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Lane Sensing and Tracing Algorithms for Advanced Driver Assistance Systems with Object Detection and Traffic Sign Recognition

P. C. Gagan Machaiah and G. Pavithra

Abstract Advanced driver assistance systems (ADASs) and autonomous vehicles are expected to increase safety, lower energy and fuel consumption, and lower pollutants from road traffic. The advanced driver assistance system's major features include lane detection and tracking. Finding color line marks on the road is the technique of lane detection. The process of lane tracking aims to help the vehicle continue traveling along a predetermined course. Hence, automatic detection of lanes using convolutional neural networks (CNNs) models has gained popularity in the current economic development. This paper also aims at detecting various objects using convolutional neural networks. In this work, we offer object classification and detection, a demanding topic in computer vision and image processing. As a result, we deployed convolutional neural networks on the Keras platform with TensorFlow support. The experimental results illustrate the amount of time needed to train, test, and generate the model using a constrained computing environment. Here, we trained the system for about 80 images which have taken a couple of seconds to detect with better accuracy. Traffic sign recognition is carried out, which is a significant area of research in ADAS. It is crucial for driverless vehicles and is frequently used to read stationary or moving road signs along the side of the road. A comprehensive recognition system is made up of traffic sign detection (TSD) and categorization (TSC). The paper also aimed at traffic sign recognition, which is crucial to consider, because traffic sign recognition is typically applied to portable devices. The model's detection accuracy is ensured as long as the speed is maintained. The model developed in this study is 99.89% accurate.

Keywords Lane sensing · Lane monitoring system · Advanced driver assistance systems (ADASs) · Lane departure warning system · Lane sensing system · Sensors · Convolutional neural networks · Deep learning (DL) · Traffic sign · Keras · TensorFlow

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1 Introduction

Around 73% of accidents are caused by driver error, such as failing to see signs or ignoring a blind area, according to statistics [1, 2], which motivates manufacturers to develop safer vehicles, with regard to the creation of ADAS. Implementation of ADAS has brought to avoid and to reduce the damage that accidents inflict by early and intimately identifying lane departure and collision.

For lane detection and tracking in various weather circumstances, such as sunny and cloudy, an algorithm will be created. The need for autonomous vehicles has grown significantly in recent years as a result of rising traffic volumes and increasingly congested roads around the world. As a result, it is important to create an intelligent driver aid system that can either notify the driver of harmful situations or intervene, while the vehicle is on the road. Such technologies will become more complicated in the ensuing decades, enabling complete vehicle autonomy. In particular, lane, object, and traffic detection are three key components in the development of such autonomous systems.

The most recent development in deep learning, the deep neural network (DNN), made easier object recognition by engaging in as much learning as possible. Machine learning algorithms, which are great at finding patterns but typically need more data, are divided into deep learning algorithms. Convolutional neural networks (CNNs) are the most widely used method for increasing the accuracy of picture classification. CNN is a unique kind of neural network that functions similarly to a regular neural network, which begins with a convolution layer.

Berkaya et al. [3] presented recognition of traffic signs as crucial in intelligent driving systems like autonomous and assisted driving. The two categories of road sign identification techniques are manual feature methods and deep learning techniques. Yang et al. [4] Traditional recognition techniques, such as particular color recognition and other feature recognition methods, needed manual labeling and feature extraction, which significantly slowed down system operation. In addition to adding to the workload, manual labeling made it challenging to ensure correctness. Chaiyakhan et al. [5] SVM and random forests are typically used in artificial feature learning techniques, although this approach might be challenging because of hazy feature boundaries in the spot recognition of images.

The development of automatic TSR systems aids the driver in a variety of ways to ensure his or her safety, which also protects the safety of pedestrians. The primary objective of these systems is to identify and recognize traffic signs, while a driver is on the road. The system can direct and warn drivers to avoid danger with the use of these features: lighting, weather changes, and signs that are damaged.

