Optimizing Traffic Sign Recognition: A Comparative Evaluation of EfficientNet and DenseNet Models

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Abstract - Traffic sign recognition plays a crucial role in autonomous driving systems, ensuring the safe and efficient navigation of vehicles. As traffic signs vary significantly in shape, color, and meaning, efficient and accurate recognition is a critical task. This research presents a performance comparison between two deep learning models, EfficientNet and DenseNet, for traffic sign classification. Both models are based on Convolutional Neural Networks (CNNs), which have demonstrated superior performance in various image recognition tasks. The study investigates the effectiveness of these models in recognizing and classifying traffic signs from a diverse dataset, using a training strategy that involves data augmentation and transfer learning. The proposed models are trained using the Adam optimizer, which facilitates faster convergence and improves training efficiency. The model’s performance is evaluated using key metrics such as accuracy, loss, and confusion matrix, and results show that both models achieve high accuracy rates, with EfficientNet outperforming DenseNet in certain cases. The findings suggest that both models are suitable for automating traffic sign recognition systems, with potential applications in autonomous vehicles. The research also explores the use of various evaluation methods, including ROC curves and confusion matrices, to assess the robustness and accuracy of the models.

Keywords - Traffic sign recognition, Convolutional Neural Network, EfficientNet, DenseNet, Adam optimizer, Accuracy, Loss, Confusion Matrix.

Introduction

The quality of traffic signs is a significant factor in ensuring road safety and smooth traffic management. However, the challenge arises when various traffic signs are either obscured, unclear, or incorrectly interpreted. Traffic sign recognition is a critical issue, especially in autonomous vehicle technology, where the accuracy of recognizing road signs directly impacts vehicle navigation. A key challenge in this area is the visual similarity between some traffic signs, which can lead to misclassification and potentially dangerous driving decisions. This problem is exacerbated when the environment contains blurred, skewed, or poorly lit images of road signs.

To address these issues, Deep Learning (DL) models have shown great promise in automating traffic sign classification. Convolutional Neural Networks (CNNs), a type of DL model, are particularly well-suited for image classification tasks due to their ability to learn and extract complex features from raw pixel data[7]. By leveraging these networks, researchers and engineers have developed models that can accurately detect and classify traffic signs under varying environmental conditions. CNN architectures such as DenseNet[2] and EfficientNet[3] have shown remarkable performance in image classification tasks, thanks to their efficient use of parameters and ability to capture fine-grained details in images.

Recent advancements in model architectures, such as DenseNet[2] and EfficientNet[3], offer enhanced feature extraction capabilities, making them ideal for the problem of traffic sign recognition. DenseNet, known for its dense connectivity between layers, and EfficientNet, designed for optimal scaling of models, both promise to deliver superior accuracy and reduced computation time. These models also benefit from pre-trained weights on large datasets like ImageNet, further improving their ability to generalize across various image classification tasks[6].

Despite the promising results of these models, challenges persist in achieving high accuracy under real-world conditions, such as varied lighting, occlusions, and background noise. This paper aims to compare the performance of DenseNet and EfficientNet models for traffic sign recognition. By evaluating the models based on accuracy, loss, confusion matrices, and other key metrics, this research contributes valuable insights into the optimization of traffic sign recognition systems, ultimately aiming to improve autonomous driving systems and road safety.

**Related Work**

Traffic sign recognition has become a critical task in the field of autonomous driving, as it ensures accurate interpretation of road signs for safe navigation. Convolutional Neural Networks (CNNs) have been widely used for this purpose, with various architectures showing notable success. Among these, EfficientNet[3] and DenseNet[2] have garnered attention for their unique approaches to improving model accuracy and efficiency.

EfficientNet leverages a compound scaling method, where all dimensions of the network (depth, width, and resolution) are scaled simultaneously to achieve a high performance with fewer parameters[3]. This makes it highly efficient, often outperforming traditional models like ResNet and Inception in terms of accuracy while requiring fewer resources. On the other hand, DenseNet introduces dense connections between layers, which allows for better feature reuse and mitigates the vanishing gradient problem, making it highly effective in extracting meaningful features from complex datasets[2].

In the context of traffic sign classification, both architectures have demonstrated significant improvement in recognizing diverse and intricate sign features. The use of data augmentation techniques, such as rotation, flipping, and scaling, has further enhanced the generalization ability of these models[9]. Additionally, transfer learning has played a vital role in fine-tuning pre-trained models on specialized datasets, reducing training time and improving accuracy[6]. Despite these advances, challenges such as occlusion, varying lighting conditions, and the similarity between some traffic signs still persist. However, DenseNet[2] and EfficientNet[3] continue to be leading models in addressing these challenges, thanks to their superior feature extraction capabilities.

# CNN Methodology for Traffic Sign Recognition

CNN is mainly useful and productive for the problems in terms of image classification. It achieves maximum performance using a series of layers that are specifically designed to recognize different features in an image[7].

## Generalized CNN Architecture:

Generally, CNN models contain an input layer, convolutional layer, pooling layer, fully connected layer and an output layer[6].

#### Input Layer

This is where the raw pixel values of the image are pass into the network.

