Behavior Estimation of Subsequent Vehicle Using Machine Learning Tool

Mr. Kaustubh S. Kalkonde
Research Scholar
Sipna College of Engineering and Technology,
Amravati, India

Dr. Nilesh N. Kasat
Professor
Sipna College of Engineering and Technology,
Amravati, India

Abstract— Autonomous vehicles are the outcome of the industrial revolution. The autonomous vehicles assure transportation of the human and goods with partial or no human intervention. Modern Advanced Driver Assistance System (ADAS) is the one of the examples of the autonomous vehicles. In such type of vehicles, since there is partial or no human intervention the success highly depends on the precise sensing of the different obstacles on the pathway. This research work is an attempt to design a system for behavior analysis of the subsequent vehicle on the pathway using advanced machine learning tools.
Keywords— Machine Learning, Haar Cascade, Sensors,

Introduction

Swift nature of technical revolution also has created a huge impact on automobile sector. This not only helped passengers to travel safely from one location to another but also helped to travel luxuriously. The positive efforts from the government policies also have made the vehicle manufacturers to provide essential safety features from the base variants of the vehicles itself. The combine efforts from the technical revolution and societal development have helped to reduce the accidents and casualties to a minimal level. Various eye catchy features which can immediately be listed includes hill hold assist, multi collision brake, electronic differential locking system, motor slip regulation, park distance control, anti-theft alarm, traction control system, brake disk wiping in addition to side and curtain airbags, GPS tracker, infotainment systems, steering control assembly and many other features. But continuous development is a key to success. Various scientists and researchers are already in the direction of designing an autonomous vehicle.

Autonomous vehicles are one in which partial human intervention or no human intervention is required. For designing such vehicles, tones of sensors are engaged in which collectively and precisely locate the various objects surrounding the vehicle and bifurcate them into different obstacles. Different sensors which are engaged in this development are, LiDAR, RADAR, stereo cameras, proximity sensors, light sensors and various other sensors. Considering the scope of the development in the autonomous vehicle development, through this research paper we are disclosing the behavior estimation of the subsequent vehicle using fundamentals of advanced machine learning tools. In the development process, we begin with the data base collection, then data filtering and pre-processing is performed. The process is followed by data augmentation then machine learning algorithm is shortlisted and training is performed. Finally, the fine tuning and validation is performed to estimate the performance of the model through various ascendency parameters like accuracy, precision, F1 score. Through the validation process, random input states are provided and model is deployed to estimate the behavior. Through the subsequent section literature review is done to list down the up-to-date technology, then, research flow is discussed along with the research outcomes with respect to various ascendency parameters.

Autonomous Vehicle: A Survey

The energy rule of conservation states that the energy can't be created nor destroyed, but it can be converted from one to another form. On this basis, the regenerative brake system is employed in composite vehicles with the support of traditional hydraulic brakes to acquire the complete braking solution with decreasing energy loss. Based on the street circumstance, the proposed system identifies its type and adapts braking performance. A regenerative anti-braking system is developed for minimization of the control system performance for the period of braking of dissimilar territories. The effectiveness of converting the lost energy into useful energy to charge the vehicle batteries has been achieved up to 35%. [1]

The current paper presented end to end framework for taillight alteration identification based on the analytical hypothesis of irregularity identification and model-based systems manufacturing ideology. Based on the analytical hypothesis, the authors [2] have segmented the visible input pattern into different shape, intensity, color and movement which is closed together with a graphical system. High reliability three-dimensional imitations have been developed to inhibit movement memory, whereas low reliability three-dimensional outcrops have been employed to develop arithmetical preceding. To compute the proposed framework, the authors have acquired successions containing RGB pictures, initial information and interpreted them for vehicles and their brake lights or taillights conditions.

