ISSN: 0974-5823 Vol. 7 No. 5 May, 2022

International Journal of Mechanical Engineering

Traffic Sign Recognition & Detection using DeepTrans Learning

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Abstract - Today, the feature of traffic sign recognition is widely used in industry by researchers working in the domains of artificial intelligence and machine learning with the goal of developing an autonomous driving assistance system. This will assist the driver's human eye and driving qualities, which cannot be assumed to be consistent for all weather conditions. Road traffic has been one of the most preferred modes of transport in India in the past few years. The number of vehicles on road is increasing every day. It was reported by the Transport Ministry of India that around 53700 vehicles were registered every day in 2015. The purpose of this research is to examine the application of deep transfer learning to use intelligence gathered from an established, standard dataset of traffic signs from a given country/region and use it to improve recognition of traffic signs from another country/region using a deep learning framework. This helps users to avoid the difficulty of data gathering and classification by utilising an established dataset from another location to help in the recognition of a desired target dataset. We used VGG 16 deep transfer learning algorithms and achieved 95.61% of accuracy. This analysis shows that transferring information between deep learning classifiers can result in a higher accuracy for traffic sign recognition than a model that uses deep learning.

Index Terms - Artificial Intelligence, Machine Learning, Autonomous Driving Assistance System, Deep Transfer Learning Algorithms.

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INTRODUCTION

Traffic signs are the visual indications to the drivers to navigate travel and also to regulate the traffic by giving the information regarding the conditions and limitations of the road [2]. Dangerous road and too high acceleration of the traffic participants are the prime cause for many accidents. To avoid these ambiguities, variable speed limitations are placed along the road in accordance to the state, density and visibility of the road [14].

Traffic Sign Recognition (TSR) is presently a study issue on which researchers are focusing in order to make driving safer. While these systems are currently being developed to alert drivers to critical traffic signals, they may eventually be able to take control of the vehicle in certain scenarios. During a trip, a lot of information is gathered through observation. The driver is the one who drives in light of these circumstances. While technology cannot interpret all visual inputs as quickly as a human can, by focusing on a single aspect of this process, the amount of effort required of drivers can be decreased [4].

The increase in vehicles certainly increases the traffic and the possibility of more accidents. In addition, the drivers make mistakes in recognizing the traffic signs which also increases the accidents. Hence, the Indian transport system requires an automated and efficient driver guidance system with the facility of traffic signs detection and informing system [5]. In many occasions, it is seen that the lack of correct decision by the drivers with respect to traffic signs, leads to accidents. The modern traffic control systems demands the utilization of advanced support systems to minimize the accidents and the traffic congestion. The identification of road signals can be achieved by the proper detection of signs at the appropriate time and the recognition of the correct sign to instruct the driver with minimum time. This can be achieved with the support of advanced computing tools with intelligent techniques [15].

The German Traffic Sign Recognition Benchmark (GTSRB) dataset is publicly available and contains more than 50 thousand images and 43 classes with VGG16 deep transfer learning model that is capable of overcoming the challenges associated with improving and providing high accuracy for traffic sign recognition [16]. Here we use Image preprocessing and data augmentation with certain parameters like rotation, height and width resizing, training set and validation split. To use a fully connected neural network to classify images necessitates a high number of layers and neurons in the network, which increases the number of parameters and leads to overfitting (memorizing the training data only) [8]. Since all neurons (carrying pixel values) are linked to one other, the input image may also lose its pixels correlation features [17].

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LITERATURE REVIEW

Palavanchu S. used For the detection, recognition, and classification of GTSRB traffic signals, five effective transfer learning models are investigated, which are accessible in Keras libraries: Xceptionnetwork, InceptionV3 Networks, Residual Networks ResNet50, VGG-16, and EfficientNetB0. The primary goal of this research is to use and analyse five recent and effective deep learning algorithms in order to determine which model can stand out in feature extraction and classification of accessible traffic sign data. These models are graded based on accuracy, loss, training duration, and model parameters. For traffic sign detection, recognition, and classification, the Xception network has been shown to be highly successful in terms of accuracy (95.04 %), minimum loss value (0.2311), and affordable speed and training time, whereas ResNet50 and EfficientNetB0 achieved good accuracy with fewer model parameters [12].

