Vehicle Pattern Recognition Using Machine Learning and Deep Learning

1Ch Lavanya Susanna Department of Information Technology & Dhanekula Institute of Engineering and Technology
2Poka V N Anil Kumar Chowdary Department of Information Technology & Dhanekula Institute of Engineering and Technology
3Tatiparthi Kamala Sree Valli Department of Information Technology & Dhanekula Institute of Engineering and Technology
4Parasa Hari Priya, Department of Information Technology & Dhanekula Institute of Engineering and Technology
5Veeragandam Sai Kumar, Department of Information Technology & Dhanekula Institute of Engineering and Technology

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Abstract - Recently, there has been increased interest in intelligent transportation systems. The most important duty in this area is to classify and locate vehicles. Differentiating between the attributes of various cars is the task's main obstacle. The fact that a wide range of cars do not adhere to lane discipline makes vehicle classification and detection a challenging problem to pinpoint. In this tutorial, we've built a convolution neural network from the ground up to categorize and recognize objects using a contemporary convolution neural network based on fast regions. For classification and detection in this study, we took into account three different types of vehicles: buses, cars, and bikes. We'll employ a method that creates a bounding box using the complete image as input.

***Key Words*:** CNN, KNN, Linear Regression, SVM

1.INTRODUCTION

Things in the image are simple for people to recognize and analyze. Humans have a quick, accurate visual system that is capable of complex tasks like object recognition and obstacle recognition. However, object recognition presents a significant problem in computer vision as we must not only classify various images but also accurately pinpoint the location of objects in each image. This commotion is known as object detection. Object detection is connected to several claims, including image classification, human behaviour analysis, and facial recognition, and can offer useful information regarding the precise meaning of pictures and videos.

2. LITERATURE SURVEY

2.1 Object detection with discriminatively trained part-based model

published by PF Felzenszwalb, RB Girshick, D Mcallester, and D Ramanan

We present an approach to object detection that combines multiscale deformable part models. With regard to the PASCAL object detection challenges, our system performs at the cutting edge and can represent highly variable object classes. Although deformable part models have gained a lot of popularity, they had not yet proven useful on challenging benchmarks like the PASCAL data sets. In order to train discriminatively on partially labeled data, our system uses novel techniques. To mine hard negative examples from data in a margin-sensitive manner, we combine a formalism we call latent SVM with hard negative examples. In terms of latent variables, a latent SVM is an MI--SVM reformulation. Once the latent information for the positive examples is specified, the training problem, which is semi-convex for a latent SVM, becomes convex.

2.2 A multi-scale cascade fully convolutional network face detector

published by Z Yang, and R Nevatia

Face recognition is difficult because faces can appear in images at any scale and in any location. With fully convolutional neural networks (FCNs) as the foundation, we suggest a three-stage cascade structure. By zooming in on the faces, it aims to determine the precise location after first suggesting possible rough locations where the faces might be. A multi-scale fully convolutional network is used at each level of the FCN cascade to generate scores at various scales and locations. Each FCN stage ends with the creation of a score map. The next stage is fed with potential facial regions. Each level results in a smaller number of proposals, and the size of the regions is also reduced to more closely fit the face. Unlike agreements made during direct negotiations

2.3 Detection and classification of moving vehicle from video using multiple spatio-temporal features, recent advances in video coding and security

Published by Wang, Y., Ban, X., Wang, H., Wu, D., Wang, H., Yang, S., Liu, S., Lai

An improved spatiotemporal sample consistency algorithm is proposed, consisting of two main stages, to address the difficulty in classifying data obtained from visual traffic surveillance sensors in a specific region of China. We proposed a method based on spatiotemporal sample consistency in the first stage, which further increased the robustness of moving object detection. In the second stage, we proposed a method based on target classification, which also corrected tracking errors. The experiments on the CD net 2014, MIO-TCD, and BIT-Vehicle show that the method we proposed successfully overcomes the negative effects in the complex environment with different types of

