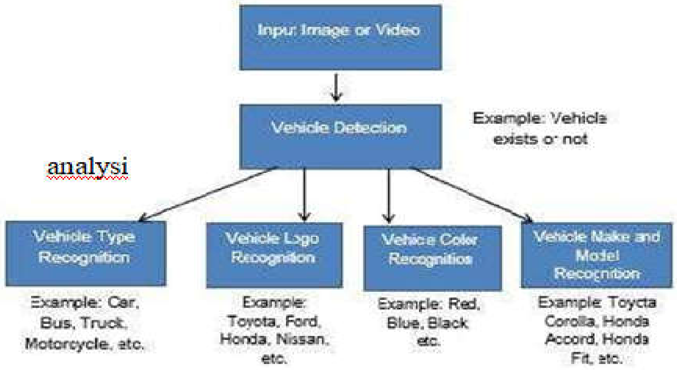
AUTOMATION AND DEEP LEARNING TO IDENTIFY VEHICLE PATTERNS AND PREDICT CAR MODEL

[1]Himagireshwar Rao Matla, [2]Bharathi Durgam, [3]Sundararajan Senthilkumar, [4]Ch.Harshita
[1,2,3]Assistant Professor, [4]UG Student, [1,2,3,4]Department of Computer science and Engineering, Rishi MS Institute of Engineering and Technlogy for Women, Kukatpally, Hyderabad.

ABSTRACT
In addition to the usual recognition of the connected license plate, a Vehicle Make and Model Recognition (VMMR) system may be extremely valuable for vehicle tracking and identification. Many applications, including autonomous vehicle surveillance, traffic management, driver assistance systems, traffic behavior analysis, and traffic monitoring, among others, require a real-time VMMR system. A VMMR system faces a particular set of difficulties and problems. A few of the difficulties include picture capture, varying lighting and weather conditions, occlusions, shadows, and reflections, a wide range of vehicles, similarities across classes and within classes, the addition or removal of vehicle models over time, etc. In this work, we present a unique and robust real-time VMMR system which can handle the challenges described above and recognize vehicles with high accuracy. We extract image features from vehicle images and create feature vectors to represent the dataset. We use two classification algorithms, Random Forest (RF) and Support Vector Machine (SVM), in our work. We use a realistic dataset to test and evaluate the proposed VMMR system. The vehicles' images in the dataset reflect real- world situations. The proposed VMMRsystem recognizes vehicles on the basis of make, model, and generation (manufacturingyears) while the existing VMMR systemscan only identify the make and model. Comparison with existing VMMR research demonstrates superior performance of the proposed system in terms of recognition accuracy and processing speed.

INTRODUCTION
In the modern world, moving people and things around is essential. Life quality and economic prosperity are both influenced by transportation. Additionally, it has negative impacts like as resource consumption, driving-related weariness, traffic congestion, and a danger to one's personal safety due to accidents. Although the prediction of the number of vehicles worldwide is not perfect, studies have showed an exponential rise. Over 1.2 billion vehicles are thought to be in use worldwide at now, and projections predict that this number will surpass 2 billion in 2035 [1] or 2040 [2]. Automated vehicle analysis is a crucial task in many applications because to the rise in vehicle population. Figure 1 shows the taxonomy of vehicle analysis. Vehicle analysis starts with the vehicle detection. Once the vehicle is detected, we can classify it basedon its class (car, bus, truck, etc.), make (Toyota, Honda, Ford, etc.), color (white, black, red, grey, etc.), or make and model (Toyota Corolla, Hando Accord, Ford Fusion, etc.). Autonomous vehicles and driver assistance, surveillance, traffic management, and law enforcement are afew of the applications taking benefit from automatic vehicle analysis. It is inconceivable for humans to monitor, observe, and analyze the ever- increasing number of vehicles manually, especially in urban environments. In contrastto the human operator, the computer vision application can monitor traffic for a longer period of time without any fatigue. The associated cost of computer applications is less and can be scaled to achieve the desired performance/cost ratio.



LITERATURE SURVEY

VEHICLE DETECTION

Vehicle detection is the basis for vehicle classification problems. Vehicle detection confirms the presence of a vehiclein an image and extracts the region of interest to eliminate the background scene. In some cases, it is not effective to use the complete vehicle as input to the classifier and only the desired region (taillights, front lights, bumper, license plate, etc.) is extracted and used. The elimination of background and unwanted vehicle's portion enhance the vehicle classification performance. Huang et al. use background subtraction to extract the moving objects and apply image processing to discard unwanted image regions [6]. Huang et al. train the system using a deep belief network to detect the vehicles. Lu et al. use YCbC color space for modeling the backgroundframe and Choquet Integral to fuse the texture features with color features [7]. An adaptive selective background maintenance model is used to solve the complex conditions and variations. Faro et al. useluminosity sensors to detect the sudden variations in illuminations without affecting the time performance; background subtraction technique is used to differentiate the vehicles from the background and segmentation scheme is applied to eliminatethe occlusion [8]. Chen et al. compute Speed-Up Robust Features (SURF) fororiginal and mirrored image and compute similarities between SURF features to find the horizontal symmetry [9]. A center lineis determined; every set of symmetrical SURF points and centerline represents a possible vehicle candidate. The shadow region is used to filter out weak candidates. A comprehensive survey of wide range of vehicle detection techniques can be foundin [10].

