Received: 7 March 2023 | Revised: 11 April 2023 | Accepted: 17 April 2023 | Published online: 19 April 2023

Artificial Intelligence and Applications
2023, Vol. 1(3) 170–178
DOI: 10.47852/bonviewAIA3202833

RESEARCH ARTICLE

Machine Learning Methodology for Identifying Vehicles Using Image Processing

Mohamad Hasanvand[1], Mahdi Nooshyar[1], Elaheh Moharamkhani[2,*] and Arezu Selyari[3]

[1]Department of Computer Engineering, University of Mohaghegh Ardabili, Iran

[2]Department of Computer Engineering, Institute of Higher Education Saeb, Iran

[3]Department of Computer Engineering, Islamic Azad University, Iran

Abstract: Using computer decision-making rather than human decision-making is one of the top priorities of prosperous nations around the world. The reduction of traffic infractions is one area that requires this field. Identifying the type of vehicle will significantly reduce traffic infractions. The aim of using image processing in the context of driving violations is to minimize time wastage, reduce human errors and optimize the use of resources. However, there is still a certain error rate associated with capturing images of offending vehicles and reading their plates, whether done manually or automatically. One solution to this problem is to use image processing and learning algorithms to accurately determine the type of vehicle involved. This approach can be particularly useful in scenarios where it is necessary to identify the traffic volume or count the number of specific types of vehicles passing through a particular area, such as a street or highway. Images of the automobiles, which serve as the paper's data source, were compiled from a variety of locations with uniform camera-to-vehicle distances. The image's background is then eliminated by removing it, and the image's features, including its morphological features, are retrieved and provided to four classifiers so they may carry out the classification procedures. This report focuses on seven different categories of Iranian vehicles. Three sets of raw, filtered and noisy images were subjected to four machine classifiers, including support vector, k-nearest neighbor, perceptron neural network and Bayesian decision theory. The images were subjected to low-pass Gaussian filtering at various frequencies, after which salt-and-pepper noise and Gaussian noise were used to make them noisy. The results demonstrate that our proposed method with the SVM algorithm has provided acceptable results with an accuracy of 97.1, which is not only more accurate than most methods up to this point but also allows the correct classification of Iranian cars.

Keywords: image processing, machine learning, vehicle, accuracy, classification

1. Introduction

Image processing is widely employed in modern society due to the advent of numerous discrete information gathering tools, including digital scanners and cameras. Communication networks like GPRS or optical fiber are used to transmit the data gathered by the city's visual surveillance cameras to the traffic control center. In the following, the growth in the number of transportation vehicles has created significant challenges for traffic regulation in recent years. Vehicle type testing is a critical component of intelligent transportation systems, enabling the detection of vehicle types and the provision of valuable information for road monitoring and traffic planning. Researchers worldwide have long been focused on vehicle type detection, which plays a vital role in constructing video surveillance of traffic conditions. Target detection is a key area of image processing and computer vision, with research methods falling into two categories: background-based modeling and methods based on apparent feature information (Taigman et al., 2014).

License plate detection and recognition are crucial components of intelligent traffic systems, but they do have certain limitations. For instance, identifying a vehicle with a fake license plate only involves detecting differences between vehicle types since the license plates of the original and fake vehicles may be identical. Therefore, simple semantic description and retrieval of a license plate is not enough for effective analysis and identification of fake plate vehicles. License plate-based detection methods face unavoidable difficulties in applications related to public security video and image detection. This is why there is an increasing demand for vehicle identification technology. Vehicle type recognition is widely used in investigating cases involving hit-and-run incidents and fake plate vehicles. It addresses several issues related to insufficient license plate information. However, this analysis is based solely on the vehicle number plate, which may delay data tracing and hinder efficient criminal case resolution. Thus, vehicle type recognition provides a critical direction for further research in the field of intelligent transportation (Ke & Zhang, 2020).

*__Corresponding author:__ Elaheh Moharamkhani, Department of Computer Engineering, Institute of Higher Education Saeb, Iran. Email: Elaheh.moharamkhani@gmail.com

And as long as the video data are not turned into statistical sequences, it will not affect how urban management decisions are made. The topic of traffic violation prevention has the potential to prevent thousands of individuals each year from suffering injuries as well as to lessen the monetary damages brought on by traffic accidents. Accidents not only put people at risk, but also result in substantial costs for the government, private sector (such as insurance companies), and individuals, due to expenses related to repairs, medical treatment, insurance coverage, and other associated costs. Thus, it is crucial and heavily stressed in developed areas to reduce accidents and infractions brought on by the manipulation of license plates. Many strategies have been put forth to reduce traffic infractions, which in turn leads to traffic accidents, and there are also codified and significant rules in this regard. In recent years, image processing has been applied to the recording of traffic infractions in an effort to cut down on human error and the waste of time and money.

