Review

Traffic Sign detection through Deep Learning

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Article info

Keywords:
Deep Learning
Traffic Sign detection
GPU architecture
Traffic Sign Recognition (TSR)
Convolutional Neural Networks (CNNS)
Region Proposal Network (RPN)

Abstract

Nowadays, thanks to the quick growth of society and the economy, cars are practically one of the most practical forms of transportation for every family. People demand to have sophisticated Vision-assisted programs that offer drivers information about traffic signs, govern driving behavior, or aid in vehicle management to maintain road safety as a result of the increasing complexity of the road traffic environment. Traffic sign identification and recognition have grown in popularity as one of its most crucial roles, drawing the attention of academics both domestically and internationally. In order to accurately instruct the driving system, real-time road pictures are first captured by vehicle cameras, which are then used to recognize and identify any traffic signs that are present on the road. However, the actual scene's driving conditions are quite difficult. Researchers have been working diligently for many years, but the identification system still needs further development and study to become useful. Although it takes a lot of time to manually evaluate significant characteristics of the image, traditional computer vision approaches have been used to recognize and categorize traffic signs. More and more academics are using deep learning technologies to tackle this challenge as science and technology advance. The primary factor influencing the deep learning method's acceptance is the model's ability to learn the deep features present in an image on its own from training samples, which is particularly advantageous in many situations where it is unclear how to design a feature extractor, such as expression recognition and target detection. This article focuses on the accuracy and high efficiency of detection and recognition based on the usage of road traffic sign detection and recognition. A deep convolution neural network algorithm is proposed to train traffic sign training sets using the open-source framework Caffe. This will produce a model that can classify traffic signs and learn and identify the most important features of these traffic signs, enabling the goal of identifying traffic signs in actual scene

1.Introduction

An essential part of the road traffic system is traffic sign the primary purposes of traffic signs are to inform drivers of information that must be taken into consideration while traveling on the current section of the road, to alert them to hazards and difficulties they may encounter, to warn them to drive at the posted speed limit and to generally guarantee safe driving. In order to minimize traffic accidents and safeguard the personal safety of drivers, it is very crucial for researchers to focus on the detection and recognition of traffic signs.

Basic signs and auxiliary signs are the two main classifications of road traffic signs. The primary sign is broken down into warning, no-go, required direction, tourist, and road construction safety signs. Among these, 43 different sorts of activity were mostly prohibited by prohibition signs. There are 29 categories in which mandated signs must notify the presence of cars and pedestrians. These signs are often placed in road sections or close to intersections where they are necessary to do so. The major purpose of warning signs, which are divided into 45 categories, is to warn pedestrians, vehicles, and drivers to watch out for harmful targets. They all have a significant impact on traffic signs. The most prevalent speed limit signs and signs forbidding left and right turns are among them, and since they are so important for motorist safety, they are the subject of the present study on traffic sign identification.

Traffic sign detection and identification are crucial for gathering information from a traffic incident. By recognizing sign information about the characteristics of the approaching road, traffic signs have been utilized to implement Advanced Driver Assistance Systems (ADAS) tasks like warning generating, trajectory planning, and map-matching. Traffic signs have either been studied by Traffic Sign Detection (TSD) or Traffic Sign Recognition (TSR) systems in the open literature. As an area of interest (ROI) in a picture, TSD is concentrated on identifying the borders of traffic signs. The TSD algorithm must identify traffic signals with the fewest possible false positives.

A TSD system is suggested in this study Its foundation is Faster Resnet V2 with Convolutional R-CNN Inception Traffic sign classification using neural networks and identification, as well as noise reduction based on a blurring mask The strategy is employed in combination with strengthen the effectiveness of detecting traffic signs. Using blur is a tactic. used to reduce noise in picture preprocessing. The suggested technique for image processing is based on blurring, or filtering, insignificant portions of a picture and highlighting those that are more informative, generating noise lowering costs, and enabling more effective instruction of the detector.

The extracted patch is not categorized by TSD. TSR covers the classification of an image's detected or extracted patch. This study suggests using deep pre-trained CNN networks to recognize traffic signs. Alex Net, the VGG16, the VGG19, the adopted deep pre-trained models for are Resnet50 and the recommended use. The Hyperparameters are then designed specifically for all incorporated pre-trained CNN architecture models. in the German Traffic Sign Recognition benchmark dataset, studies on recognizing traffic signs, and There are performance comparisons.