2.4 Vehicle detection and classification based on deep neural network for intelligent transportation applications

Published by Tsai, C.C., Tseng, C.K., Tang, H.C., Guo, J.I

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 03 | March - 2023 Impact Factor: 7.185 ISSN: 2582-3930

In this study, an improved method for vehicle detection and classification based on deep learning technology is proposed for use in intelligent transportation systems. By tweaking the current CNN architecture for intelligent transportation applications, we improve the Convolutional Neural Network (CNN) architecture. When the FPPI is 0.1, the proposed design achieves an accuracy with a miss rate of about 10%. The proposed design, when implemented on an Nvidia Titan-X GPU, can deliver performance of about 720480 video at 25 frames per second in a variety of lighting conditions (day, night, rain). On three target vehicle classes—small vehicles (sedans, SUVs, and vans), large vehicles (buses), and trucks—the proposed model can achieve 90% accuracy.

2.5 Automatic moving vehicle detection and classification based on artificial neural fuzzy inference system
Published by Murugan, V., Vijaykumar, V.R.

Automatic vehicle detection on the road is the main goal of this work. Cameras are positioned both vertically and horizontally to capture input traffic video scenes. Preprocessing, vehicle detection, tracking, structural matching, feature extraction, and classification are some of the six main steps in the proposed system. Preprocessing in this suggested method entails color conversion and noise removal. Background subtraction and the Otsu thresholding algorithm are used to detect vehicles. In the third step, the Kalman filter is used to track moving vehicles over time. The Active Shape Modelling method is utilized in the fourth step to recover the 3D shape of the vehicle in order to

3.PROPOSED SYSTEM

The manual enforcement of traffic laws, such as the posted speed limit, is insufficient. Police and manpower are not available in sufficient numbers to monitor traffic and vehicles on the roads and check them for speeding. Therefore, we need to install sophisticated speed calculators that can accurately detect cars on the road and calculate their speeds.
Two fundamental conditions, namely the accurate detection of cars on roads and their velocity measurement, must be met in order to put the aforementioned idea into practice. To train our machine to recognize the object, in this case the car, we can use the OpenCV software, which employs the Haar cascade.

4.METHODOLOGY

By employing restricted fields, image localization pinpoints the location of these things in the image while image classification identifies which objects are present in the image, such as a car or bicycle rail. The convolution neural network needed to identify various things, including a car, bus, and motorcycle, in order to classify the images. Object detection can therefore be characterised as picture categorization and localisation.
Image categorization and localisation are the two components of object detection.
Gathering training data is step one of the procedure, followed by training the model and prediction of fresh photos as steps two and three. Below figure 1 is a display of the scheme's stream.

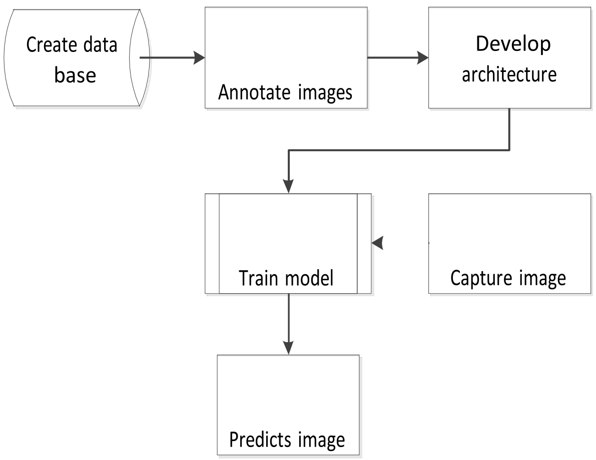


Figure 1. Work flow of object detection

Gather Training Data

In order to acquire data that is as close to the data that should ultimately be anticipated, a camera is utilised for this duty. Each object in the data set collection has 1000 photos. Following image capture, a set of photos is retrieved, scaled, and ground truth labelling is created using the location and labels of the object of interest. However, this task is fairly time-consuming and complex.