The main goals of this paper are as follows:

- Introducing the proposed method
- Comparison of several approaches
- Modeling using machine learning and image processing
- Vehicle identification with high accuracy

This arrangement also applies to the remainder of the paper. We will discuss the related works in the Section 2, the proposed method in the Section 3, the experiment results in the Section 4 and the conclusion in the Section 5.

2. Related Work

Lan et al. (2011) proposed that a magnetic sensor can be used to measure changes in the magnetic field created by a vehicle passing over it and that examining the frequency spectrum of these changes can help identify different types of vehicles based on their magnetic signatures. They experimented with a data collecting system and a magnetic sensor system that was specially constructed. They captured magnetic signals from several vehicle kinds and used FFT and PCA algorithms to analyze the data. The findings demonstrated that their approach was successful in identifying and classifying automobiles, obtaining a 92.86% accuracy rate. They also put their magnetic sensor system on a highway and recorded data from passing automobiles to test the efficacy of their technique in a real-world setting. The findings demonstrated that their system had a 94% accuracy rate for detecting and classifying automobiles in real-world settings.

Yan et al. (2016) suggested a real-time vehicle recognition system based on two major techniques: histograms of oriented gradients (HOG) and AdaBoost classification. Using HOG, which records the distribution of gradient orientations in the image, the method entails extracting features from an image. They next train a classifier based on these attributes using AdaBoost classification. The learned classifier is then applied to real-time film to identify automobiles. They proposed method was evaluated on a dataset of 1,200 positive and 1,800 negative samples, achieving an accuracy of 95.1% for vehicle detection.

The suggested method in Suhao et al. (2018) tries to address the drawbacks of conventional approaches, which rely on handcrafted features and have trouble adjusting to various settings. The strategy is divided into two steps: feature extraction and classification. In order to automatically extract pertinent features from input photos, the authors use a convolutional neural network (CNN) in the feature extraction stage. They use a support vector machine (SVM) classifier to divide vehicles into one of five categories during the classification stage: bus, car, motorcycle, truck or van. Using a sizable dataset of traffic scene photographs, the usefulness of their method is assessed, and it yields encouraging findings, with an accuracy of 84.4% for vehicle type categorization.

Using morphological approaches, Ranga et al. (2010) devised a system for categorizing cars. This method divides the pre-processing of raw input photos into three stages: vehicle detection, followed by vehicle sorting. A picture is used as the reference image during the pre-processing stage before being changed into a grayscale image, which will ultimately turn the image black and white. The input image also goes through these processes. A vehicle picture is discovered by subtracting these two images – the input image and the reference image. The binary images of the vehicles from the three 45-degree vertical, horizontal and diagonal directions start to expand now that the boundaries of the Sobel have been uniformized. Then, the void will be filled with a set of backdrop pixels that cannot be filled by filling the background. The next step is the classification of vehicles, which at this point are broken down into three categories: large-, small- and medium-sized vehicles. The quantity of picture pixels that was acquired in the preceding phases can be used for this. And they tested their algorithm on a dataset of 50 images containing different types of vehicles.

In order to categorize automobiles, Bayesian networks were suggested as a solution by Kafai et al. (2011). In this study, cars are categorized based on how they seem from behind. Pickup trucks, trucks, minivans, sedans, and other vehicles are divided into categories. To do this, features are chosen from the retrieved features of the described image and categorized into the aforementioned classifications. When classifying automobiles, the same hybrid dynamic Bayesian network is utilized. This study proposes three different sorts of features, including back lights, the distance between lights and license plates, and vehicle size. The distance from the plate and the angle between the plate and the lamp are determined for each width light. A Gaussian mixture model is utilized to detect the motion of the vehicle in order to identify it. In order to detect whether a pixel is in the background or not, Gaussian distributions are utilized. A pixel belongs to the background if its three channel averages – R, G and B – are within three standard deviations. Now that the car has been isolated from the background, it is time to determine the shadow's vertical axis and delete it. The resulting image's edges are removed. Afterwards, the bubbles are filled to create a binary image. The sequential floating forward selection algorithm (STIS) is now used to select the most crucial characteristics from the extracted features. In specifically, the proposed method produced a promising outcome for vehicle categorization with an overall accuracy of 89.81%.

The algorithm presented by Mithun et al. (2012) takes video frames as input, detects motion pixels using TSI and recognizes those motion pixels as being from the vehicle. After that, the image's edges are located, and morphological processes are used to fill in the gaps. Following the detection of the vehicle's frame, the k-nearest neighbor classification technique is used to extract features including width, length, primary and secondary diameters, and other dimensions. The proposed method was tested on a publically available dataset and achieved an overall accuracy of 91%.

CNN-based algorithms were proposed by Zhao et al. (2016) to categorize cars. The CNN method receives the output from the random concentration filter after the input picture has been processed through it. Implementations of the method include sedan, van, truck, bus and SUV. They test their strategy on two datasets: CompCars and PKU VehicleID. Their methodology surpasses multiple state-of-the-art algorithms on both datasets, reaching top-1 and top-5 accuracy rates of 87.35% and 96.41%.These findings show that the proposed method is effective for vehicle classification tasks.

