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Comparative Analysis of Transfer Learning-Based CNN Approaches for Recognition of Traffic Signs in Autonomous Vehicles

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Abstract. Traffic signs recognition has a crucial role in enhancing the safety and efficienty of autonomous vehicles (AVs). This AVs can contribute to a cleaner and healthier environment by improving fuel efficiency, minimizing travel distances, and deacreasing air pollution. Many artificial intelligence (AI) approaches contribute to develop AVs. Therfore, Convolutional Neural Networks (CNNs) have shown remarkable performance in image classification tasks for AVs, inculding traffic signs recognition. However, training deep CNNs from scratch for traffic sign recognition requires a significant amount of labeled data, which can be time-consuming and ressource-intensive to obtain. Transfer Learning, a technique that leverages pre-trained models on large-scale datasets,offers a promising solution by enabling the transfer of learned feautres from one task to another. This paper presents a comprehensive comparative analysis of three popular transfer learning based CNN approaches, namely ResNet, VGGNet, and MobileNet,for the recognition of traffic signs in the context of AVs.

Keywords- Traffic signs recognition, Convolutional Neural Network, Transfer Learning, Environment, ResNet, VGGNet, MobileNet, Data augmentation, Autonomous Vehicles

1. Introduction :

AVs have the potential to positively impact the environment through reduced emissions,alleviation of traffic congestions,promotion of shared mobility, and optimization of routing and navigation. Therfore, the development of AVs relies on the advancement of AI. AI plays a pivot role in enabling AVs to perceive their surroundings,make desicions, and perform complex tasks .
With the rapid advancement of AVs technology, accurate and efficient recognition of traffic signs has become crucial for ensuring safe navigation on roads. Traffic signs convey vital information such as speed limits, warnings, and regulation, which AVs need to interpret accurately to make informed decisions.

However,training CNNs [1] from scratch for traffic signs recognition can be challenging due to the scarcity of labeled data and the computational ressources required. Transfer learning offers an effective approach to adress these challenges by utilizing pre-trained models that have been trained on large-scale datasets, such as ImageNet [2]. By leveraging the learned features from these pre-trained models, transfer learning enables CNNs to generalize and recognize traffic signs efficiently,even with limited labeled data.

This paper focuses on comparing three popular transfer learning-based CNN architectures, namely ResNet [3], VGGNet [4], and MobileNet [5], for the recognition of German traffic signs in the context of AVs. The German traffic sign dataset [6] is chosen due to its relevance in the development of AVs operating in Germany and its diverse set of traffic sign classes and variations. By analyzing and comapring these three CNN architectures, we aim to evaluate their performance,robustens, and suitability for traffic sign recognition in AVs.

Fig1 : Images from the German Traffic Signs

To conduct a comprehensive analysis, we utilize a carefully curated dataset consisting of German traffic signs, capturing a wide range of classes,shapes, colors, and environmental conditions.The dataset is augmented and pre-processed to accountfor various real-world scenarios that autonomous vehicles may encounter. The performance evaluation of ResNet,VGGNet, and MobileNet models is conducted using rigorous evalution metrics, including accuracy.

The remainder of this paper is structured as follows : Section 2 provides a literature review of existing approaches in traffic sign recognition and transfer learning for autonomous vehicles.Section 3 describes the methodology and experimental setup, including dataset details, pre-processing techniques, and training configurations.Section 4 presents the comparative analysis of ResNet,VGGNet, and MobileNet models, discussing their performance and limitations.. Finally,Section 5 concludes the paper and outlines potential directions for future research in this field.

2. Literature Review :

Traffic sign recognition is a critical component of AVs, enabling vehicles to interpet and respond to traffic regulations accurately. Over the years, several approaches have been proposed to tackle the chalenges associated with traffic sign recognition, with recent advancements in transfer learning techniques showing promise in improving the performance of recognition models. This littérature review aims to provide an overview of existing approaches in traffic sign recognition and the application of transfer learning for AVs.