Training a Model using deep learning

Since the convolution operation is only run once for each image and a characteristic chart is generated as a result, the network architecture is based on the fastest R-CNN. quicker layers The input, middle, and final layers of R-CNN. The input size strikes a compromise between the quantity of spatial features the detector must choose from and the execution duration. The fundamental elements of the intermediate levels are the like convolution, a network. Sets and pools for ReLU. Repeating these levels is necessary to build a deeper network. Typically, fully connected, Softmax loss classification, and regression layers for image localisation make up the final CNN layers. In this paper, a brand-new CNN is created, and the nonlinearity of Leaky-ReLU between fully linked layers is exam

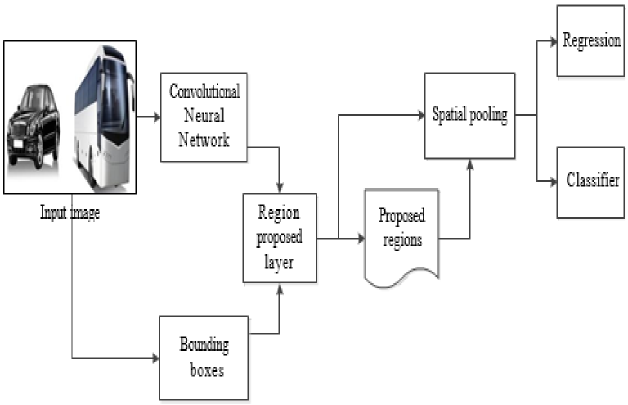
Fast RCNN for image classification and localization

In Fast RCNN, we transmit the input image to CNN, which in turn creates maps of revolutionary objects. With these maps, regions of the proposal are extracted. We then use the RoI pool layer to convert all the proposed areas into a fixed size so that they can be transferred to a fully connected network. The RCNN fast approach is as follows

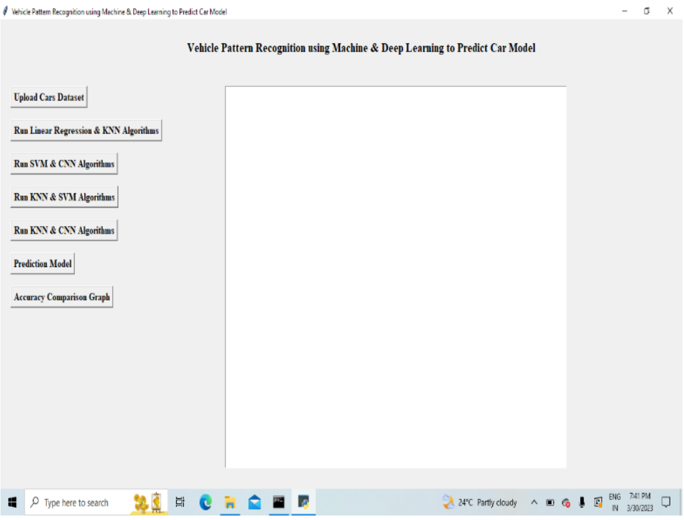
1.To take input image using a camera.

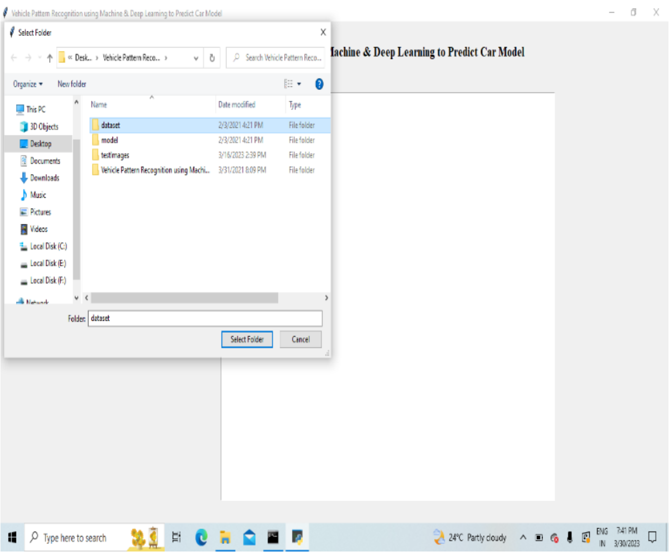
2.The input image is transferred to ConvNet,which returns the region of interest.