Montanari et al. (2015) In order to identify and categorize three different types of vehicles on a road, this research presented a system that combines the VOCUS2 bottom-up visual attention approach with a Bag of Features (BoF) and several SVMs. The vehicles included motorcycles, trucks and cars. A GoPro camera installed in the lower base of an unmanned aerial vehicle (UAV) circling the road was used to capture input photographs for the system. Although this study only addresses the initial stages of an autonomous system. The final algorithm classified the three different types of cars with an accuracy of 79.82%.

Pandya & Bhatt (2015) proposed a method for classifying and detecting moving items, which includes the processes of detecting moving objects, eliminating shadows and bothersome objects and classifying moving objects. Moving object identification is accomplished using GMM and AOI extraction techniques. To increase classification accuracy, the detected object must be shadow-free. This goal was accomplished in the shadow elimination category. All of the observed objects might not be automobiles, after all. So, it is necessary to get rid of such bothersome objects, which was accomplished in the unpleasant object removal phase. And last, using the AdaBoost classifier, the remaining items are categorized into the correct classifications, such as bikes and non-bikes. 79.82% accuracy is attained using 77 videos and a 70.30% training: testing ratio.

Tang et al. (2017) proposed method comprises of three major steps: vehicle detection, feature extraction and classification. The scientists utilized a combination of histogram of oriented gradients (HOG) and SVM classifiers to detect vehicles. The HOG features capture the vehicle's shape and look, while the SVM classifier is taught to distinguish between vehicles and non-vehicles. They extracted color and texture features from observed vehicle zones for feature extraction. Color characteristics were recovered using color histograms, whereas texture features were extracted using local binary patterns. They tested the suggested method on a dataset of traffic surveillance photos and found that it was 95% accurate for vehicle detection and 97.3% accurate for vehicle recognition.

Vijayaraghavan & Laavanya (2019) introduced a technique for object recognition and classification that employs CNNs and SVMs. Also, they talk about the difficulties in detecting and classifying vehicles, such as occlusion and variations in lighting, and show how their suggested method can overcome these difficulties to reach high accuracy. According to the findings of their tests, their suggested system performs better than the ones already in use, obtaining an accuracy of over 87% in vehicle classification and over 90% in vehicle detection. Overall, this study offers insights into the use of deep learning to enhance the precision of vehicle identification and categorization in real-world circumstances.

Kim et al. (2020) examine three prominent object recognition algorithms, Faster R-CNN, YOLO and SSD, for real-time vehicle type recognition. They also do trials on a publicly available dataset to assess each algorithm's accuracy and processing speed. In terms of accuracy and processing speed, the results reveal that YOLO surpasses both Faster R-CNN and SSD. In particular, YOLO achieved 93% accuracy, while Faster R-CNN and SSD achieved lower accuracy. In terms of processing performance, YOLO averaged 67 frames per second (FPS), while Faster R-CNN and SSD averaged 5 and 20 FPS, respectively.

Habib & Khan (2021) suggested an improved method for categorizing various vehicle kinds using a CNN. The performance of four alternative CNN architectures is compared by the authors using a dataset made up of six different vehicle kinds. The suggested optimized CNN architecture exceeds the competition with a testing set accuracy of 96.4%. The study assesses the model's resistance to variations in lighting and background noise. The results imply that the suggested method may find use in autonomous vehicle systems, parking management and traffic monitoring.

Azimjonov & Özmen (2021) suggested building a revolutionary bounding box (Bbox)-based vehicle tracking system and enhancing Yolo's vehicle categorization accuracy. A new car dataset is created for this purpose by adding 123,831 object patterns to 7216 photos that were taken from movies of highways. A CNN-based classifier and nine machine learning-based classifiers were chosen. After that, the dataset was used to train the classifiers. The most accurate classifier out of 10 was chosen to be combined with Yolo. By doing this, the Yolo-based vehicle detector's categorization accuracy rose from 57% to 95.45%. In four highway films, the categorical/total vehicle counting tasks were applied using vehicle detectors 1 (Yolo) and 2 (Yolo + best classifier), vehicle trackers 1 and 2 (Kalman filter-based and Bbox-based, respectively), and vehicle detectors 1 and 2. The results of the vehicle counting demonstrate that the created methodology (vehicle detector 2 + vehicle tracker 2) outperformed the other three vehicle counting systems used in this study, with a 13.25% improvement in vehicle counting accuracy.

