enumerate vehicles determined on an adjustable containing box measurement to identify and monitor automobiles based on their approximated position relative to the recording device. The Area of Interest, also known as the A.O.I., is determined by designating boundaries for each outward and northbound in the photograph. While the technique has been enhanced to account for particular climate variables, it is unwilling to monitor vehicles whose orientations changed. Najiya and Archana developed a vehicle recognition and categorization approach employing time-spatial images and numerous virtual identification lines [9].

A two-step K nearest neighborhood (K.N.N.) technique categorizes automobiles employing shape-invariant and texture-based characteristics. Measurements confirm that the suggested technique is more accurate and has fewer errors than current approaches because it takes into account varying illuminating circumstances. Zhang and Khan [10] presented an automotive identification and classification system for densely populated intersections. In this approach, background suppression and the method known as Kalman filtering are implemented for finding and tracking automobiles. In contrast, a classification method based on linear discriminant analysis is employed to classify automobiles appropriately. Identification of automobiles in a video-based transportation surveillance program is the initial and most crucial phase with one, as it has an enormous effect on other computer programs, including the monitoring and categorizing of automobiles; therefore, reliable identification and separation of the background object that is moving are crucial. Several methods, such as frame differentiation, are utilized for background recognition [11], [12]. Establishing a variance is a straightforward approach to detecting and segmenting the background because it is founded on the close connection between successive motion images.

To identify automobiles on roadways, robust systems and approaches with efficient methods for extracting are required. In this regard, we proposed a robust approach for detecting vehicles in complex traffic scenarios. Initially, we consider unstructured data video-based data input [13], applying preprocessing steps such as frame conversion and background subtraction methods. After this, we detected the vehicle via change detection and body shape model.

This step is followed by the features extraction method in which we extract the energy features and directional cosine. The next step is applying the data optimization method over-extracted features vector. We apply an association rule-based mining approach, and finally, we apply random forest for classification [14]. The main contribution of this research is as follows:

- We applied a robust method for complex datasets and achieved higher accuracy.
- Features extraction method to find more precise and accurate results.
- Robust and advanced data mining method to save computational cost and extra processing.

2. Background Study

A. Computer visions and traffic surveillance

In the area of computer vision, the capacity to identify automobiles in digital images is essential for a wide range of instances [15], including real-time traffic monitoring, shipping, transportation planning, and congestion control devices at a crosswalk, as well as modern systems for driver [16]. For example, monitoring [16] and analysis techniques on urban traffic roads share rapid, productive data resulting in enhanced security and traffic flow, such as caught automobiles lane traversing, automobiles parked across the roads, traffic overload, and counting vehicles that are passing, as well as calculating the license plate quantity, category, speed, and direction or lane of passing vehicles [17]. Specifically, vehicle recognition is one of the basic features of sophisticated systems that provide driver assistance. The field of computer vision plays a crucial role in various applications, particularly in the identification of automobiles in digital images. The ability to accurately detect vehicles in images is essential for tasks such as real-time traffic monitoring, transportation planning, congestion control, and driver assistance systems [17]. It enables the analysis of urban traffic patterns, detection of lane crossings, identification of parked vehicles, and counting of passing vehicles [18].

The difficulty stems from the wide variety of vehicle appearances (e.g., dimensions, form, and position) and the reduction in clarity caused by sensor interference or unfavorable atmospheric circumstances (fog, rain). In addition, variable enlightenment absence and a cluttered setting make identifying items more difficult than usual. Satellite imagery may contain an intricate background of an urban or rural landscape; consequently, automobiles appeared very dissimilar, making it more challenging to locate instructive elements in the environment.