1.1. Motivation for the article

Other survey publications by renowned Deep Learning experts have been published throughout the years. The reality that technology is never static, nevertheless, cannot be denied. Scientists and researchers are continually inspired to reach higher standards by ongoing improvements and the always rising expectations from a vocabulary that already exists. Furthermore, the number of related terms, such as Machine Learning, Artificial Intelligence, Neural Networks, Deep Learning, etc., has significantly increased in recent years.

Therefore, it was imperative to review the present standings and capabilities of the new-age Deep Learning ideas while keeping in mind the current scenario of ongoing improvements in the field of Deep Learning. This study completely satisfies the expectations based on contemporary Deep Learning ideas by highlighting contemporary requirements and their corrective solutions in the sector of traffic sign detection. Thus, after evaluating recent research that used Deep Learning principles in the traffic detection area, the authors realized the need for undertaking a systematic literature assessment. In order to accurately identify the current standings, challenges, issues faced by the subjective domain, and its immediate remedial solutions proposed by incorporating the concept of Deep Learning over the years, the most prestigious research done in the field of traffic sign detection has been carried out from an existing database and presented in the study.

1.2. Our contributions to the research article

The research piece has been structured such that:

- The study presents the idea of Deep Learning from its inception, along with numerous updates periodically.
- Various Deep Learning communication methods have been in-depth examined.
- The study's structure emphasizes the fundamentals of the concept term, progressively covers the functional features of the domain, and also draws attention to the constraints and difficulties the traffic sign detection domain faces.
- Detailed observations have been conducted to investigate the idea of precision traffic sign detection utilizing Deep learning with respect to the rising market while keeping contemporary needs in mind.
- Based on upcoming difficulties, future research directions in the field of traffic sign detection-based Deep Learning have been outlined.

2.Deep Learning: an overview

Deep learning is currently achieving significant breakthroughs and success across a variety of industries, including computer vision and its numerous medical applications, industrial automation, driver assistance, and natural language processing, which has captured the public's attention over the past ten years thanks to the development of sophisticated virtual assistants. The development of open-source toolboxes like TensorFlow, which made the deployment of deep neural networks much simpler, big data sets that grew larger and easier to access, and the modern GPU architecture made computing times much shorter than on CPUs, and these factors are the main causes of this success. Deep learning, however, is not a new phenomenon; over time, it has just gone by many names. Between 1940 and 1960, it was initially known as cybernetics, with the premise that a perceptron could mimic the human brain by computing a linear function in a cell body akin to synapses in place of dendrites and axons. Later, with backpropagation training restricted to a few neural network layers in the 1980s and 1990s, its designation changed to connectionism. Due to their high computational cost, neural networks were difficult to train until they were finally rebranded as deep learning in 2006 with the work of Hinton et al, ushering in a new era for neural networks. The aforementioned article put out a fresh method for efficiently pre-training and fine-tuning deep belief networks.

The Mark I Perceptron, which could train one neuron, was the first perceptron algorithm implementation. Later, in 1960, Widrow and Hoff created Adaline for a single-layer network and Madaline for a multi-layer network. Backpropagation, which wasn't invented until 1986 with the work of Rumelhart, was not used in the training of such models. resulting in the accomplishment of LeCun et al. in 1998, who with the help of the MNIST dataset, successfully trained a convolutional neural network to detect handwritten letters of the alphabet.

Deep neural networks were thought to be computationally expensive and hence impractical until the work of Hinton et al. offered a method to efficiently train them. The first neural network-based breakthrough in voice recognition occurred four years later, cutting the mistake rate by about 30%. However, the most well-known breakthrough was in picture identification in 2012 with the ImageNet classification using deep convolutional neural networks.