Xingjian Li et al. introduced a regularisation strategy for transferring the behaviours and semantics of the source network to the target network by reducing the difference between the feature maps generated by the convolution layers of the source/target networks using attentions. We created a normalised learning technique called DELTA that models the difference of feature maps with attentions between networks, with the attention estimates produced by supervised learning [3].

They used the most recent version of the YOLO algorithm series, YOLOv5, to evaluate its performance. Furthermore, they determine which model is most suited for the TSR between YOLOv5 and SSD. They use a modified dataset of traffic signs in their experiment, which comprises 2,182 traffic sign images divided into eight types. Then, using the Google Colab platform, they run a well-designed experiment and observed that the accuracy of YOLOv5 is up to 97.70 percent for all classes, with the mean average precision in each class exceeding 90.00 %. As a result, SSD achieves an overall accuracy of 90.14 %. However, for the class with fewer samples, the recognition rate is just 78.32 % [16].

Gao D. et al. offer a migration learning-based traffic sign recognition method. To learn low-dimensional features that are resilient to known natural noise, this approach proposes to employ the NSLC-AE architectural model to reconstruct clean data from complex data (source and target data. That is, in the low-dimensional space, utilise local restrictions and discriminant information to discover semantically related samples for each sample, and then in the high-dimensional space, build clean data for model training. Because high-dimensional natural noise can generally be separated into one or more hidden variables in low-dimensional space, whereas interference features in low-dimensional space can replicate the impact of numerous natural sounds [4].

S. Zhou et al. introduced a convolutional neural network-based system for recognising road traffic signs. In natural environments, traffic signs are distorted by variables such as lighting, occlusion, missing, and distortion, reducing identification accuracy. This article provides an improved VGG (IVGG) model based on the VGG model. The IVGG model consists of nine layers; in comparison to the original VGG model, it incorporates a max-pooling operation and a dropout operation following numerous convolutional layers in order to capture the important features and reduce training time. The article presents a strategy that incorporates dropout and Batch Normalization (BN) procedures after each fully connected layer in order to significantly expedite model convergence and hence achieve a higher classification impact. The experiment makes use of the German Traffic Sign Recognition Benchmark (GTSRB) dataset [13].

They proposed a deep convolutional neural network (DCNN) model for accurately classifying benign and malignant skin lesions using a deep learning technique. Preprocessing consists of three steps: firstly, they apply a filter or kernel to remove noise; second, they normalise the input images and extract features that aid in accurate classification; and third, we augment the data to increase the number of images, which improves classification accuracy. To assess the proposed DCNN model's performance, it is compared to many transfer learning models, including AlexNet, ResNet, VGG-16, DenseNet, and MobileNet. The model is evaluated on the HAM10000 dataset, and they achieved the highest training and testing accuracy of 93.16 % and 91.93 %, respectively [7].

TRAFFIC SIGNS DATASET

This section summarises the machine learning techniques that were used to look at the GTSRB dataset [9]. This was done as part of the IJCNN 2011 competition, The German Traffic Sign Recognition Benchmark, which was held in 2011. To train and test a neural network for object recognition [14], a large dataset is required. The German Traffic Sign Recognition Benchmark (GTSDB) [15] has 43 classes [18].