Furthermore, vehicle recognition is a fundamental feature in advanced driver assistance systems, allowing for the early detection of potential conflicts and the prevention of rear-end collisions. Traditional methods for traffic surveillance, such as using electric circuits on roads to count vehicles, can be costly and limited in their capabilities. Therefore, there is a need for novel and improved techniques for vehicle recognition. However, vehicle detection and identification present inherent challenges due to the wide range of vehicle appearances, variations in lighting conditions, and the presence of complex backgrounds in images [19], such as urban or rural landscapes.

To detect moving vehicles on roads effectively, reliable systems and efficient extraction methods are required. The emergence of artificial intelligence (AI) and computer vision technologies has paved the way for the development of robust video-based surveillance systems that can handle large volumes of real-time traffic data. These technologies have reduced the need for manual labor and improved the accuracy of vehicle recognition. Despite these advancements, challenges persist in vehicle detection. Daytime detection can be hindered by reflections caused by sunlight, leading to misclassification or interference. Night vision detection, on the other hand, faces difficulties due to inadequate illumination, making it challenging for classifiers to identify vehicles accurately [20], [21]. Overcoming these challenges is crucial for the development of effective and reliable vehicle recognition systems.

B. Detecting, counting, and classifying vehicles

Researchers have employed various strategies and methodologies to develop technologies for detecting, counting, and classifying vehicles. These approaches have utilized video-based tracking, optimized simulation loops, high-mounted observation cameras, adjustable frameworks, time-spatial images, and artificial intelligence techniques such as the K nearest neighbor (KNN) algorithm and Kalman filtering. This study aims to address the limitations of existing techniques and propose a robust approach for detecting vehicles in complex traffic scenarios. The proposed approach involves preprocessing steps such as frame conversion and background subtraction, vehicle detection using change detection and body shape models, features extraction utilizing energy features and directional cosine, data optimization, and classification using association rule-based mining and random forest. The key contributions of this research include achieving higher accuracy in complex datasets, employing advanced features extraction methods, and utilizing efficient data mining techniques to reduce computational costs [22].

C. Architecture and the proposed technique

In the subsequent sections, this paper will discuss the architecture of the proposed technique, describe the experimental method employed, compare the results with contemporary approaches, and conclude by summarizing the findings and potential implications of the suggested framework. The following is the comprehensive document's chronology: System Design section explains the technique's architecture, which consists of a video as input of the system, preprocessing, vehicle detection, features extraction, data optimization, and classification. The Experimental Evaluation section describes the experimental method and relates it to modern approaches. Conclusion section represents the conclusion of the suggested framework.

3. System Design

In this segment, we provide the comprehensive facts of our proposed method; initial consideration is given to video-based data input, with preprocessing stages including frame conversion and background subtraction. The vehicle was then detected using change detection and a body shape model. The next stage is the features extraction method, in which the energy features and directional cosine are extracted. The next stage is to apply the data optimization method to the vector of over-extracted features. We employ an association rule-based data mining strategy, followed by random forest classification. Fig. 1 represents the detailed phases of the proposed method which consist of six (6) steps to propose this efficient data analytics framework for vehicle detection via machine learning prediction method:

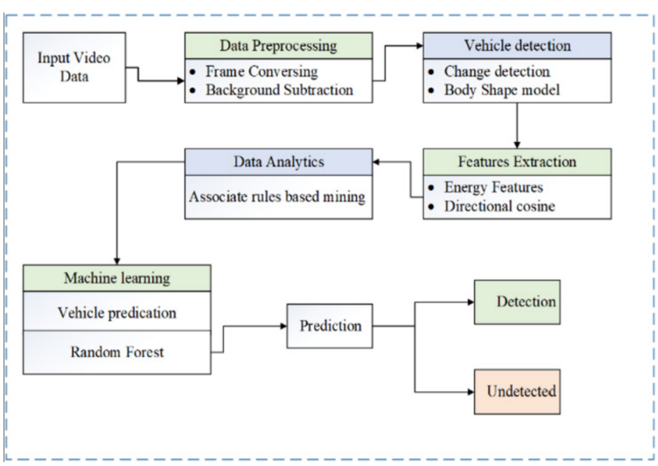

Figure 1. The architectural diagram of the proposed framework

- **Data gathering**. We use video based RGB data for conducting the experiment and performing the other operations. Example of images and dataset description as depicted in Fig. 2.: Video Tested Dataset and Suggested Evaluation Measures VRiV Video Testbed Dataset section includes information regarding (a) the planned VRiV testbench that will have videos that are 38.5 seconds long apiece. The recordings were conducted in a bustling urban environment, with a particular focus on the vehicles driven by volunteer candidates, whose exact specifications, including make, model, year, and color, were well-documented. This emphasis on detail was driven by considerations of security for both the participants and the overall project. The example photos for the VRiV dataset are displayed in Fig. 7.
- **Preprocessing**. In this section, we address the preliminary processing procedures for video information. The initial procedure transforms recording to frames, then resizes captured frames to reduce computation expenses and effectiveness. The example results of preprocessing and background subtraction are presented in Fig. 2.
- **Vehicle Detection**. Extraction of the area of interest and identifying vehicle silhouettes requires two procedures, successive splitting and contour material combination. This binary margin exit method strengthens the following limitations of the RGB contours generated in the previous processing phase. The example results of vehicle detection are presented in Fig. 3.
- **Features extraction**: In this step, we extract valuable features to locate details that can be used for external computing. We extract the energy features and directional cosine features. The results images of energy features and directional cosine features are displayed in Fig. 4 and results of energy features displayed in Fig. 5.
- **Data Optimization**: Associate rule-based mining: We employ association-based data mining approaches to optimize data and minimize repetition. The correlation control features extraction design enables us to choose the most distinct characteristics from the obtained collection, eliminating unnecessary and abnormal features that influence measurement and prediction.

- **Classification and Detection**: Random Forest: The classifying methodology comprises a collection of tree structures for regression and classification, with each predictor factor generated from a randomly chosen alignment factor from the sample dataset. Nevertheless, each tree employs an element's weight to decide the most significant class for a given exercise set. Fig. 6 shows the model and working of random forest.

a. Preprocessing

In this section, we address the preliminary processing procedures for video information. The initial procedure transforms recording to frames, then resizes captured frames to reduce computation expenses and effectiveness. In the element authentication scene, the viola Jones procedure separates the objects from the source image [23], [19]. The Viola-Jones method is primarily used for identifying objects, where the entire process is slow. However, the identification phase is rapid. Viola Jones retrieves the rectangular-shaped Haar-based qualities using a conversion method.

$$G(x) = \alpha 1G1(x) + \alpha 2G(x)$$

Where $G(x)$ = objective function, x = number of clusters, α = constant. Inside the opening where slides, recognition, and detection operations happen, the highest and lowest value of the initial image has been established, and a characteristic set is established for each scale component. Each filter comprises a description coupled with the features to aggregate them. The resilient classifiers are concatenated, and the filtering technique is used to identify the elements. 01 is the outcome of the identification procedure, and its occurrence might have been 0 or 1. Then, k-means is utilized to maximize the background elimination and human contour separation. The K-Means strategy is an unstructured technique used to arrange environment-related inclinations. It combines or distributes the collected data based on the K-centroids into K-clusters or portions. An automated method is utilized if there is unclear data (i.e., averages despite designated groupings or categories). The purpose is to determine the amount of similarity between the collected statistics and the group that K follows. When using K-means categorization, the total number of quadratic readings across every terminating point and the vectors that support it must be limited.

$$K = \sum_{j=1}^{m} \sum_{i=1}^{p} ||x_i^j - o||^2$$

Where J = unbiased function, m = numeral bunches, p = value of cases,x event, and o = centroid, Figure 2 shows the detailed results.