A. Traditional Computer Vision Approaches :

Early approaches to traffic sign recognition relied on handcrafted features and tradditional computer vision techniques. These methods typically involved extracting shape,color, and texture features from traffic sign images and using machine learning algorithms such as Support Vector Machines (SVM) [7] or Random Forests [8] for classification. While approaches achieved reasonable results, they often struggled with variations in lighting conditions,occlusions, and complex backgrounds.

B. Deep Learning-Based Approaches :

With the rise of deep learning, CNNs have emerged as a powerful tool for traffic sign recognition. CNNs can automatically learn discriminative feautures from raw image data, making them well-suited for complex recognition tasks, One notable CNN architecture for traffic sign recognition is LeNet-5, wich was one of the pioneering models in this field. LeNet-5 demonstrated the potential of deep learning in achieving high accuracy on benchmark traffic sign datasets.

C. Transfer Learning for Traffic Sign Recognition :

Transfer learning has gained significant attention in recent years as technique to address the data scarcity issue in traffic sign recognition. By leveraging pre-trained models on large-scale image datasets, transfer learning enables the transfer of learned features to the task of traffic sign recognition. One common approach is to use pre-trained CNNs, such as those trained on ImageNet, and fine-tune them on traffic sign datasets. This transfer of knowledge allows models to generalize betten and achieve higher accuracy, even with limited labeled traffic sign data.

D. Application of Transfer Learning for AVs :

Transfer learning has found pratical applications in the development of autonomous vehicle systems. By utlizing pre-trained CNN models, researchers have achieved significant improvments in traffic sign recognition for autonomous vehicles. The use of transfer learning has shown enhanced performance in terms of accuracy, robustness to variations in lighting and environmental conditions, and the ability to recognize a wide range of traffic sign classes.

3. Methodology :

For this study, a comprehensive dataset of German traffic signs is used. The dataset comprises a diverse collection of traffic sign images,capturing various classes,shapes,colors, and environmental conditions.The dataset is carefully curated and annotated to ensure accurate and reliable ground truth labels for training and evaluation purposes. It inculdes a sufficient number of samplet for each traffic sign class to provide a representaive distribution.

-Pre-processing Techniques :

Before training the models, a series of pre-processing techniques are applied to the dataset. These techniques aim to enhance the quality and consistency of the data, as wel as augment the dataset to acount for variations that may be encountred in real-world scenarios. Common pre-processing techniques include :

a. **Image resizing :** The images are resized to a fixed input size suitable for the CNN models under consideration. Resizing ensures compatibilty and consistent input dimensions during training and evaluation.
b. **Data augmenation :** to increse the dataset's diversity and robustness,various data augmentation techniques are applied. These techniques inculde random rotations, translations, and flips to simulate different viewpoints and orientations of traffic signs. This helps the models generalize betten and improves their ability to handle variations in lighting and environmental conditions.
c. **Normalization :** The pixel values of the images are normalized to a standard rangeto ensure consistency and facilitate convergence during training.

-Pre-trained models :

In neural networks, a pre-trained model is model that was trained on large benchmark dataset. In the case of CNN, the most common models that are trained on more than a million images, from the ImageNet database, are :

- **ResNet** : ResNet, or Residual Neural Network, is a groundbreaking deep learning architecture introduced in 2015. It addresses the vanishing gradient problem by utilizing skip connections or shortcuts that allow information to flow directly across layers. This enables the training of very deep networks, reaching depths of over a hundred layers,while maintaining or even improving performance. ResNet has achieved remarkable succes in computer vision tasks and has influenced the design of many other deep learning models.
- **VGGNet** : VGGNet,short for Visual Geometry Group Network,is a convolutional neural network architecture known for its simplicity and effectivenss in image classification tasks. Developed by reasearchers from the University of oxford in 2014, VGGNet feautures a uniform design with stacked layers and small 3*3 filters. Its straightforward structure allows it to capture intricate image features and patterns.VGGNet has different configurations,such as VGG16 and VGG19, indicating the number of layers in the network. Despite its computational intensity, VGGNet achieved remarkable results and influenced subequent network designs and research in computer vision.
- **MobileNet :** MobileNet is an efficient convolutional neural network architecture designed for mobile and embeded devices. Developed by Google in 2017, it aims to provide high accuracy while minimizing computational resources and energy consumption. MobileNet achieves this through the use of depthwise separable convolutions,which reduce computation by separating spatial and channel-wise convolutions it also employs a width multiplier technique to balace model size and accuracy. MobileNet has become popular for on device machine learning applications,enabling image recognition and object detection directly on mobile devices and Iot platforms. Its efficiency and compactness have made it a cornerstone in the field of mobile deep learning