Kolukisa et al. (2022) offer a study that uses deep learning approaches to classify vehicles using 3D magnetic sensors. The study's major goal is to provide an accurate and efficient system for categorizing automobiles based on their magnetic signatures. For vehicle type categorization, the paper suggests two deep learning models: CNN and long short-term memory recurrent neural network. The proposed models are tested against a real-world dataset of 3-D magnetic field data from various types of vehicles. The accuracy and f-measure performances are improved by 92.92% and 93.42%, respectively, by the soft voting ensemble technique using a deep learning classifier, according to comparative performance data.

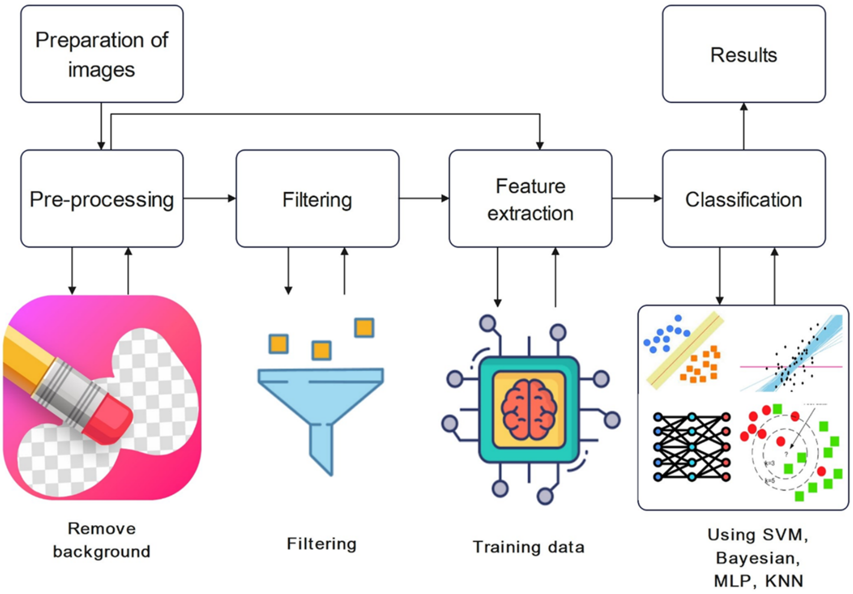
Eight renowned CNN architectures were used in this paper's comparison analysis by Kherraki & El Ouazzani (2022) to categorize photos of emergency vehicles. An effective deep learning system has been designed and put into place to automatically distinguish between emergency and regular vehicles in traffic scenes. To uniformize the image sizes, they first preprocessed the Vidhya Emergency Vehicle dataset. Each CNN design now has three additional layers, including "GlobalAveragePooling2D" to shrink the size of the input image and speed up training, "Dropout" to prevent overfitting, and "Dense" to increase the number of output classes. After simulations of each architecture, we discovered that DenseNet121, which has an accuracy of 95.14%, an F1 score of 93.87% and an average order memory of 27.5 MB, is the best model for real-time emergency vehicle categorization.

In this paper, morphological traits of cars were used in the photographs to accurately detect and separate them. It is evident that these picture properties are quite-sensitive and necessitate the use of appropriate methodologies in order to provide a trustworthy and persuasive answer. In other words, if correct methods and methods are not followed, the accuracy of car detection and distinction will decline, and the results will be ignored. Accurate and trustworthy results can be obtained because to the great sensitivity of morphological parameters of cars and the selection of relevant methodologies. As a consequence, the use of morphological characteristics of cars in detection and differentiation algorithms plays an important role in generating accurate and trustworthy results, and more accuracy and efficiency may be accomplished by employing appropriate and modern methods.

3. Proposed Method

In Figure 1, we briefly show the steps of the proposed method.

Figure 1
Flowchart of proposed method



- Preparation of images: The preparation of images for seven different car models taken from a fixed distance and angle in various natural environments.
- Image preparation: Pre-processing is the process of removing background from automobile photos using thresholding and image subtraction algorithms.
- Filtering: It creates filtered images with low-pass Gaussian filters to examine the effects of a suggested technique on normal and noisy images.
- Feature extraction: This stage discusses the variables utilized for vehicle categorization, which are generally measurement-related and include, among other things, vehicle length, breadth, distance between rear lights and areas occupied by the vehicle in the image. These measures are translated from pixels to centimeters using scaling, and image pre-processing is done to find the plate and rear lights.
- Classification using (SVM, Bayesian, MLP and KNN) algorithms: At this step, we used SVM, Bayesian, MLP and KNN algorithms to model our proposed method.
- Findings and evaluation: The findings demonstrate the superiority of the SVM algorithm.

3.1. Preparation of images

Images were prepared using a camera (mp13Canon) in an open area without any measures in terms of light and in a completely natural and dynamic environment. The images were taken from a fixed distance (3 m and 15 cm) from camera to the vehicle, and the camera angle to the vehicle is in one direction.

These images were provided in different environments, which will increase the integrity of the design. The seven images in each of the seven classes of discussion (including Peugeot 405, Peugeot Pars, Pride, Peykan, Samand LX, Nissan pickup, Tondar 90) were prepared. Figure 2 depicts examples of images used.