Aghdam et al. [6] proposed rapid advancement of deep learning in recent years which has altered the detection process. Over time, the study of neural networks has gained popularity among academics. With the invention and quick adoption of neural networks, tedious human annotation is no longer necessary because these networks can easily extract the features from an image. The network may obtain many features, particularly for complex images, and these features are ultimately employed for target

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classification. Bouti et al. [7] developed deep learning's advancement which has accelerated the development of traffic sign recognition. To get a good classification impact on the GSTRB dataset, LeNet model has been developed.

The remainder of the essay is structured as follows. The previous works are briefly summarized in Sect. 2. The methodology is given in Sect. 3, whereas evaluation results are presented in Sect. 4. In Sect. 5, conclusions and recommendations for future work are made.

2 Previous Works

The model-based technique for lane detection uses geometric characteristics [8–10]. Training and categorization are the two phases of the learning-based strategy. The building of a model, such as program variables, is done during training using previously recognized errors and system characteristics.

Kang et al. [11] developed a kinematic-based fault-tolerant system that is proposed to recognize the lane even if the environment makes it impossible for it to capture a road image. The kinematic model projects the lane by considering variables such the vehicle's length and speed. Using a clothoid cubic polynomial curve road model, the camera input is provided. The lane coefficients of the clothoid model will be available in the absence of camera input. The lane restoration strategy is employed to overcome this loss. The anticipated lane is determined by the road's curvature and past curvature rate.

A lane detecting system was proposed by Priyadarshini et al. [12]. A grayscale image is created from the recorded video. The noise is eliminated by applying a Gaussian filter. The edges are found using the Canny edge detection technique. Using a Hough transform, the length of the lane is determined. A Raspberry Pi-based robot equipped with ultrasonic sensors is used to replicate the proposed method in order to calculate the separation between nearby cars.

Video processing methods are covered for identifying how the illumination of the lanes changes in an area of straight-line roadways. The study emphasizes the approaches used, including selecting the right color space and identifying the ROI. Following the capture of the desired image, a color segmentation procedure utilizing region splitting and clustering techniques is carried out. The merging process is then used to avoid noise. Hong et al. [13] covered video processing methods for identifying how the illumination of the lanes changes in an area of interest for straight-line roadways. The study emphasizes the approaches used, including selecting the right color space and identifying the region of interest. Following the capture of the desired image, a color segmentation procedure utilizing region splitting and clustering techniques is carried out. The merging process is then used to suppress the noise in the image.

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As it can be difficult to detect the lane and maintain the lane on course under various circumstances, Son et al. [14] presented a method that exploits the lighting feature of lanes under diverse conditions. The process entails figuring out the deleting point, and clever edge detector which is used to assess the image's bottom half, and in the second stage Hough transformation is used to choose the yellow or white lanes. Based on the illumination characteristic, the usage of the white and yellow lanes are created to obtain the lane's binary representation. The lanes are traced, and the intercepting angles are created on the y-axis, they are grouped to create long lanes if there is a match.

An autonomous lane-changing system with three modules—perception, motion planning, and control—was suggested by Chae et al. [15], and they proposed LIDAR sensor input which is used to identify nearby cars. During motion planning, the vehicle selects a mode, lane-changing, and then plans the necessary motion while taking into account the safety of adjacent vehicles. For longitudinal acceleration and choosing the steering angle, a model predictive control (MPC) based on a linear quadratic regulator (LQR) is utilized. For lateral acceleration, stochastic model predictive control is employed.

A reinforcement learning was proposed by Wang et al. [16]. There are two different kinds of lane change controllers used: longitudinal control and lateral control. The intelligent driver model, a car-following model, is selected as the longitudinal controller. Reward learning is used to implement the lateral controller.

Suh et al. [17] considered the yaw rate, acceleration, and lane change time which are the basis for the reward function. A Q-function approximator is suggested to achieve continuous action space in order to get around the static rules. A specially created simulation environment is used to test the proposed technology. It is anticipated that extensive simulation will be used to evaluate the approximator function's effectiveness in various real-time settings.