One of the first large datasets was MNIST (Modified National Institute of Standards and Technology), which contains tens of thousands of scanned handwritten digits and their labels and was widely used to test various machine learning algorithms. The growth in dataset size was a significant factor in the development of deep learning. Larger and more complex datasets like ImageNet, which contains millions of annotated examples, emerged as digital data became more widely accessible, redefining modern neural networks. The implementation of neural networks on a CPU, however, becomes inadequate as the quantity of the datasets increases and the networks become deeper. Thus, as soon as GPUs became programmable and flexible, researchers began to construct neural networks on them after seeing the similarities between computing graphic techniques and neural network algorithms. Steinkraus initially successfully developed a 2 layer fully connected neural network in 2005, and he demonstrated that NNs are well suited for the parallel processing that GPUs enable by achieving a 3X speedup CPU-based implementation. After that, GPUs were used for more than just accelerating 3D graphics, and the GP-GPU general purpose GPU and NVIDIA's CUDA programming language were made available, enabling their widespread use in deep learning. In 2009, Raina et al. found that deep belief network training time could be reduced from several weeks to just one day, which was about 70 times faster. Software frameworks also had a significant impact on the development of deep learning. Theano, PyLearn2, Torch, DistBelief, Caffe, MX Net, and TensorFlow are just a few of the open-source frameworks that were created. The advancement of deep learning was greatly aided by Google's deep learning teams, Google Brain and DeepMind, as well as other top tech giants like Microsoft and Facebook. These organizations published their research in the area and made investments in machine learning startups. In light of this development, the second portion of this paper will discuss several deep learning models after an initial introduction. After that, we'll explore their training techniques in the third part before presenting some deep learning applications in various industries and talking about their drawbacks in section four, where we'll end with a conclusion.

3. Applications of Deep Learning

Deep learning is currently poised to revolutionize modern life as we know it. The goal of NVIDIA and Nuance's partnership with an AI marketplace for diagnostic imaging, which was successfully accomplished in various research projects, is the same as that of the many cutting-edge applications powered by big tech companies like Amazon with Alexa and its checkout-less supermarket Amazon go, Google with Google Home, and its DeepMind team's efforts to automate the healthcare system with AI applications. Other well-known contemporary deep learning uses include commercially available driverless automobiles with an autopilot, however, researchers are still developing completely autonomous vehicles. Deep learning is frequently used for process or quality control in industrial automation. Some deep learning applications in various domains are shown in Table 1. When deep learning is used, certain problems arise. When the basis for a conclusion is not given, it is unclear how to trust the black box's judgment. This problem arises in medical diagnosis when the process or factors leading to a certain forecast are just as crucial as the diagnosis itself. They require a lot of data to be correct, which is another issue that has to be brought up. In addition to these worries, there are still several open issues that might cause significant difficulties. For instance, hostile instances in image recognition might result in security lapses. The networks are susceptible to some perturbations that are carefully designed to cause the model to accurately predict the incorrect class. Another issue relates to the exploration-exploitation dilemma in the field of reinforcement learning. The agent should be able to optimize a reward function and adapt its behavior to the surrounding circumstances. To maintain the machine's excellent conduct, the incentive must be defined with care. Otherwise, it will behave irrationally in an effort to maximize the reward at the expense of moral principles. Its implementation in autonomous vehicles raises serious safety concerns due to the possibility that a computer may choose an optimal course of action that puts human lives at risk.

3.1 TRAFFIC SIGNS DETECTION AND IDENTIFICATION

A. Data Set

Despite the convolutional neural network's impressive advancements, there are still relatively few applications in the area of traffic sign identification and recognition at the moment. This is mostly a result of the dearth of datasets for traffic signs. A substantial amount of traffic sign data must be used as the foundation for training and verification of a deep convolution neural network traffic sign recognition model. In contrast to European nations, China has comparatively few datasets on open traffic signs. Currently, GTSRB in Germany, GTSDB in Germany, and KUL in Belgium are the more well-known traffic sign databases. The detection and recognition of traffic signs are studied in this work using the GTSRB and GTSDB traffic sign datasets. These two datasets contain real scene maps in addition to a variety of complicated traffic signs, including those with tilt, uneven illumination, distortion, occlusion, and comparable backdrop colors. To test the algorithm's capability, a range of sophisticated and challenging to differentiate traffic signals were used.