With the exponential growth of enhanced driver support systems, there is an increasing necessitates for widespread consideration techniques to estimate the road safety of such systems. An automated machine calculating the parameters can have high threshold values. To control off-road activities, the authors have expanded the traditional driver assistance systems for collision avoidance. Based on element cloud optimization and utmost probability assessment, severe parameterization and system selection steps are proposed. The most important contribution of this research is the outputs show that drivers have incomplete illustration intimidating observation during off-road braking. [3]

Vehicle braking light identification is one of the key components of vehicle stopping sight distance. In several conditions, the braking performance of the vehicles was not unswerving in available literature surveys. The proposed research measures braking distances to the predicted and unpredicted objects. For the predicted objects, it was observed that the driver applied the brake quickly which activates the taillights. For an unpredicted object, some vehicles were tackled with necessitate to stop for an unpredicted object beside the road. Several parameters such as braking distances, car speeds and average deceleration are calculated for every braking scheme. [4]

The authors in [5] have proposed an actual moment vehicle speed controlling system known as the actual moment energy deceleration controlling system. Navigation technologies such as traffic lights details and front identification sensor information are developed to recognize deceleration incidents. The proposed actual moment energy deceleration controlling system has employed two speed controlling tactics with dissimilar levels of the controlling horizon. If the vehicle is identified within a threshold range, then a model prognostic planning-based energy proficient slow down approach that integrates the crowd condition in front of the vehicle and develops vehicle to vehicle communication with the prior vehicles is initiated to reevaluate the speed route of the vehicle to assure a collision avoidance.

Advance vehicles are outfitted with several smart systems to assist drivers in ensuring contented and risk-free driving. These systems are known as enhanced driver support systems. The main objective of the intelligent driving system is object identification and observing employing a front camera which gives essential details for accidents prevention and urgent braking. The authors [6] have proposed object identification and tracking for smart driving. Viola-Jones algorithm and YOLOv3 have been employed as object identification techniques. The Viola-Jones algorithm is employed to generate object identifiers in which identifications are tracked in video frames. YOLOv3 method utilized for object identification. The proposed techniques are assessed in terms of precision and processing speed.

Intelligence emergency braking is employed to control or slow down the vehicle when an unavoidable object is identified. In addition to recognized advantages when it is functional to passenger vehicles, intelligence emergency braking systems also show potential when functional to vehicles intelligence emergency braking. On the other hand, the possibility of a vehicle's intelligence emergency braking system as practically applied to passenger cars in the real world is unspecified. The authors [7] have performed several rides testing on vehicles subjected to intelligent decelerations by employing vehicles intelligence emergency braking system.

Front accident alarming signal system becomes more popular as the Defense advanced research projects agency challenge. The main intention of this method is to decrease the requirement of human being involved in driving and enhance the level of automated function of vehicles. For smart vehicles front accident alarming method is proposed. An image processing algorithm is employed to identify the brake lights of the vehicles driving in front at nighttime. To prevent the backward accident risk, the region of led lights, the vehicles speed and the dimension of the largest taillights are used. Such a signal can be given to the driver as an alarming signal to prevent the front accident. RGB image detector algorithm is used to detect red indicators. [8]

The vehicle identification and tracking algorithms for driver support systems require strong characteristic extraction and tracking techniques despite road and light situations and precise assessment of vehicle location. Many traditional research techniques are available which identify the vehicle in the daytime with good lightning circumstances. By employing sonar and visual sensors, the authors have proposed novel vehicle identification and tracking system despite road and light situations. The authors [9] have utilized the sonar sensor for identification and distance prediction within 15 meters and utilized an image sensor beyond 15 meters. This technique can identify the light situation by monitoring several pictures. In the daytime, the vehicle can be detected by processing characteristics such as vertical boundary, proportion rate and lane data. At nighttime, the extracted features are bright areas caused by the brake lights, taillights and head lights.

Day by day due to the increasing overcrowding in metropolitan regions, the requirement for more energy and time efficient vehicles has been increased. As the number of vehicles increases, there is a higher risk of collision between vehicles. The techniques like driver supportive systems are required to avoid collisions. The purpose of the presented study was to access the practicability and quantitative prospective advantages of a vehicle automatic emergency braking system in front collisions. Another goal was to detect available possibilities of vehicle automatic emergency braking systems in the region of powered motorcycles. The vehicle automatic emergency braking system has shown to be an inventive protection mechanism in the field of powered motorcycles. [10]

Recently the automobiles industry employing artificial intelligence techniques to improve vehicle protection. Instrumentation system-based techniques are also utilized to sense the atmosphere circumstances and become accustomed to the vehicle response. In the paper [11], the authors have proposed a visual light communication method for economical messaging between two vehicles. For road safety applications, visual light communication is an economical technique to incorporate with the automatic transport model. Vehicle taillights can be used to send messages to apply emergency brakes in order to take preliminary action to avoid collisions or accidents. A sample vehicle-to-vehicle communication model is constructed with high dependability and low complication.