Szegedy et al. [18] object detection with deep neural networks: Recently, deep neural networks (DNNs) have demonstrated excellent performance in image characterization tasks. Take this paper's author one step further and use DNNs to address the location of object recognition, focusing less on the grouping and more on the accuracy of different classes. They present the selected site as a problem that resists covers as a situation that restrains the questionable but practical strategy. Showcase a multi-scale basic leadership approach that generates low-effort, high-decile protest finders from some-arrange applications. Pascal VOC has the strategy's most advanced implementation.

Benjamin and Goyal [19] Using deep neural networks for item identification are a vibrant area of exploration that has made significant strides in recent years, according to a survey. The paper illuminates the most current developments in this area while condensing the historical background of neural network research recorded using benchmark datasets for the recently developed sensory system computation. Finally, a few examples of applications in this area are provided.

In 2015, Hijazi and colleagues [20] used convolution neural networks (CNNs) to solve pattern and image recognition problems because they have several advantages over competing technologies. Samer Hijazi describes the difficulties in utilizing

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CNNs within installed frameworks and should illustrate the Cadence® Tensilica® Vision P5 Digital Signal Processor (DSP) Key Features in Imaging and Computer vision as well as the software that make it appropriate for CNN applications in many image-editing applications and in relation to identification tasks.

Srinonchat and Pohtongkam [21] by recording the texture of items from daily life that were separated into sections based on the various portions of the human palm, this paper shows how to recognize photographs of out-of-touch objects. Data stream using a segmentation of 15, 20, and 26 regions produced 15, 20, and 26 vectors, respectively. In each sequence of tests, the total of each segment is calculated and converted to a binary picture. The vector data is then sorted to carry out the 300-series train process and a second 300-series testing procedure.

Malykhina and Militsyn [22] present a hypothetical scenario for processing aerial photos, which includes neural network-based image categorization, binarization, filtering, looking for specific items, identifying highways, and tying target to the terrain using cross-correlation function. Both object classification and picture classification have used neural networks. Due to the variety of objects' shapes, sizes, and rotations, classification errors that did not surpass 10% may be regarded as satisfactory.

The problem of road traffic sign recognition (TSR) has been the subject of numerous studies in the literature. Paclik et al. [23] claim that the pioneering research on automatic traffic sign detection was originally conferred in Japan in 1985. Following that, different techniques were developed by various researchers in order to create a successful traffic sign recognition and detection system (TSDR) and to reduce all of the aforementioned problems. Preprocessing, detection, tracking, and recognition are the first four phases of an effective TSDR system.

Tagunde and Uke [24] enhanced that the aesthetic appeal of photographs is the primary objective of preprocessing. Based on two crucial properties, such as color and form, various methods are utilized to reduce the impact of surroundings on the trial photos. Gündüz et al. [25] aimed to find a traffic sign that has been verified following a thorough search for candidates (TS) inside the input image, traffic sign detection seeks to recognize zones of interest (ROIs) in which it is meant to find those signs. Various methods were suggested to find these ROIs. The most often used techniques for color-based thresholding include HSV/HIS transformation [26, 27].

Region growing [28], YCbCr color indexing [29], and color space conversion [30] are three examples. Shape-based algorithmic program was developed to strengthen the observation stage because color data can be easily influenced by poor lighting or changing weather conditions. There are numerous methods for detecting shapes, and they are widely known for their effectiveness and quick processing times. The most well-liked ones include edges with Hough transformation [31, 32]. Similarity detection [33], distance transform matching [34], and Haar-like features [35] are also well known for their shape detection.

Chaudhary et al. [36] proposed the path planning problem with fixed impediments together with other robot navigational issues. Finding an optimal and collision-free route to the target is the goal of the path planning issue. A variety of network topologies and training technologies are employed to create model network which predicts

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the turnout inclination that the point-mass robot will use to elude barrier on the way to the goal. In this essay, the performance of various feedforward neural network models will be compared and contrasted. The outcomes indicate that the 10 neuron feedforward neural network model with Bayesian regularization outperformed the others. The models has been utilized in two distinct situations to avoid obstacles. The robot's paths demonstrate that it has safely navigated around potential hazards and arrived at its target.