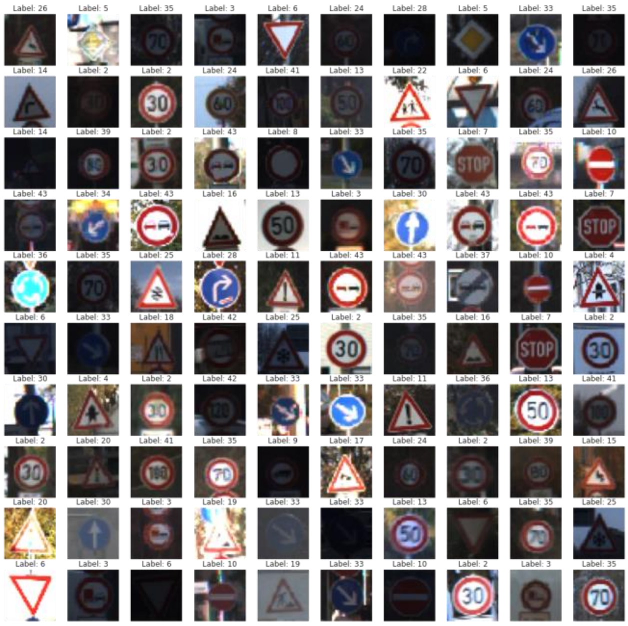

Figure 1. Sample images of GTSRB Dataset

METHODS

FETURE EXTRACTION

Feature extraction is a critical approach in image processing since it divides the image into further manageable groups before subsequent processing [1]. We extract a large number of features in our study that helps in detecting and recognising the pattern.

VGG16 NETWORK

VGG-16 - In 2014, Karen Simonyan and Andrew Zisserman published a study titled Very Deep Convolutional Network for Large Scale Image Recognition. Karen and Andrew constructed a sixteen-layer network using convolutional and fully linked layers.

RESULTS

The transfer learning technique was used to develop the traffic sign recognition and categorization systems [11]. In this work, pre-trained CNN architecture– VGG16, used to develop models for traffic sign classification [6, 10]. Initially, these architectures were trained to different types categorise of objects. As a result, they were fine-tuned using our dataset, specifically to classify 43 different types of traffic signals. The models were trained on a laptop equipped with an Intel i5 CPU, 4 GB RAM, and an Nvidia GeForce mx450 graphics card. It took many hours to train these models, as they are equal in size and have a similar number of parameters.

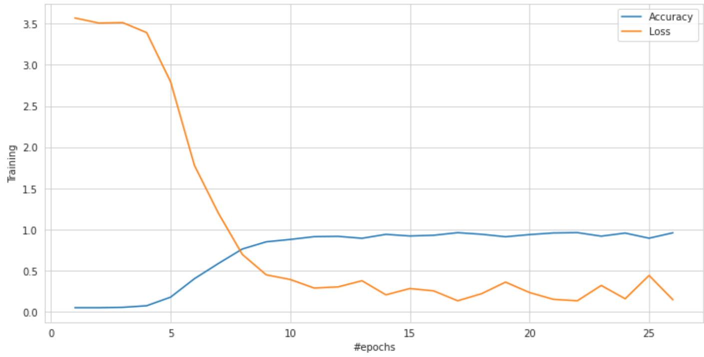

Figure 2. Training accuracy result of GTSRB

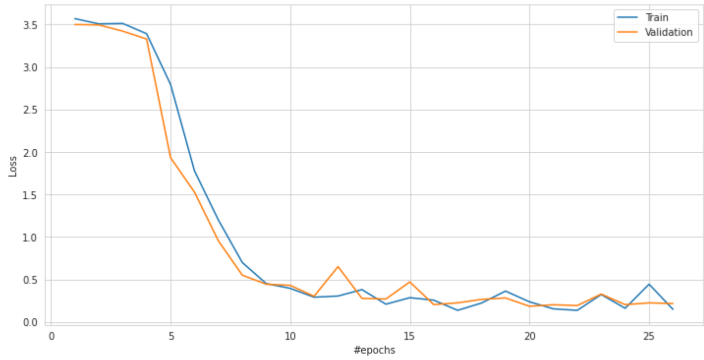

Figure 3. Training loss result of GTSRB

Limitations and Future Studies

We proposed in this research strategies for identifying and categorising traffic signs that are based on transfer learning. Traffic sign recognition systems are expected to be used in real-world applications such as autonomous cars and driver assistance systems, and models trained to identify and categorise traffic signs must be implemented on reduced devices. As a result, we implemented really just designs with the smallest model sizes and minimum parameters. We performed experiments using pre-trained VGG16. In this article, we used a transfer learning-based VGG 16 model to recognise and classify traffic signs. The dataset utilised from GTSRB was already in poor condition, as seen by the images demonstrating a test accuracy of 95.16%. Additionally, we discovered that transfer learning models are extremely durable and accurate even when trained on a poor dataset. For future work on this research, we would aim to develop more transfer learning models for object detection in unfavorable and challenging conditions, as well as make recommendations for road safety.

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