Figure 2. Preprocessing results (a) Original RGB image (b) Pre-processed image (c) subtracted background image

b. Vehicle Detection

Extraction of the area of interest and identifying vehicle silhouettes requires two procedures [24]: successive splitting and contour material combination. This binary margin exit method strengthens the following limitations of the RGB contours generated in the previous processing phase. Using space transformation, closeness diagrams are generated at boundary points. Throughout the development of the highest point features, the native optimum from the pre-computed model is incorporated to create slope static data along the asymmetrical apexes. Following is the scientific equation beneath vehicle recognition:

$$Ty = n \sum t\, x = 1 \left||\alpha x| - |\beta|\right| where\ z = 1, 2, 3, 4$$

where α means the centroid standards of the trails packed in the confusion security, β denotes the original arcs of the inspection figures, and γ signifies the partiality among the stored values of the confusion counter and the innovative pathways. Figure 3 shows the illustration outcomes of vehicle prototype detection.

(a) (b) (c)

Figure 3. Example results of vehicle detection (a) background subtraction with optimized values, (b) and (c) vehicle detection with bounding boxes

c. Features Extraction

The following section describes a unified approach for extracting valuable features to locate details that can be used for external computing. We extract the energy features and directional cosine features. Algorithm 1 shows the complete picture of the feature extraction method.

Algorithm 1: Features Extraction

Input: Input_data
Output: Feature_v($fe_{1,}$)
$Extarcted_{features}Vector$ ← []
$Data$ ← GetData_F_Fi()
Data_size_Fi ← GetData_Fi_size()
Technique PAP(Video, Images)
$Features\_Vect$ ← []
Denoise_Input_Data ← Pre_processing()
Sampled_Data(DenoiseData)
While exit invalid state do
$[EF, DCf]$ ← ExtractlFeatures(sample data)
$Feature\_Vect$ ←[] $[EF, DCf]$ ←
Return MainfeaturesVector

1. *Energy Features*

The context-aware performance feature E(t) analyzes the power index-based matrices using a set of indices ranging from 0 to 10,000 across an understood contour (see Figure 6). The downloaded matrix is then processed through a threshold established in advance, and the result is an I.D. vector. The following is how the fifth equation, which depicts the connection between the energy attribute vector, should be written:

$$E(ti) = \sum_{0}^{m} lv(I)$$

Where $E(ti)$ is the energy vector, I is a directory amount, and $_{Iv}$ RGB is the standard of the directory pixel. Figure 4 illustrates the energy features and results over the input frame.

Figure 4. Results of energy features

2. *Directional cosine*

Directional cosine features and an approach for extracting multiple features have been implemented for this topic.

Motion capture statistics, the rotation of unbroken images, and animation-captured information were utilized for creating fluid, unpredictable behavior. In this situation, the method for determining features evaluates the journey from the starting point to its endpoint and assigns the product concerning a particular color. The color scheme for each successively increasing place will remain unchanged. The quantitative evaluations were conducted, and each revealed component was incorporated into the matrix. Equation 4 explains the mathematical awareness of directional cosine characteristics as follows:

$$Df = \sum\{sine(u,v) \rightarrow sine(\bar{u},\bar{v})\}$$

where Df denotes the arc of directional cosine, sine(u,v) the critical argument of shape with angle, and ei$(\bar{u},\bar{v})$ illustrations of the relative of the surface area with an angle of the vehicle symbol. Figure 5 demonstrates the graphical demo of directional cosine features.