In a very short period, e-vehicles have changed the transportation scenario in nations around the world. Simultaneously, it is observed that there is an increased rate of hospitalization of e-vehicles drivers with a high occurrence of injuries. The authors [12] have done the field survey and surveillance to find out the influence of protective use of e-vehicles, and to investigate the driver's knowledge and performance. Precise information concerning the braking system of e-vehicles was evaluated along with information concerning road safety rules and reported earlier period protection related activities. It was observed that only one fourth of the e-vehicle drivers could properly recognize the braking system of the e-vehicle they had previously used.

In the automotive industry intelligence, driver support systems are extensively popular. To control vehicles that are supported by such systems, drivers should have to specifically understand their rules and restrictions. The proposed investigation focused on the rapidly growing technology of emergency braking and elucidates the human beings sympathetic to the intelligence braking system. The percentage of people who misunderstood the concept of the braking system is low, but there are some human beings with the misapprehension that the intelligence braking system could identify bicycles or pedestrians. [13]

Many conventional vehicle identification techniques utilize color as an essential component for detection. Though, complicated paths and varying lightning situations can affect the efficiency of such precise law and threshold-based techniques. The authors [14] have proposed a new technique for the identification of vehicles during nighttime employing deep learning categorizers for varying lighting situations. Vehicle identification using dynamic learning during nighttime is further extended to recognize the features of the vehicles by identifying turning and brake indications. The proposed technique has reached an efficiency near 99% and 1% of false identifications.

Proper detection of the pedal signal is an important characteristic in a driver support system. The primary objective of this characteristic is to avoid any counterfeit identification of the brake pedal signal. In addition, it gives a warning signal to the driver concerning brake control failure. Besides suitable execution, the characteristic must be tested comprehensively in order to construct its full verification before its usage in a vehicle. Polyspace and rational test authentic instant tools are employed for testing this characteristic. The authors [15] have focused on the execution and testing of brake pedal signal investigative in the vehicle.

The reducing cost of cameras made it possible to be easily mounted in front of the vehicle and optical devices have made it cost-effectively feasible to develop intelligent systems for the identification of accidents prevention. In nighttime in front vehicles are recognized only by their brake lights and these signals are important as they provide an alarming signal to the driver to avoid accidents. The authors [16] have proposed Nakagami distribution based novel visual based technique has been introduced for the identification of taillights during dark time by observing the brake lights. Instead of observing the characteristics like position, size and symmetry of the rear-facing vehicle, the proposed technique focused on invariant characteristics to model taillight dispersion in the frequency domain and hence accomplish the identification procedure in a part-based approach.

In an intelligent driving support system, vehicle following is one of the essential functions. Recognition and identification of brake light signal necessary to avoid an automatic vehicle from front-end accidents or collisions. To generate collision alarming signals sensors such as acoustic sonar and enhanced driving support system models can be employed. To recognize the vehicles and to detect the tail or brake lights in real-time, the authors [17] have constructed a new two-level technique. A multi-layer observation neural network is utilized to learn brake light patterns from large datasets. The vehicles can be categorized as normal and brake employing the deep learning categorizer. The vehicle can be recognized rapidly by integrating a multi-level lax fusion system and a camera.

Identifying Brake lights or turn indications can help the driver to understand the vehicle's future activities prediction. Visual light communication systems employing vehicle taillights can communicate with drivers to prevent accidents. In dissimilar lighting situations, complexities with obstructions and perceptions, traditional techniques are challenging. A contrast of deep learning techniques is presented based on its prospective to compute real-time scenes. A cascading technique is employed to perform down sampling of pictures to identify vehicles. The proposed technique [18] is employed to enhance identification, especially for small obstacles. Also, this technique provides acceptable outputs and can process 40 frames per second.