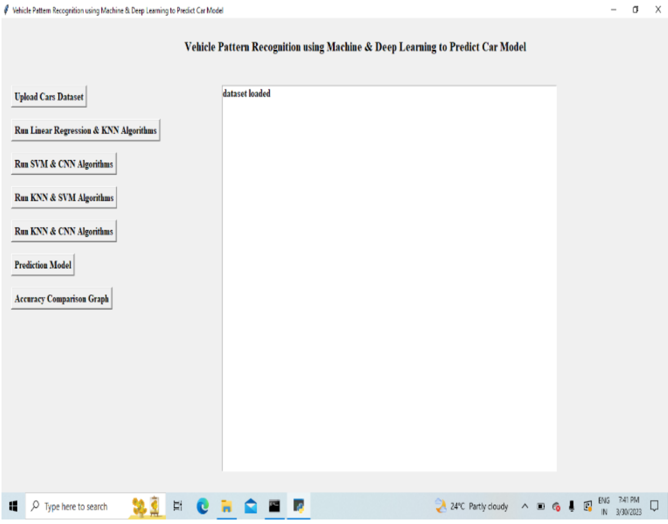
3.Apply the RoI pool level to the extracted areas. Finally, these areas are transferred to a fully connected network, which classifies them, and also return boundingblocks, using both linear and softmax regression layers. Theflow is displayed in Figure 2.