VEHICLE TYPE RECOGNITION

Vehicle Type Recognition (VTR) classifies the vehicles into broad categorieslike car, bus, van, truck, bike, etc.; the exact make and model of the vehicle is not identified in VTR. An automated VTR system is helpful in applications like urban traffic studies and analysis, electronic toll collection, etc. Wang et al. use the geometrical information to construct features and adopt simple Euclidean distance-based matching to categorize the vehicle into three types [11]. Dong et al. propose a two-level semi-supervised Convolution Neural Network (CNN) to learn local and global features and utilize softmax regression to categorize the vehicles in six classes [12]. Fu et al. propose a VTR system based on hierarchical multi-SVMs and can handlecomplex traffic scenes and partial occlusion [13]. Irhebhude et al. combine a local binary pattern histogram, Histogram of Oriented Gradient (HOG) and region features and use correlation-based feature selection to select discriminative features [14]. They use a support vector machine (SVM) to classify the vehicles into four categories.Vehicle Make and Model Recognition Classical VMMR research classifies vehicles based on make and model only. Classical systems use local features to represent the vehicle's region of interestand require these features to be converted into global features' representation in

some cases. Scale Invariant Feature Transform (SIFT) [15], SURF [16] and HOG [17] feature extraction techniques are used by many researchers. Nearest Neighbors Classifier (NNC), Artificial Neural Networks (ANN), and SupportVector Machine (SVM) are the mostwidely used classifiers for VMMR systems. Boukerch et al. presented a real-time VMMR system and evaluated it in [18]. SVM is used as single multiclass classifier and ensemble of the multi-class classifier.In this approach, the authors describe SURFfeatures dictionary for global representation. They evaluate two dictionary building approaches; single dictionary and modular dictionary and report an accuracy rate of 94.5% with aprocessing speed of 7.4 images per second. Noppakun Boonsim and Simant Prakoonwitpropose a one-class classifier-based approach under limited lighting [19]. The proposed approach uses one-class SVM, decision tree, and K-Mean Nearest Neighbor (KNN) for classification and a majority vote of three is used for final prediction. They use rear view images toevaluate their proposed system. A grid- based method is used for shape features andaspect ratios of different attributes of taillight and license plate are used torepresent geographical features. A genetic algorithm is used for feature subset selection which improves the accuracy slightly from 93.4% to 93.8%. Edges based features are explored in [20–24]. In these approaches, dependence on edges can lead to failure of the system due to occlusion. Petrovic et al. concatenatethe raw pixels, Sobel edges, edge orientation, Harris corner response, normalized gradient and other imagefeatures to build feature vector and apply principal component analysis to reduce the dimensionality of the feature vector [20].The Nearest Neighbors method is used to classify the vehicle make and models.Pearce et al. use KNN and Naïve Bayes for classification and use canny edges, Harris corners and Square Mapped Gradient (SMG) to construct the feature vector [21]. They propose to concatenate Locally Normalized Harris Strengths (LNHS) or SMG for global representation. The authors use the small and simplistic dataset to evaluate the proposed system. Vajas et al. [22] also use concatenated SMG for global representation and Clady et al. [23] use concatenated oriented contour points from Sobel edges. Both Vajas and Clady use Nearest Neighbors as a classifier for their
proposed VMMR system. Munroe et al. usecanny edges and classify using several techniques like KNN, ANN, C4.5, and decision trees [24]. SIFT based VMMR systems are proposed in [25–28]. Psyllos et al. use atwo-step approach [28]. They use phase congruency to identify the vehicle logo and then SIFT features to identify the specific model. Probabilistic Neural Networks are used for classification. against simple and non-occluded images. Different viewpoints and variation in illumination are also not considered. Even then a low accuracy rate of 54% is reported. Dlagnek use SIFT and a bruteforce matching algorithm in his work [25]. Exhaustive matching, used in this work, isa very time-consuming process. Baran et al. use SIFT, SURF and HOG features and define dictionaries for global feature representation [26]. Baran use multi-class SVM with very large dictionaries to represent the input images. Fraz et al. extract SIFT features and form a lexicon comprising of all the features from trainingdataset as words [27]. Fisher encoded representation is used to compute thelexicon for image features, SIFT. The Fisher encoded scheme is computationally expensive and the authors report the processing time of about 0.4 s for every image. Jang et al. use SURF features and bag-of-words model for global featurerepresentation [29]. The authors have created a dataset using multiple toy cars and a structured matching technique for classification. A global feature representation based ona grid pattern is proposed in [9,30]. Hsieh etal. divide input image into a grid and compute SURF and HOG for each blockindependently [30]. The authors train ensemble of SVM and combine the results to determine the final decision. Chen et al.
[9] compute HOG features for the grid- based pattern and concatenate HOG features for global representation. By testing our system with their dataset, we show that our system performs well in terms of recognition accuracy andprocessing speed. The grid-based schemes assume a fixed camera and are prone tofailures in cases where the camera height, pitch or yaw may change, resulting in vehicle views which the system might notbe trained for.