Figure 2
Examples of raw images used

3.2. Filtering

Considering that the distance and angle of camera relative to the vehicle in all images is non-stationary, it can easily remove the background of images by subtracting the background and just keep the image of the vehicle for the next stages. In this way, first, the background image without the vehicle was taken to the binary state using image thresholding operation and the same operation was carried out for the image with the vehicle. Then by subtraction of two images, the resulting image is a picture containing a binary car and, of course, some bubbles that are removed by filtering the area of bubbles, and the resulting image is the image of the vehicle. Now, the background is separated by summing the original image of the vehicle and the binary image of the vehicle that was obtained in the previous step. Subtraction is that each pixel in the original image is subtracted from the counterpart pixel in the foreground image, and if the image is more than a given value, then the image is not the background, and if it is more, the image is background (Gonzalez, 2009; Liu et al., 2009). Equations (1) and (2) are shown below, respectively:

$$D = (x, y) = |f_p(x, y) - f_f(x, y)| \tag{1}$$

$$mask(x, y) = \begin{cases} 0 & if\ D(x, y) \geq T \quad foreground \\ 1 & if\ D(x, y) \leq T \quad background \end{cases} \tag{2}$$

Here f_p is the background image and f_f is the original image. The value of T is different in colored images, which here, because the image is in binary form, the value of T can be set larger than 1. The removal operation of small holes (bubbles) is that all areas smaller than the smallest possible area that is related to Pride vehicle are removed. Removed background examples are shown in Figure 3.

Figure 3
Examples of removed background

3.3. Instruments

The filtered and noisy photos are also analyzed in addition to the regular ones. They were destroyed by using low-pass Gaussian filters with various frequency beams to create filtered images. In order to explore the effects of the suggested technique on these photos, images are destroyed in two phases utilizing salt-and-pepper noise with various densities as well as Gaussian noise with various frequency rays. An illustration of filtered and noisy image degradation is shown in Figure 4.

The purpose of filtering is to describe the analysis of filtered and noisy photos using low-pass Gaussian filters with various frequency beams and to explore the effects of suggested techniques on these photos by destroying them in two phases utilizing salt-and-pepper noise with various densities as well as Gaussian noise with various frequency rays.

3.4. Feature extraction

The morphological and quantifiable aspects of any image are some of its most approachable elements. It can be argued that classification and

Figure 4
A sample of filtered and noisy degraded images

detection will be extremely accurate in any image if we can properly extract the observed attributes (under the assumption that the angle and proximity of the camera lens to the item are stable, with an error coefficient to roughly reflect reality). At this point, it is necessary to extract the vehicle-related elements from the photos in order to categorize them. In this paper, we attempt to leverage attributes that are primarily measurement-related. These qualities consist of:

1. Vehicle length
2. Vehicle width
3. The upper distance of the rear light to the vehicle ceiling
4. Lower distance from rear light to vehicle floor
5. Distance between two vehicle rear lights
6. Vehicle rear light length
7. Vehicle rear light width
8. Vehicle plate vertical distance to the rear light
9. The area occupied by the vehicle in the image
10. Main vehicle diameter
11. Minor vehicle diameter
12. Vehicle plate horizontal distance from the rear light

In the following, Figure 5 illustrates these items.

The important point in these features is that all of the measurements are in MATLAB program in terms of pixels, which are converted to centimeter by the use of scaling in a real environment. The measure of scalability is the length and width of the plates in a real environment and in the image environment. To measure the aforementioned features, we first pre-process the

Figure 5
12 features used

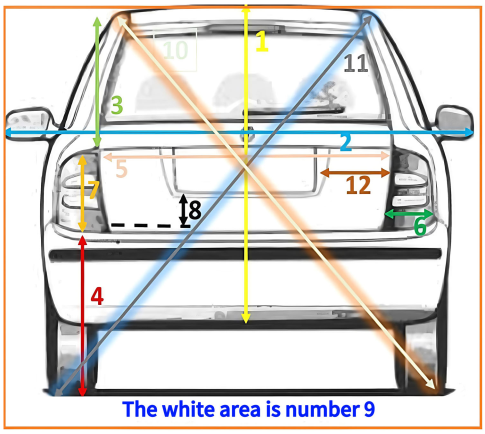


Figure 6
A sample of tail light location extraction from vehicle images

images that result in finding exact location of the plate and exact location of the rear lights.

In order to find the exact location of the rear light of the vehicle, the red color thresholding operation was used since the rear light of all standard vehicles is red. In this way, it considers the red color as white and above and below the limits as black. Finally, an image is obtained in which the vehicle lights are white and the rest of the image is black as shown in Figure 6.