-Training Configurations :

The transfer learning based CNN models (ResNet,VGG,EfficientNet) are trained using the pre-processed dataset. The training configurations include :

- **Model initialization :** The pre-trained weights of the respective CNN models (pre-trained on ImageNet) are used as the starting point. This initialization enables the models to leverage the learned features from a large scale general image dataset.
- **Optimization algorithm :** A suitable optimization algorithm, such as stochastic gradient (SGD) or Adam [9], is employed to train the models. The learning rate, momentum,and other hyperparametrs are set based on empirical experimentation to optimize the training process.
- **Loss function :** A loss function, typically cross-entropy is utilized to measure the dissimilarity between predicted and ground truth labels during training. The loss function guides the models to update their weights and improve their recognition performance.
- **Evaluation metrics :** The performance of the models is evaluated using various metrics,including accuracy, precision,recall, and F1-score. These metrics provide insights into the models ability to correctly classify traffic sign

images and their effectivness in differentiating between different traffic sign classes.

The training process is typically performed on suitable hardware setup, such as GPU, to expedite the training time and accommodate the computational requirements of the CNN models.

By following this methodolgy and experimental setup, the comparative analysis of Resnet,VGGNet, and MobileNet models for German traffic sign recognition can be conducted, providing insights into their performance, robustness, and suitability of autonomous vehicle applications.

4. Experimental Results :

After training our transfer learning based CNN models such as ResNet, VGGNet, and MobileNet. We use accuracy train (Train-accuracy) and accuracy test (Val-Accuracy) that are two commonly used metics to evaluate the performance of our models.

Model	Train-accuracy	Val-accuracy
VGGNet16	0.9426	0.7132
VGGNet19	0.9142	0.6572
ResNet50	0.5258	0.4724
ResNet101	0.6450	0.4946
MobileNetV2	0.9796	0.7760
MobileNetV3	0.5345	0.3343