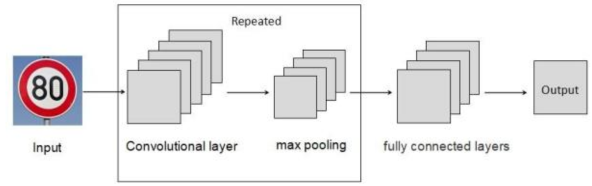
Figure 1. Different type of traffic signs

B. Image Processing

The picture is normalized such that each pixel's value falls between the range of 0 and 0.5 before being fed into the neural network. Adjust the values of each pixel to achieve this. The reason behind this is that the neural network functions better when the raw data is between 0 and 1. The experiment chose to employ a color traffic sign rather than convert it to grey since people categorize it according to the color of the symbol, and the computer may benefit from this.

C. Network Structure

In order to detect and identify traffic indicators, this research employs a VGG-16 network structure as the front-end network structure of the SSD method. Three fully connected layers, a SoftMax, and five stacked convolutional layers make up the majority of the VGG-16 network. A local convolutional network structure is formed by each stacked convolution layer, which is composed of numerous common convolution layers and is followed by a pooling layer. The output of the last fully connected layer is utilized as the input of the SoftMax layer after the convolution kernel pooling operation and the three fully connected layers are finished, and eventually, the result of the traffic sign identification is acquired.



D. Feature Extraction and Training Model

In this study, a traffic sign identification and recognition model are built once the data set has been trained. The model employs the convolution layer to extract the global convolution feature from each input picture and then performs probability and regression analysis on the coordinates of the target item on different scale feature maps. Finally, the final test results will be accurate since a non-maximum suppression method was used to remove the redundant test box and identify what kind of road traffic signs should be used.

F. R-CNN Inception Resnet V2

Four categories are used for item detection and recognition on preprocessed photos. Traffic sign detection based on three categories—prohibitory, dangerous, and mandatory—is successfully tried within. Another experiment used the GTSDB dataset and 43 types of traffic signs to train the object detector, however this time the object detector performed poorly. It appears that effective training for the object detector could not be produced due to the small training sample sizes available in the GTSDB dataset for the 43 distinct classes. Additionally, grouping all traffic signals into a single class and attempting to teach the detector in this manner may not be realistic. Because the variance inside of this class would be rather high this time, which might negatively affect the training of the object detector. For the purpose of detecting objects, algorithms are used. When employing R-CNN, the areas of the provided picture that could contain an object are located using conventional methods such as selective search based on pixel values and edges. Following that, a CNN and SVM are applied to each of these areas in order to extract and classify features. Before doing a selective search, Fast R-CNN first runs the input through a CNN to produce an activation map. Then, using a selective search strategy, areas are located on this activation map, and

the regions are then categorized using Artificial Neural Networks (ANN) and the SoftMax classifier. Only one image is sent to a CNN, which saves computational resources compared to sending a huge number of images. The Faster R-CNN method is also introduced in order to make the model operate even more quickly. By adopting a separate network called the Region Proposal Network (RPN) in place of a selective search, Faster R-CNN introduces region suggestions after passing the input picture through a CNN. It is most likely a blend of RPN and Fast R-CNN with regard to the Faster R-CNN. To detect objects, it adds an RPN and uses a complete CNN.
The Inception Resnet V2 feature extractor is used in this study to produce region suggestions using Faster R-CNN. This feature extractor is employed as the CNN through which the input picture is first sent in order to produce a feature map. Then, using RPN, the region suggestions are made on this feature map. Finally, the fully connected ANN receives and classifies the regions chosen by this RPN on this feature map. As previously said, this categorization is done in this stage amongst four groups.
Inception V2, like its predecessor, becomes the most successful in the ILSVRC2014 tasks with regard to the Inception Resnet V2 feature extractor [22]. This network uses Inception units instead of a conventional sequential CNN, which allows it to grow in depth and breadth without incurring additional processing costs. The computational advantage of Inception units and the residual connections are combined in Inception Resnet V2, which provides advantages for optimization.
G. CNN-based Classification
A CNN classifier is utilized once traffic indicators have been detected. The GTSRB dataset was used to train the model. Table II lists the parameters for the CNN classifier, which is trained across 40 epochs with a batch size of 32 and a learning rate of 0.001 using the Adam optimization method. The photos are downsized to 40x40 in accordance with the mean width and height values of the training data in the GTSRB dataset as well as the traffic signs in the training images in the GTSDB dataset. Using the GTSRB dataset, training and test accuracies are respectively 100 and 98.52 percent. The extracted areas, or ROIs, from a picture of a traffic scene, are categorized using this CNN, concluding the step of traffic sign detection and recognition.