On the other hand, for detecting the precise location of the license plate, firstly the image is taken to the binary state, and then, its edges are detected by Sobel edge detection algorithm. After that, a proper filter starts to expand and amplify the edge lines, and then with thresholding and another expansion, a normal image with a clear license plate is obtained. Threshold values are obtained for thresholding and widening operations by trial and error. The segmentation is done by sliding concentric window algorithm, and finding connected points is done by connected components analyze algorithm. Finally, by applying the area filter, the areas above and below the common limit are removed, and the final image contains the plate edges in the actual car location. Figure 7 from the right to the left shows the process of doing work on Peugeot 405:

Figure 8
The combination of two images of the location of the plate and the location of the rear light

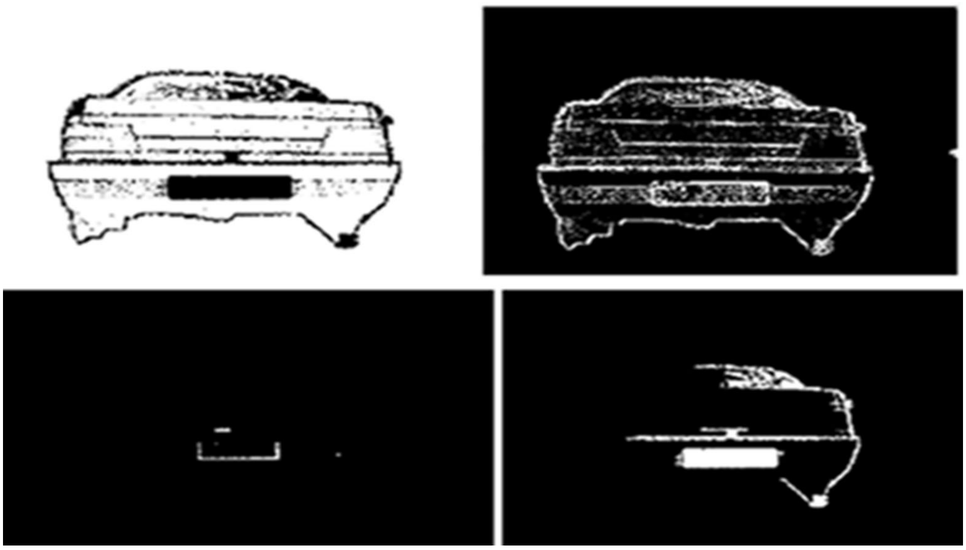
An image can be produced by adding the image of the location of the plate, and the image of the location of the rear light that many of the aforementioned features would be found on it. Figure 8 is the sum of the two previous images.

After the measurement has been done to determine features, classification of images that is based on the found features begins.

3.5. Classification

The classification stage begins after feature extraction and data pre-processing from images. The information is divided into two categories: training (80%) and testing (20%). The training dataset is then used to train machine learning models. The accuracy of the model is then evaluated using the testing dataset and the results

Figure 7
The steps of extracting the exact location of the plate from the vehicle images



from the previous stage. Lastly, gradient descent optimization methods are utilized to optimize the model's parameters.

4. Experimental Findings

Table 1 provides a broad overview of this paper by listing the accuracy, kind of classifier and vehicles utilized in the study in several papers that are compared to the current paper:

In this method, the image's yellow, blue and red channels are all located together, along with its white, red and density channels, which are all located and centered individually. The desired object is then highlighted in a single image that is created by subtracting the photos from one another, moving them into low-contrast and high-contrast sections and eventually combining all images in all repetitions.

Our proposed method has two main advantages:

(A) our paper is designed to classify vehicles in categories of vehicles, not the size of vehicles; (B) our paper used machine learning as a classifier that can be used for the high number classes. On the other hand, in our paper on images, low-pass Gaussian filter with different radius (low, medium and high) and pepper-and-salt and Gaussian noise is applied, which results in high performance of this paper. Raw images are filtered by Gaussian method with the frequency radius available in Table 2:

Using two techniques, including pepper-and-salt noise (with densities available in Table 3) and Gaussian noise (with available variances in the table below), raw images are also made noisy:

Table 4 shows the comparison of the proposed solution on normal, filtered and noisy images with SVM learning (Cortes & Vapnik, 1995), Bayesian (Ben-Gal et al., 2007), multilayer perceptron neural network (Rosenblatt, 1961; Rumelhart et al., 1985) and k-nearest neighbor (Altman, 1991; Hall et al., 2008):

Table 4 shows that the SVM machine learning method performs better than the other three methods in classification in 12 feature space on all three image groups. The above diagram shows that SVM classification algorithm and MLP neural network perform better than the other two methods in classifying the noised data. According to the results, it was found that not only for the data of raw images but also for classification of data related to noised images and filtered images, SVM algorithm performs better than other algorithms and only MLP neural network algorithm is as accurate as SVM algorithm. MLP algorithm is not noticed because of its time-consuming nature and structural complexity of neural networks. Therefore, the hypothesis of the paper that is based the classification of vehicles with high accuracy by the use of machine learning and the extracted features (vehicle length, vehicle width, the upper distance of the rear light to the vehicle ceiling, lower distance from rear light to vehicle floor, distance