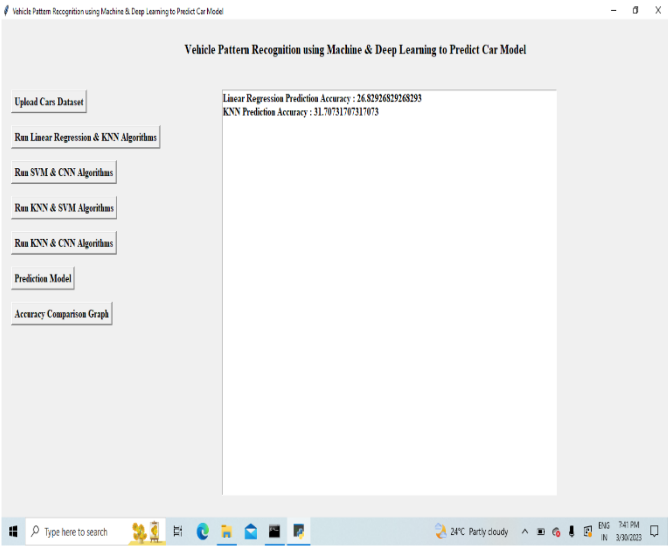


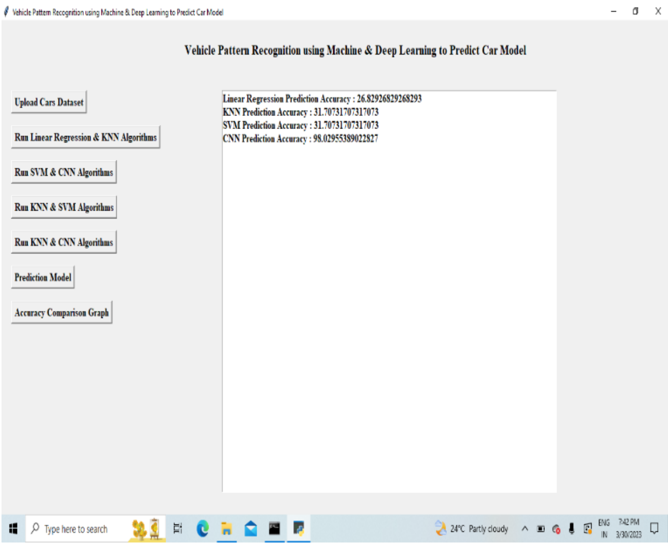
5.RESULTS

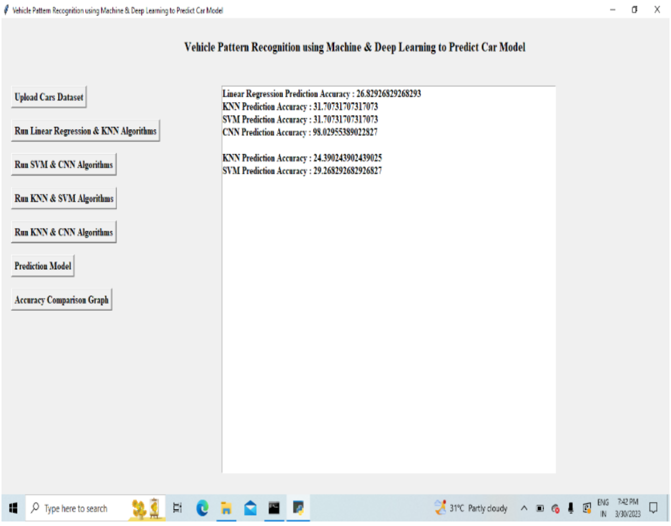


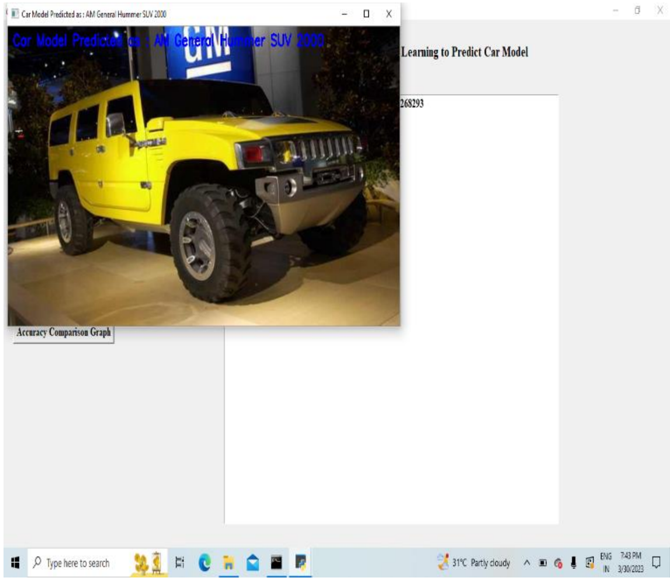


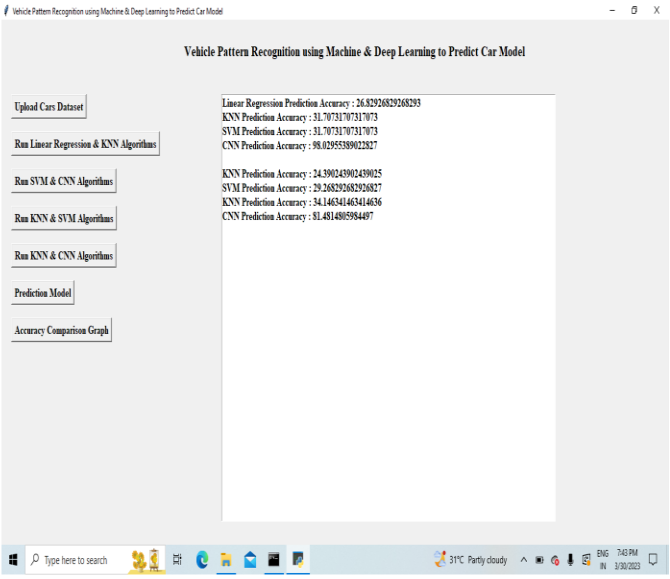







Vehicle Pattern Recognition using Machine & Deep Learning to Predict Car Model
Upload Cars Dataset
Run Linear Regression & KNN Algorithms
Run SVM & CNN Algorithms
Run KNN & SVM Algorithms
Run KNN & CNN Algorithms
Prediction Model
Accuracy Comparison Graph
Linear Regression Prediction Accuracy : 26.82926829268293
KNN Prediction Accuracy : 31.70731707317073
SVM Prediction Accuracy : 31.70731707317073
CNN Prediction Accuracy : 98.02955389022827
KNN Prediction Accuracy : 24.390243902439025
SVM Prediction Accuracy : 29.268292682926827