As the graph of vehicles is increasing exponentially, enhanced vehicle protection is an important matter of concern for the automobile industry. In nighttime recognition of taillights are mostly essential for drivers as they provide a warning signal to apply brakes. The authors [19] have proposed a new technique for the identification of taillights during dark time employing a camera by evaluating a signal in frequency field and spatial field. The experimental results show that the proposed system can effectively and proficiently identify the taillights under dissimilar traffic and lightning situations and showed its practicability in real-world applications.

For a vehicle, the security of the passengers as well as the pedestrians on the road is also important. The examination of the security system is provided to reduce the accident with pedestrians utilizing intelligent braking of the vehicle. The examination is based on when the pedestrian is identified in the camera, the detection of alarming signal and when the accident is about to happen, the cars without human intervention apply brakes immediately. [20]

Vehicle Behavior Estimation : Development

While designing the model for estimation of the behavior of the subsequent vehicle, it is essential to assume that the each of the vehicles are having tail lamp assembly which can be used to forecast the movement of the subsequent vehicle. The inside of the development of the model can be best discussed using the following systematic block diagram.

Fig. 1: Model Structure for Vehicle Behavior Analysis

The proposed model is designed and developed using the python language. Python is the language which is interpreted language which means the syntaxes and semantics are so designed, the statements will be executed immediately rather than compiling and executing the statements. In the development of the model, different database containing diverse possibility of tails lamp operations are collected from the kaggle. In the very first step the database assessment is carried out in which the number of classes or categories in which the database is available are shortlisted and imported in the model. To increase the accuracy of the model, first of all the car from the frame is scanned and then the tail lamps status is observed. The number of data samples in each category are compiled and preserved for pre-processing purpose. In python, for image processing, open cv library is used. While performing the pre-processing, since the open cv read the images in BGR form it is converted into RGB file format for further processing and display purpose. Further, each of the image from different categories are converted into standard 128x128 image size format.

Then the database is prepared for training. Ideally 30% of the database is used for validation purpose and 70% of the database is used for training purpose. This data splitting is done in each category of the database for 128x128 RGB color image size. As the number sample images are higher will be the training and validation accuracy and lower will be the training and validation loss. To assure this, data augmentation process is carried out, in the model each of the database image is horizontally flipped, rotated for 60^0, zoom for 40% and shifted height wise and width wise for 50%. By configuring the database images through these constraints, the database is increased from thousands of images to lacks of images for training and validation purposes.

Next, the xception model is configured for imagenet weights of 128x128 RGB image size, softmax and activation function and using the Adam optimizer. The model is trained for 10 epochs using batch size of 64 samples. After completion of training of the model, summarization is reported. The model assessment is carried out using different ascendency parameters like accuracy, precision, F1 score and support. Finally, the performance evaluation is carried out by practically importing the database images and predicting the output.

Vehicle Behaviour Analysis: Outcome

The outcome of the present model is disclosed through the subsequent section. In the very stage the database is read into the model. The samples images from the tones of database are shown in the following figure.

Fig. 2: Sample Database Images

More than 38000 sample images in distinct categories are read into the model and converted in to the uniform format of 128x128 RGB file format. After execution of this uniformity the following output is depicted.

$$Shape\ of\ X:\ (36858, 128, 128, 3)$$

The pre-processed database is prepared for training purpose. The 30% of the database is preserved for validation purpose and 70% of the database is used for training purposes. The outcome cam be depicted as follows:

$X\_train\ shape:\ (18060,128,128,3)$
$y\_train\ shape:\ (18060,4)$
$X\_val\ shape\ :\ (7740,128,128,3)$
$y\_val\ shape\ :\ (7740,4)$
$X\_test\ shape:\ (11058,128,128,3)$
$y\_test\ shape:\ (11058,4)$

Further, the data augmentation is performed in which the each of the sample image if flipped, rotated, zoom, horizontally and vertically shifted and training of the model is carried out.

The training of the model begins with

$$loss: 0.5703 - accuracy: 0.8000 - val\_loss: 0.4186 - val\_accuracy: 0.8592$$

While the training of the model ends with

$$loss: 0.0881 - accuracy: 0.9695 - val\_loss: 0.0751 - val\_accuracy: 0.9747$$

While the model has been summarized, the following statistics have been recorded.

$$Total\ params: 20{,}869{,}676$$
$$Trainable\ params: 20{,}815{,}148$$
$$Non-trainable\ params: 54{,}528$$

The training accuracy and the validation accuracy of the model is recorded through the training process and is depicted through the following figure.