Xiao et al. [37] identified advantage of the prior structural knowledge of lane markings, and we suggest a recurrent slice convolution module (referred to as RSCM) in this study. A unique recurrent network structure with several slice convolution units makes up the proposed RSCM (called SCU). The dissemination of earlier structural information in SCU could give the RSCM a stronger semantic representation. Additionally, we construct a distance loss taking the previous lane marking system into account. The overall loss function created by combining segmentation loss and distance loss can be used to train the lane detection network more steadily. The outcomes of the experiments demonstrate the potency of our approach. On lane detection benchmarks, we achieve good computing efficiency while maintaining reasonable detection quality.

Yao and Chen [38] suggested an enhanced attention deep neural network (DNN), which consists of two branches working at various resolutions and is a lightweight semantic segmentation architecture designed for fast computation in little memory. The suggested network creates dense feature maps for prediction tasks by integrating tiny features obtained from local pixel interactions in global contexts at low resolution. On two well-known lane detection benchmarks (TuSimple and CULane), the introduced network achieves results that are comparable to those of state-of-the-art techniques. It also has a faster calculation efficiency, averaging 258 frames per second (FPS) for the CULane dataset, and only needs 1.56 M model parameters in total. The application of lane detection in memory-constrained devices is made realistic and meaningful by this study.

3 Methodology

Our proposed system main objectives are stated below:

i. lane sensing and lane tracing
ii. object detection
iii. traffic sign recognition.

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3.1 Lane Sensing and Lane Tracing

Data Acquisition

The data for the lanes was gathered from Website. Training has been made for the collected dataset. Here, it entails the gathering of data. Figure 1 shows the input data collected from the Website.

Data Preprocessing

The video input is converted to mp4 format and shrunk before training and fitting the model. Once after preprocessing, the model is given to the processed data. The process of putting raw data into a format that is comprehensible is called data preprocessing. Given that we cannot work with raw data, it is also a crucial stage in data mining. Before using machine learning, the data's quality should be examined.

Data Augmentation

Data augmentation is done in order to prevent overfitting of the model. By creating additional data points from existing data, a group of techniques known as "data augmentation" can be used to artificially enhance the amount of data. This includes making minor adjustments to the data or creating new data points using deep learning models.

Model Training

The model is trained using deep learning algorithm and convolutional neural network which has two main layers such as convolutional layer and the pooling layer. Finally, the trained CNN model gives the better result by sensing and tracing the lane from given input data.

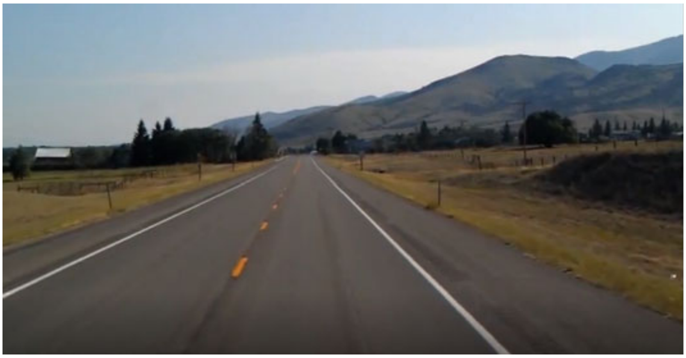

Fig. 1 Input data for lane sensing and lane tracing

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Fig. 2 Input image given for object detection

3.2 *Object Detection*

We use Python to compose the program. Figure 2 is the data input given to the model for object recognition. For feature extraction, we take into account the following 5 features: RGB-RGB values can be used to represent colors (going from 0 to 255, with red, green, and blue). In order to interpret the results, the computer would be able to perform this task and extract the RGB estimation of each pixel. When the framework translates a new image, it similarly transforms a scope into the image before checking samples of numbers against data it is confident about. At that point, the framework has assigned a certainty score to each class. Grayscale: A grayscale version of the image is created. Typically, the predicted class has the most astounding certainty score.