Table. Results of our Approach

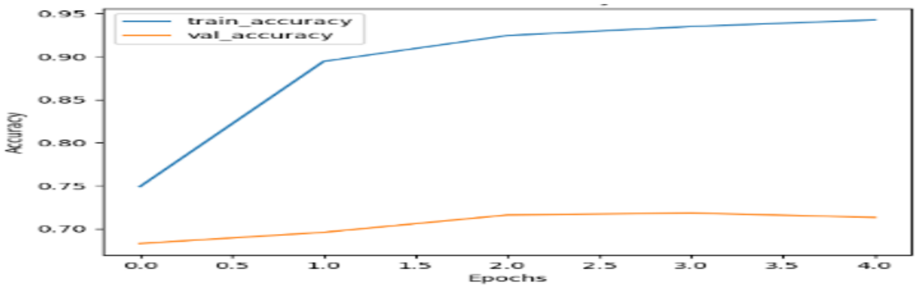

Fig 2. Model Accuracy for VGGNet16

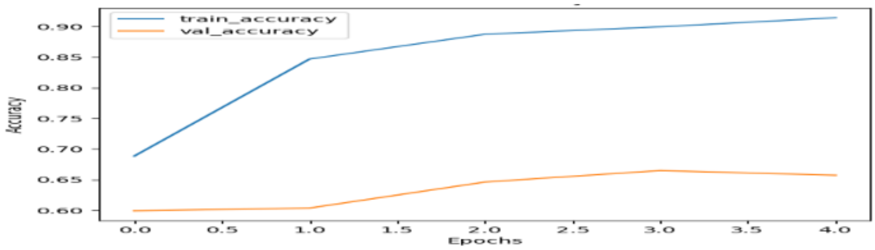

Fig 3. Model Accuracy for VGGNet19

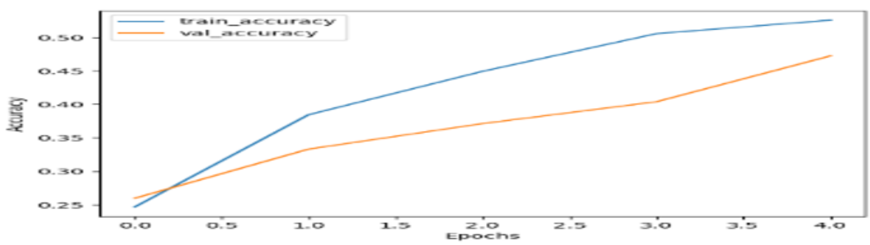

Fig 4. Model Accuracy for ResNet50

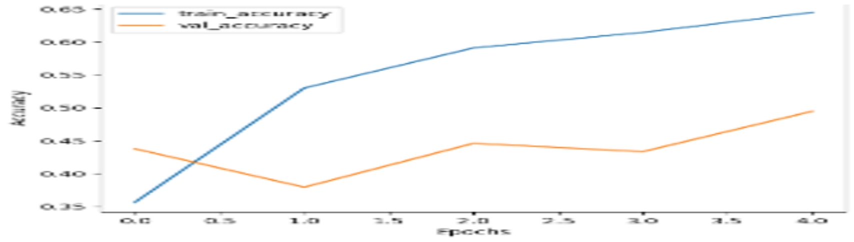

Fig 5. Model Accuracy for 101

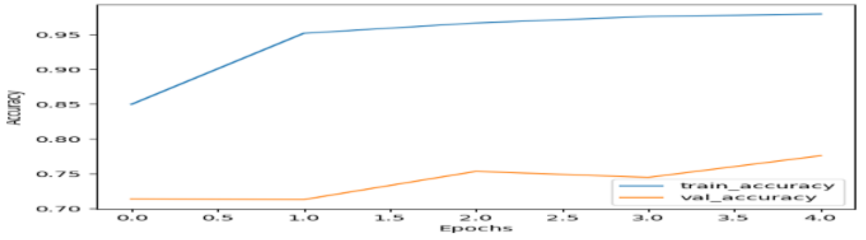

Fig 6 : Model Accuracy for MobileNetV2

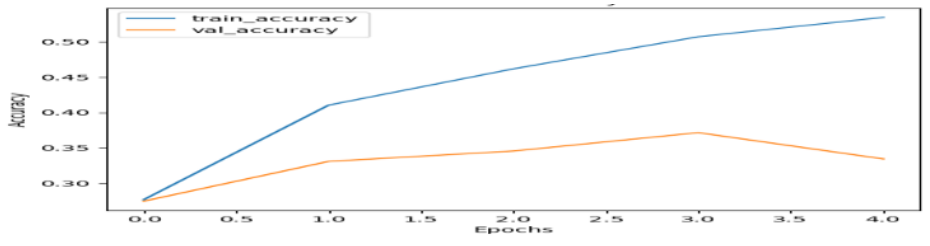

Fig 7 : Model Accuracy for MobileNetV3

5. Conclusion and Perspectives :

In this paper, we used VGGNet (VGGNet16, VGGNet19), ResNet(ResNet50, ResNet101), and MobileNet (MobileNetV2, MobileNetV3) for German traffic signs recognition. After training and testing the models as shown in Table and figures, we came to conclude that MobileNetV2 gives the best accuracy compared to other models to classify german traffic signs.It means that MobileNetV2 is more suitable for classification of this dataset.

AI approaches are instrumental in development of autonomous vehicle to perceive their surroundings,make desicions, and perform complex tasks . This paper contribute to development of AVs using the most famous AI approaches that is transfer learning based CNN approaches for classification of traffic signs. Recently, Many Researches dedicated there works to develop AVs technology using AI, especially to maximise environmental benefits of AVs

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