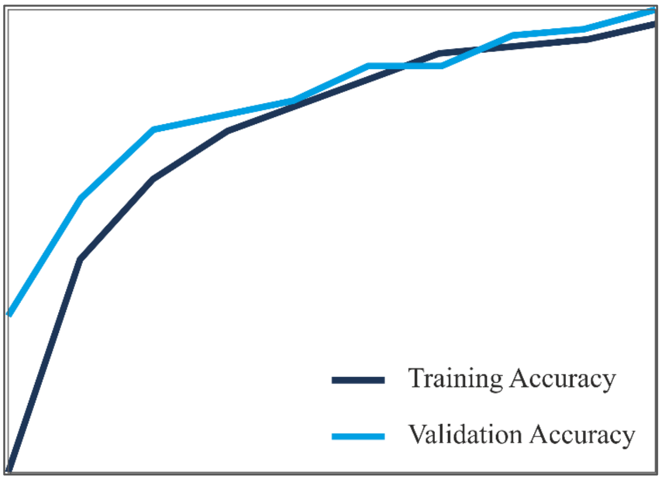


Fig. 3: Training and Validation Accuracy

At the same time, training loss and validation loss is also plotted at the time of training of the model and is depicted through the following figure.

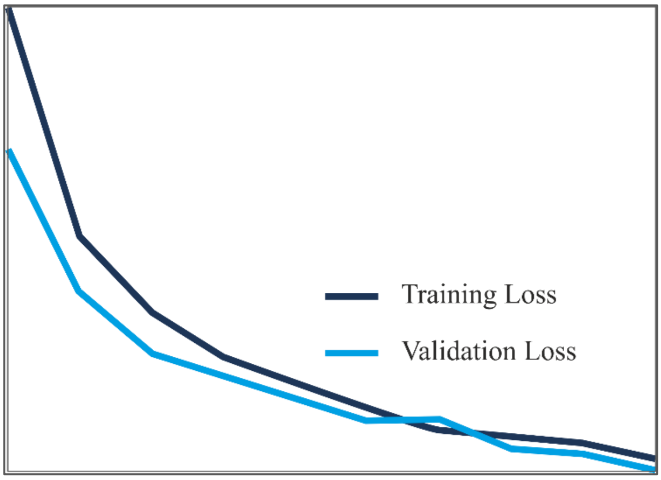
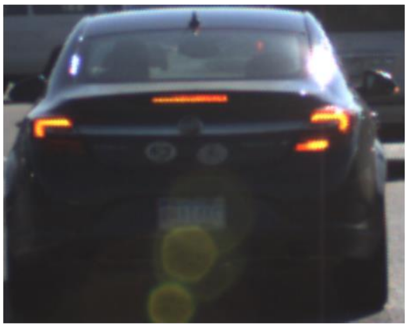


Fig. 4: Training Loss and Validation Loss

Finally, the outcome is assessed with respect to the different parameters like accuracy, precision, recall and F1 score. It is observed that, the accuracy of 99% is recorded while validating the model. On the other hand, average precision of 99% is recorded while validating the model for different classes of the images. The F1 score reaches to 100% for 5943 support and recall also reaches to 100% for same support values. While testing the model, random blind input is given to the model for estimation, the model has correctly predicted the sample input image, which is shown in the following figure.



Prediction: Braking

Fig. 5: Outcome of Model for Blind Input Image

Conclusion

Behavior estimation model for subsequent vehicle is developed using machine learning model. Sample database comprising of distinct image samples are feed into the model. The image database is read and pre-processed for conversion into RGB and unique format. Data augmentation is performed. The Xception model is configured for imagenet weight, global average pooling, softmax activation function and adam optimizer. The model is trained for 10 epochs. The model is summarized and the it is validated by giving random blind input to the model for validation purpose. The model accurately classifies the input image and hence it is possible to precise estimate the behavior of the model with overall accuracy of 99% and average precision of 98% values.

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