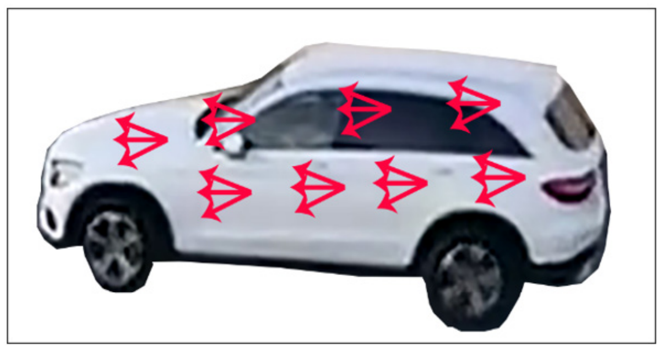

Figure 5. Results of directional cosine features

d. Data Optimization: Associate rule-based mining

Association-based data mining approaches were employed to optimize data and minimize repetition. The correlation control features extraction design enables us to choose the most distinct characteristics from the obtained collection, eliminating unnecessary and abnormal features that influence measurement and prediction [25], [20]. It is a bottom-up strategy that starts with an unfilled feature set and generates distinct characteristics as optimization algorithms are chosen [26]. As a result, the standard deviation of the square of error can be diminished, resulting in characteristics with greater significance. This method aids in minimizing the number of significant characteristics in vacuum research. However, characteristics mining analyses and processes on particular objective measures for the optimal solution are essential for analyzing gait and prognosis.

A mathematical illustration of the procedure for association-based data mining as:

$$Av_{i,j} = (k_i - k_j)\frac{(\Sigma_i - \Sigma_j)}{2}(k_i - k_j)^t$$

where $Av_{i,j}$ are the mined adjusted features vector k_i are the mean of extracted features, Σ_i are represented as covariance and k_j are the means of additional class.

e. Classification and Detection: Random Forest

The classifying methodology comprises a collection of tree structures for regression and classification, with each predictor factor generated from a randomly chosen alignment factor from the sample dataset. Nevertheless, each tree employs an element's weight to decide the most significant class for a given exercise set (see Fig 6). In this research, the random forest algorithm develops a tree at every position according to arbitrary features or a mixture of features. The procedure generates training data by continually getting *N* samples with substitutions, where *N* is the size of the first verification collection used for every provided characteristic pair. Every example (pixel) is categorized by choosing a category that received the most votes from the forest's distinctive species. Developing a structure based on trees required the decision to acquire property and a purification method [26], [22]. There are many strategies for identifying qualities for deductive tree-making decisions, with almost all assigning an objective consequence to the distinguishing attribute.

In the decision tree idea, the complementary details relation condition and the resulting coefficient of the relationship parameter belong to the most commonly utilized flexible filtering techniques. The random forest approach to classification uses the geometric mean, which examines the level of influence of a subclass-related variable as a consideration in selecting attributes.

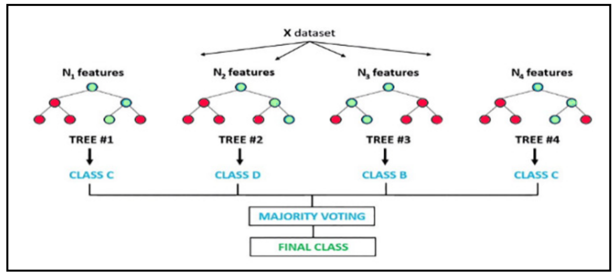

Figure 6. Presentation of random forest detailed model

4. Experimental Evaluation

Dataset Description

This section encompasses the empirical investigation of our proposed system for detecting vehicles in complex traffic scenarios. The efficacy of the VDML framework under consideration was assessed on a publicly available benchmark dataset, namely VRiV dataset [27], [26], [23], correspondingly. The VRiV dataset comprises a maximum of 47 video sequences, with an average duration of approximately 38.5 seconds per video. The recorded videos feature a traffic scenario and specifically highlight the vehicles of volunteer candidates, whose make, model, year, and color information is accurately documented. The example photos for the VRiV dataset are displayed in Figure 7.