Then, the dataset is trained using CNN which is capable of extracting the features and classifying them accurately. The object recognition model has been created to recognize the object in terms of category with the ability of giving better results.

3.3 *Traffic Sign Recognition*

To test the recognition accuracy of the network on the validation set, the target neural network built in this study is trained on the training set. The training is continued on the training set in accordance with the validation set's findings. Finally, the network's accuracy on the test set is evaluated. The distribution of the 43 German traffic sign recognition benchmark (GTSRB) categories is shown in Fig. 3. The vertical coordinate is the number of each category, while the horizontal coordinate is 43 categories. To balance the dataset, this paper so employs approaches for data improvement.

Imgaug, a machine learning library for processing pictures, is used in algorithm improvement. There are numerous ways to improve an image, including rotation, blur, grayscale, etc. As a result, this article employs Imgaug to enlarge the GTSRB data and split it into manageable clusters for network training, which strengthens the network's capacity for generalization and also lightens the computer's computational

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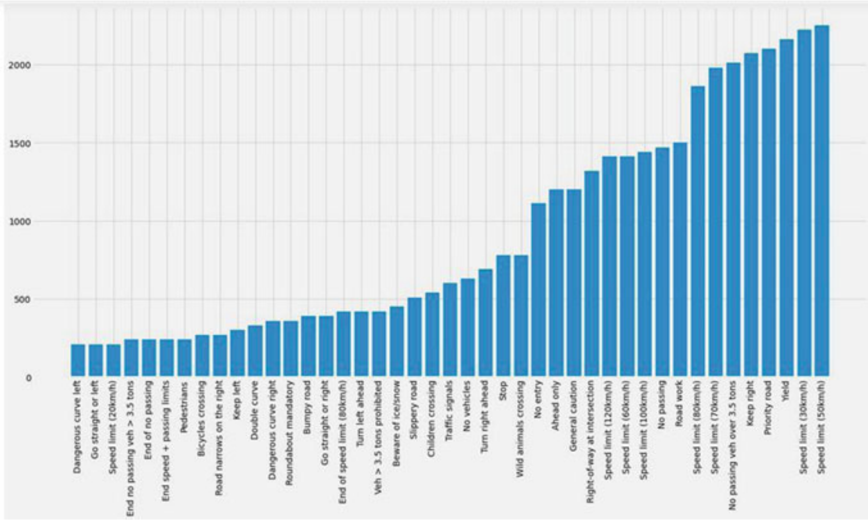

Fig. 3 Distribution classes of traffic signs

burden. A popular way of image enlargement to increase network generalization ability is data augmentation. In order to increase dataset size and increase effectiveness, this study implements data improvement, to conduct 50% picture shading on the training set, 50% image color conversion, and random cropping and filling of specified pixels.

The convolutional neural network in this study, which we refer to as TS-CNN and has a total of 10 layers, is developed. Pooling and convolutional layers make up the majority of the network. By gradually adding additional convolutional layers, removing the feature map from the feed in image, using max-pooling to minimize the dimensionality of the feature map, and getting features at various feature scales by combining more layers. In order to classify the traffic signs, the fully connected layer uses soft extremum functions after performing dimensional transformation on the input features.

Figure 4 represents the flowchart for our proposed system.

4 Evaluation Results

Figure 5 shows the output result for lane sensing and tracing to the given input using convolutional neural network. Figure 6 gives the accurate picture of classifying the object with high recognition rate for the given data sample.

In Fig. 7, traffic sign recognition has been made with CNN algorithm, accuracy, and loss metrics which has shown in the figure. Finally, the model has obtained 99.29% accuracy.