Car Model Predicted as : AM General Hummer SUV 2000
Learning to Predict Car Model
Accuracy Comparison Graph


Vehicle Pattern Recognition using Machine & Deep Learning to Predict Car Model
Upload Cars Dataset
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Run KNN & CNN Algorithms
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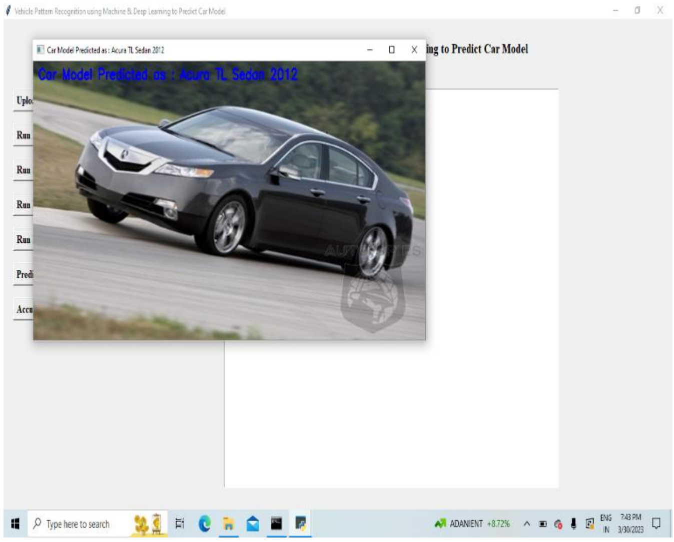
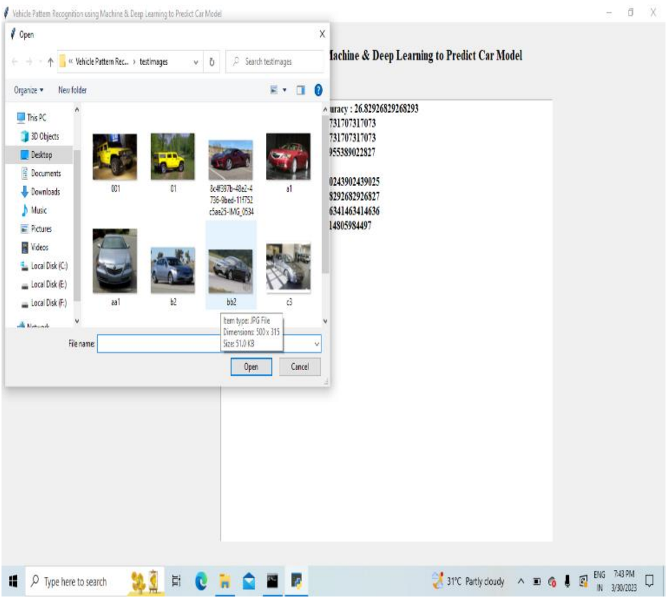
KNN Prediction Accuracy : 24.390243902439025
SVM Prediction Accuracy : 29.268292682926827
KNN Prediction Accuracy : 34.146341463414636
CNN Prediction Accuracy : 81.48148059584497


Car Model Predicted as : Acura TL Sedan 2012
Car Model Predicted as : Acura TL Sedan 2012
ing to Predict Car Model


Open
Organize
New folder
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File name:
Open
Cancel

6.CONCLUSION:

Moving cars are separated using frame subtraction and masking techniques. The time between frames and any recognised corners that an object travelled in that frame are used to determine speed. To distinguish between one or more cars, frame masking is utilised as the final step. It was possible to identify speed with an average inaccuracy of +/-2 km/h.

7.ACKNOWLEDGMENT

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