Table 1
Comparison of several approaches

References	Classification methodology	Vehicle types	Features	Maximum classification accuracy
Lan et al. (2011)	ISVM	Automobile, trucks, motorcycles	Magnetic signals	92.86%
Yan et al. (2016)	AdaBoost	Automobile and truck	Length and width	95.1%
Suhao et al. (2018)	SVM-CNN	Car, minibus, Suv	Using deep learning	84.4%
Ranga et al. (2010)	Comparative	Large-small-medium	The number of pixels	–
Kafai & Bhanu (2011)	SVM	Pickup-Minivan-SUV-automobile	Distances and dimensions	89.81%
Mithun et al. (2012)	KNN	Carriage-riding-jeep-van-bus	Width-area-ratio of length to width-length of main and minor diameter, etc.	91%
Zhao et al. (2016)	CNN	Sedan-Van-Truck-Bus-SUV	Pixel	96.41%
Montanari et al. (2015)	SVM	Truck-automobile-bike-and anonymous	Bag of Features	79.82%
Pandya & Bhatt (2015)	Adaboost	Motor- and non-motor	Pixel	90.11%
Tang et al. (2017)	AdaBoost	Lavida, Tiguan, Cruze, Corolla	Gabor wavelet transform and a local binary pattern operator	97.3%
Vijayaraghavan & Laavanya (2019)	CNN	Bus, car, bike	R-CNN	87%
Kim et al. (2020)	YOLO, SSD, Faster R-CNN	Car, mini_van, big_van, mini_truck, truck	Feature map using convolutional layers	93%
Habib & Khan (2021)	CNN	Truck, bus, bike, van, jeep, buggy, rickshaw	Feature map using convolutional layers	96.4%
Azimjonov & Özmen (2021)	CNN	Bicycle-bus-automobile-motorbike-truck	Pixel	95.45%
Kolukisa et al. (2022)	Deep learning (LSTM + GRU + VGG16)	Light, Medium, Heavy	3-D magnetic sensor	92.92%
Kherraki & El Ouazzani (2022)	CNN	Vehicle-emergency vehicle	Dimensions size	95.14%
Proposed method	SVM	Pride-Peugeot 405-Peykan-Nissan-Thunder 90-Samand LX-Parse	Dimensions-length-space-distances	97.1%

Table 2
The quantity of frequency radius that was used to filter the images

The frequency radius's number	The frequency radius's value
Frequency radius 1	1000
Frequency radius 2	500
Frequency radius 3	200
Frequency radius 4	100

Table 3
The type and quantity of noise added to the images to make them noisy

Noise type	Noise level (density or variance)	
Pepper and salt noise (density)	0.1	0.5
Gaussian noise (variance)	650	5800

Table 4
Comparison of accuracy on normal, filtered and noisy images with two machine learning methods

Images type/class type	SVM	Bayesian	MLP	KNN
Normal images	97.1%	90.9%	92.9%	88.6%
Filtered images	78.6%	77.7%	74.3%	74.28%
Noisy images	82.9%	66.7%	82.9%	82.7%

between two vehicle rear lights, vehicle rear light length, vehicle rear light width, vehicle plate vertical distance to the rear light, the area occupied by the vehicle in the image, main vehicle diameter, minor vehicle diameter, vehicle plate horizontal distance from the rear light) from the four proven classifiers, and according to the results obtained among the four classifiers, the SVM is the best.

5. Conclusion

Traffic violation prevention is a subject that averts the risk of severe physical harm and death for thousands of people each year and lowers the financial losses brought on by traffic accidents. The classification accuracy in this area can be taken into account in accordance with the purpose of classification for the cars specified in this research. For this reason, machine learning science was used in addition to scientific methodologies to improve classification accuracy. To do this, photos of the active environment were first captured, and the backdrop was then subtracted from the background image. The 12 elements that were recovered as required features from the resulting images had their features extracted by the four classifiers, and the classification was completed. Finally, as previously stated, the final accuracy of our proposed method using the SVM algorithm was 97.1% greater than previous efforts in this field. The algorithm's use on filtered and noisy images in this research also produced positive results. On the other hand, it can be claimed that this article is somewhat localized based on the automobiles covered in this paper, which include the majority of the vehicles in Iran. Of course, by altering the vehicles, it is also possible to reach desirable results.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

References

Altman, N. S. (1992). An introduction to kernel and nearest-neighbor nonparametric regression. *The American Statistician, 46*(3), 175–185.

Azimjonov, J., & Özmen, A. (2021). A real-time vehicle detection and a novel vehicle tracking systems for estimating and monitoring traffic flow on highways. *Advanced Engineering Informatics*, *50*, 101393.