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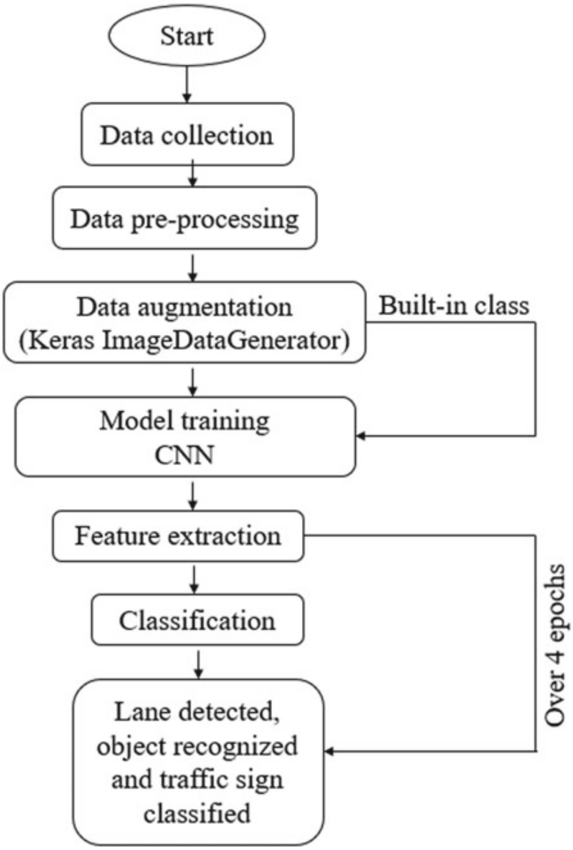

Fig. 4 Flowchart for our proposed system

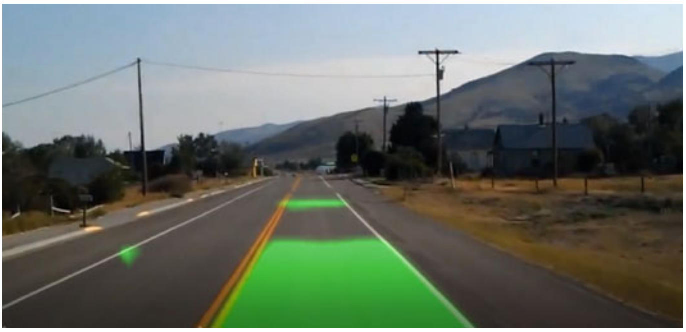

Fig. 5 Detecting and tracing the lane

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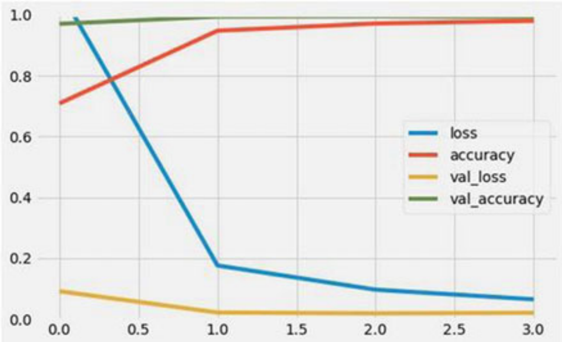
Fig. 6 Object recognition with two different classes

Fig. 7 Loss and accuracy after 4 epochs



5 Conclusion

For the goal of lane detection and tracking in this work, CNN-based approaches were applied to automated driving assistance systems (ADAS). For the detection and tracking of the lane, we suggested an efficient and reliable approach. The suggested algorithm is simple, and the intended algorithmic program is successful and validated.

In this study, we used an online dataset to train and test object identification in images. We tested for single classes like people and cars. We determined that a significant factor in the development of neural network systems is the issue of computational resources. Considering that we tried out Python. To build a model, speed up processing, and analyze the object recognition system across more categories, it requires the bare minimum of time.

This paper suggests a lightweight convolutional neural network suited for classifying and recognizing traffic signs. The network successfully recognizes traffic signs using straightforward convolution and pooling operations, theoretically ensures the algorithm's calculation efficiency, and is tested using GTSRB data. This network also features a straightforward architecture, strong scalability, and processing time that is faster than the detection speed of existing techniques. In future, we plan to experiment with new benchmark datasets and recognize traffic signs in bad conditions.

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