TABLE II. CNN CLASSIFIER ARCHITECTURE

Layer Type	Architecture	Input Size
Convolution	32 5x5 filters, step size 1	40x40x3
Convolution	64 3x3 filters, step size 1	36x36x32
Pooling	2x2 filter, step size 2	34x34x64
Convolution	32 5x5 filters, step size 1	17x17x64
Convolution	64 3x3 filters, step size 1	13x13x32
Pooling	2x2 filter, step size 2	11x11x64
Fully Connected	256 neurones	1x1600
Fully Connected	128 neurones	1x256
Classification	43 neurones	1x128

4. Open issues, and challenges.

A way to determine which class instances an object belongs to is called object detection. Self-driving cars must categorize the many items that are present in a picture and the exact positions of these elements in order to obtain a comprehensive 3D perspective of the surroundings. The three categories of object detection for semantic scene understanding are as follows:
1. Region suggestion or region choice: Using a multi-scale sliding window to scan the whole picture was the method of area selection that was most widely used prior to the development of DL. The sliding window approach, however, is computationally expensive for self-driving automobiles and falls short of the requirement to thoroughly locate every location of an item in real-time.
2. Feature extraction: For feature extraction, methods including the Haar-transform, Haar-like features, and histograms of oriented gradients (HoG) were often utilized. These methods do not, however, offer resilience to varying environmental variables in self-driving scenarios.
3. Classification: Following perception and localization of the objects, classification is carried out using ML techniques like MLP and SVM. The deformable components model (DPM), which has been developed in self-driving situations, is now widely accepted for object categorization.

4.1 Future research directions

The development of traffic sign detection capability for scene perception and object identification to maneuver safely is one facet of these problems. Future projects that will help to accomplish these goals are listed below:

• The AI systems make judgments based on a cost-benefit analysis and carry out a move that has the lowest cost and biggest benefit. The self-driving automobile would still carry out a risky maneuver if doing so was the least expensive alternative. This necessitates a rethink of vehicular AI's cost/reward strategy.

• To comprehend both space and time, driving scene segmentation and comprehension can be combined with temporal information transmission. Automatic captioning of pictures, localization, and detection may be produced using a variety of DL architectures, such as RNNs.

• Data collection under dangerous weather situations, such as rain, hail, and snow, is an imminent future task, as is research on self-driving cars' navigation without human assistance. Transfer learning is one of the current problems since DL models can't transfer representations to unrelated domains. Applying transfer learning across domains is a research direction that may result in new ways to analyze scenes and real-time item recognition. Videos may be supported via modifications to the current SSD technology. Vehicle footage captured at 40 frames per second (fps) is included in a freshly published dataset that may be used to evaluate current cloud-based DL in real-time.

5. Conclusion

A deep learning-based object identification framework and a deep learning-based classifier are suggested as part of a traffic sign detection and recognition system. Additionally, a blurring-based picture preprocessing method is described to improve object detectors' training effectiveness by reducing noise. This preprocessing method essentially performs a masking operation on the areas where a traffic sign is statistically unlikely to exist. Experimental research demonstrates that the suggested system functions effectively and that the suggested picture preprocessing strategy enhances the object detector's performance. This preprocessing strategy may be thought of as a broad strategy to improve the performance of any object detector.
The implementation of pre-trained CNN models VGG16, VGG19, Alex Net, and Resnet50 in this research is aimed at the creation of traffic sign recognition systems. A brief history of earlier CNNs implementations for computer vision is followed by a discussion and comparison of the architectures of the chosen VGG16, VGG19, Alex Net, and Resnet50 models. The GTSRB public datasets are then used to construct and test these models. Therefore, all pre-trained deep CNN models perform well in terms of accuracy when it comes to categorizing and identifying traffic signs. With somewhat better accuracy, precision, recall, and f1 score performance criteria than other models, Alex Net outperforms them. This suggested application will be implemented in hardware on FPGA in subsequent development.

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