Ben-Gal, I., Ruggeri, F., Faltin, F., & Kenett, R. (2007). *Bayesian Networks. In Encyclopedia of Statistics in Quality and Reliability.* USA: Wiley & Sons.

Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, *20*, 273–297.

Gonzalez, R. C. (2009). *Digital Image Processing*. India: Pearson Education.

Habib, S., & Khan, N. F. (2021). An optimized approach to vehicle-type classification using a convolutional neural network. *Computers, Materials & Continua*, *69*(3), 3321–3335.

Hall, P., Park, B. U., & Samworth, R. J. (2008). Choice of neighbor order in nearest-neighbor classification. *Annals of Statistics*, *36*(5), 2135–2152. https://doi.org/10.1214/07-AOS537

Kafai, M., & Bhanu, B. (2011). Dynamic Bayesian networks for vehicle classification in video. *IEEE Transactions on Industrial Informatics*, *8*(1), 100–109.

Ke, X., & Zhang, Y. (2020). Fine-grained vehicle type detection and recognition based on dense attention network. *Neurocomputing*, *399*, 247–257.

Kherraki, A., & El Ouazzani, R. (2022). Deep convolutional neural networks architecture for an efficient emergency vehicle classification in real-time traffic monitoring. *IAES International Journal of Artificial Intelligence*, *11*(1), 110–120.

Kim, J. A., Sung, J. Y., & Park, S. H. (2020). Comparison of Faster-RCNN, YOLO, and SSD for real-time vehicle type recognition. In *2020 IEEE International Conference on Consumer Electronics-Asia*, 1–4.

Kolukisa, B., Yildirim, V. C., Elmas, B., Ayyildiz, C., & Gungor, V. C. (2022). Deep learning approaches for vehicle type classification with 3-D magnetic sensor. *Computer Networks*, *217*, 109326.

Lan, J., Xiang, Y., Wang, L., & Shi, Y. (2011). Vehicle detection and classification by measuring and processing magnetic signal. *Measurement*, *44*(1), 174–180.

Liu, Z., Chen, Y., & Li, Z. (2009). Camshift-based real-time multiple vehicle tracking for visual traffic surveillance. In *2009 WRI World Congress on Computer Science and Information Engineering*, *5*, 477–482.

Mithun, N. C., Rashid, N. U., & Rahman, S. M. (2012). Detection and classification of vehicles from video using multiple time-spatial images. *IEEE Transactions on Intelligent Transportation Systems*, *13*(3), 1215–1225.

Montanari, R., Tozadore, D. C., Fraccaroli, E. S., & Romero, R. A. (2015). Ground vehicle detection and classification by an unmanned aerial vehicle. In *2015 12th Latin American Robotics Symposium and 2015 3rd Brazilian Symposium on Robotics*, 253–258.

Pandya, H. A., & Bhatt, M. S. (2015). A novel approach for vehicle detection and classification. In *2015 International Conference on Computer Communication and Informatics*, 1–5.

Ranga, H. P., Kiran, M. R., Shekar, S. R., & Kumar, S. N. (2010). Vehicle detection and classification based on morphological technique. In *2010 International Conference on Signal and Image Processing*, 45–48.

Rosenblatt, F. (1961). *Principles of Neurodynamics. Perceptrons and the Theory of Brain Mechanisms*. USA: Cornell Aeronautical Lab Inc Buffalo.

Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1985). *Learning Internal Representations by Error Propagation*. USA: MIT Press.

Suhao, L., Jinzhao, L., Guoquan, L., Tong, B., Huiqian, W., & Yu, P. (2018). Vehicle type detection based on deep learning in traffic scene. *Procedia Computer Science*, *131*, 564–572.

Taigman, Y., Yang, M., Ranzato, M. A., & Wolf, L. (2014). Deepface: Closing the gap to human-level performance in face verification. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 1701–1708.

Tang, Y., Zhang, C., Gu, R., Li, P., & Yang, B. (2017). Vehicle detection and recognition for intelligent traffic surveillance system. *Multimedia Tools and Applications*, *76*, 5817–5832.

Vijayaraghavan, V., & Laavanya, M. (2019). Vehicle classification and detection using deep learning. *International Journal of Engineering and Advanced Technology*, *9*(1S5), 24–28.

Yan, G., Yu, M., Yu, Y., & Fan, L. (2016). Real-time vehicle detection using histograms of oriented gradients and AdaBoost classification. *Optik*, *127*(19), 7941–7951.

Zhao, D., Chen, Y., & Lv, L. (2016). Deep reinforcement learning with visual attention for vehicle classification. *IEEE Transactions on Cognitive and Developmental Systems*, *9*(4), 356–367.

How to Cite: Hasanvand, M., Nooshyar, M., Moharamkhani, E., & Selyari, A. (2023). Machine Learning Methodology for Identifying Vehicles Using Image Processing. *Artificial Intelligence and Applications* 1(3), 170–178, https://doi.org/10.47852/bonviewAIA3202833