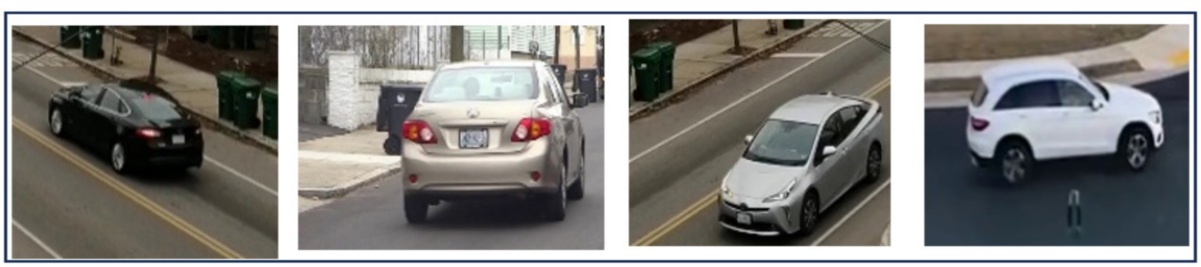

Figure 7. Example images of VRiV dataset

Result Analysis

The quality of the model can be assessed through evaluation. We utilized the evaluation metric, including recall and precision, for the purpose of object detection. In order to assess precision and recall accurately, it is necessary to conduct a reassessment of both classification and localization. The task at hand involves the classification of objects, specifically vehicles, in the context of our research. The objective is to accurately identify the presence of said objects within an image and to determine their respective class.

The vehicle tracker on video surveillance was trained using a random forest approach. The process of tracking the vehicle was successfully executed by subjecting a trained vehicle detector to a video data set for testing purposes. The algorithm partitioned the film into individual frames at a frequency of 30 frames per second and identified objects present in the initial frame. The centroid position of the identified image was utilized to track it in subsequent frames.

Table 1. Comparison of state-of-the-art methods with proposed VDML system

Methods	**Precision (%)**	**Recall (%)**
Support Vector Machine (RBF)	81.46	78.67
Decision Trees	82.39	79.32
XGBOOST	82.64	79.56
Proposed System	83.87	81.69

Table 1 indicates the vehicle detection framework of the VRiV dataset, which achieved the precision of 83.87%.

5. Conclusion

The utilization of artificial intelligence has outperformed conventional image processing techniques in addressing object detection concerns. We develop an effective data analytics framework for vehicle detection through the fusion of machine learning techniques with careful attention to dataset acquisition, feature extraction, model choice, training, assessment, and implementation. On the other hand, the efficacy of the trained models is evaluated through the analysis of diverse factors. The variables encompass precision and recall metrics. The experimental results have shown that the proposed VDML has attained a better recognition rate when compared with other state-of-the-art methods.

The paper discusses the importance of vehicle recognition in computer vision and its various applications, such as real-time traffic monitoring, transportation planning, and driver assistance systems. The existing challenges in vehicle detection and identification are highlighted, including variations in vehicle appearances, lighting conditions, and complex backgrounds. The article presents an overview of different methodologies and techniques used for vehicle detection, counting, and classification, ranging from video-based tracking to artificial intelligence algorithms.

The proposed approach in the article aims to address the limitations of existing techniques by introducing a robust method for detecting vehicles in complex traffic scenarios. The approach involves preprocessing steps, such as frame conversion and background subtraction, followed by vehicle detection using change detection and body shape models. Features extraction methods, including energy features and directional cosine, are applied, and data optimization techniques are used to improve the accuracy and efficiency of the system. The classification is performed using association rule-based mining and random forest.

The key contributions of the proposed research include achieving higher accuracy in complex datasets, employing advanced features extraction methods, and utilizing efficient data mining techniques to reduce computational costs. The article also discusses the architecture of the proposed technique and provides details on the preprocessing, vehicle detection, and features extraction stages. Results and illustrations are provided to demonstrate the effectiveness of the proposed approach.

The article also presents a comprehensive framework for vehicle recognition in computer vision, addressing the challenges and limitations of existing techniques. The proposed approach shows promising results and offers potential implications for improving traffic surveillance systems and driver assistance technologies.

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