EXISTING SYSTEM:

The VMMR problem can be treated asa multi-class image classification problem, where each class represents a specific makeand model. However, more challenging anddiverse challenges are associated with VMMR as compared to other problems. The vehicle images used in our work reflect real world situations as they are captured in diverse weather conditions, with different lighting exposures, having partial occlusion (e.g., pedestrians), and from different viewing angles. The underlying goal is to discover the ability ofsupervised learning to resolve the applied computer vision problem of identifying themake, model, and manufacturing year of vehicles given the stringent limitation of the problem environment.

Disadvantages

Few of the challenges are listed below

- Image acquisition in an outdoorenvironment.
- Varying and uncontrolled illuminationconditions.
- Varying and uncontrolled weatherconditions.
- Occlusion, shadows, and reflections incaptured images.
- A wide variety of available vehicleappearances.
- Visual similarities between differentmodels of different manufacturers.
- Visual similarities between differentmodels of the same manufacturer.

.Tiny differences depending on the generation (group of consecutive manufacturing years).

PROPOSED SYSTEM:

The proposed VMMR system classifies vehicles images based on make, model, and manufacturing year while the existing VMMR systems can only identify the make and model. Vehicle modelstypically keep the same design shape for about five years before it is modified. We are using the term generation to describe the vehicle model having the same physical appearance but manufactured over one or more years. This article is organized as follows: Section 2 discusses the related work. The detailed system design along with feature extraction, machine learning techniques and VMMR datasets are discussed in Section 3. Theefficiency and performance of the proposed VMMR is discussed in Section

4. Section 5 concludes the paper andprovides direction for future work.

ADVANTAGES

Designing VMMR requires the identification of the specific vehicle in terms of its manufacturer, model, and generation. The vehicle detection module verifies the existence of a vehicle in the current imageand the vehicle detection process also localizes the vehicle within the image

MODULES:

1) Upload Car Dataset: using this module we will upload Car dataset

2) Train Linear Regression & KNN Algorithm : using this module we will build training dataset for car dataset training and gettingaccuracy.
3) Train SVM & CNN Algorithm: using this module we will build training dataset for car dataset training and getting accuracy and compare previous accuracy.
4) Train KNN & SVM Algorithm : : using this module we will build training dataset for car dataset training and getting accuracy andcompare previous accuracy model.
5) Train KNN & CNN Algorithm : using this module we will build training dataset for car dataset training and getting accuracy and compare previous accuracy modeland predict car model.
6) Prediction Model: using this modulewe will predict car model name from uploaded dataset.
Accuracy Comparison Graph: usingthis module we will predict car model uploaded dataset in graphical representation like bar chart.

5. SYSTEM REQUIREMENTS

The project involved analyzing thedesign of few applications so as to make the application more users friendly. To do so, it was really important to keep the navigations from one screen to the other well orderedand at the same time reducing the amount oftyping the user needs to do. In order to makethe application more accessible, the browser version had to be chosen so that it is compatible with most of the Browsers.

CONCLUSION

In comparison to current VMMR systems, the real-time VMMR system presented in this study performs better in terms of recognition rate and processing speed. This work use a publicly accessible NTOU-MMR dataset based on reasonable hypotheses. The dataset has been altered to now contain a vehicle's generation along with its make and model. To represent the photos and categories the automobiles, we employed HOG, GIST, and RF. Our approach is ideal for real-time applications with a greater identification rate, as demonstrated by the experimental investigation. The suggested technique performs admirably in difficult circumstances where cars are partially obscured, partially out of the picture, or difficult to see owing to bad illumination. This system can provide great value in terms of vehicle monitoring and identification based on vehicle appearance instead of the vehicles' attached license plate. The existing VMMR research focuses on recognizing vehicles sufficiently to report only their make andmodel. We have included generation as another parameter. Thus, our VMMR system recognizes a vehicle and providesinformation about vehicle make, model and generation. Although the proposed VMMR system outperforms the previous systems, it can be further enhanced. Image feature vectorshave a large number of features/dimensions. Dimensionality reduction techniques can be explored to reduce this number. A publicly available better and larger dataset with more vehicle types will benefit the research in this area. Deep learning techniques can also beexplored with a bigger dataset.

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