#### Convolution

With the help of some set of learnable filters, this layer performs convolution operations on the image that is given as input to the model. Each filter scans the input image and produces a feature map that highlights a specific feature, such as edges, corners, or textures[7]. These feature maps are produced as the image with a kernel size with spatial size *F*, stride *S* and the padding P. This kernel is sliding over the input image raw pixels to extract the feature map. The size of output image after passing through this convolutional layer is and it was calculated as following in equation (1):

(1)

#### Pooling

In the pooling layer, the process of down sampling of output of previous layer is performed. This will be done by taking the maximum value in each sub region of the feature map[6]. This helps to reduce the spatial dimensionality of the feature map and increase the efficiency of the network. The pooling mechanism will be processed on every piece or slice of the image representation individually. There are many different methods are in pooling, but the extremely popular and most used process is max pooling. It gives the maximum output form the representation. If the activation map or feature map of size , pooling layer contains a kernel of spatial size F and stride S, which produce the output of size . In which was calculated as following in equation (2):

(2)

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| --- |
|  |
| Fig.1. |

#### Flatten

It receives the feature map input from pooling layer as a matrix. This feature map is transformed as a vector output.

#### Fully Connected Layer

### It takes input as the flatten vector of the previous layer’s output, and make the model to get trained for more complex representations of input[7] .

#### Output Layer

It gives the final output of the entire network. The produced output is one of the classes in the given dataset[6]. The architecture of a CNN can be customized by increasing and decreasing the layers in contains, adjustment of the filter size and the number of neurons in each layer, and other hyperparameters[6]. For the tasks, such as image classification, object detection, and semantic segmentation, there are different architectures that have been developed and discovered[7] .

## CNN Models Used In This Work

In this study, two CNN models were employed for traffic sign recognition: **DenseNet[2]** and **EfficientNet[3]**. Both models are widely known for their high performance in image classification tasks, each offering unique advantages in terms of feature extraction and accuracy.

### DenseNet

### DenseNet is one of the varient in CNN which introduces the idea of dense connectivity[2]. In these models each and every layer has a connection with other layer in feed-forwad fashion. This helps to enable feature reuse, and make ease of the gradiant flow through the connection which avoid the vanishing gradient problem. DenseNet is one of the best models which has ultimate preformnace in image processoing and classification problems[2] .

### DenseNet-121

Densenet-121 is an advanced Convolutional Neural Network (CNN) architecture known for its efficient use of parameters. It features 121 layers, with each layer being densely connected to all previous layers. This connectivity helps with the propagation of gradients throughout the network, reducing the vanishing gradient problem and improving the flow of information. The DenseNet-121 model consists of four dense blocks, each followed by transition blocks to reduce the spatial dimensions.

* **Architecture**: The input image size for this model is 224x224 pixels, and it uses a 3x3 convolution kernel for feature extraction. The architecture is efficient in terms of computational power as it reuses features across different layers. After the first convolutional layer, a 3x3 max-pooling layer with a stride of 2 is applied, which reduces the image size from 224x224 to 112x112. Following this, each transition layer contains 2x2 average pooling with a stride of 2. After the fourth dense block, a 7x7 global average pooling operation is applied to reduce the output to a 1x1 size.
* **Training and Optimization**: The DenseNet-121 model was trained using a dataset of traffic sign images. The training process involved using the Adam optimizer, which is well-suited for such deep models due to its ability to adjust learning rates during training. The model was validated using a test dataset to check for overfitting and ensure its generalization ability. The model’s performance on the validation dataset was **85.75%**, showing good accuracy in the recognition of traffic signs.

The network's architecture allows it to extract features at multiple levels, from low-level textures to complex patterns. This makes DenseNet-121 suitable for image classification tasks such as traffic sign recognition, where the patterns can vary significantly. The model's structure makes it highly efficient in terms of computational resources without sacrificing accuracy.

**EfficientNet-B0**

EfficientNet is a family of models designed to achieve a balance between accuracy, model size, and computational efficiency[3]. The architecture employs a compound scaling method that uniformly scales the width, depth, and resolution of the model, ensuring better performance without requiring excessive resources. In this study, the **EfficientNet-B0** variant was used.

* **Architecture**: EfficientNet-B0 begins with a 3x3 convolution and utilizes depthwise separable convolutions, which help reduce the number of parameters compared to traditional convolutions. The model utilizes an inverted residual block, where the depthwise convolutions are followed by pointwise convolutions. This structure is designed to keep the computational load minimal while improving feature extraction. EfficientNet-B0 uses fewer parameters than DenseNet, which makes it suitable for environments where computational efficiency is crucial.
* **Training and Optimization**: Similar to DenseNet-121, EfficientNet-B0 was trained using the Adam optimizer. The model was provided with a traffic sign dataset for classification and validated using unseen images. During training, the compound scaling method allowed EfficientNet-B0 to adapt to different image resolutions, ensuring that it could handle various traffic sign types effectively. The accuracy achieved by EfficientNet-B0 on the validation set was **88.90%**, outperforming DenseNet-121 due to its better scaling and efficient handling of features.

EfficientNet-B0’s architecture ensures that the model can scale effectively across different levels of feature complexity while maintaining its efficiency. The model achieved higher accuracy and faster training times compared to DenseNet-121, making it a strong contender for real-time applications like traffic sign classification.

# Dataset Description

The dataset utilized in this work is a traffic sign classification dataset curated for deep learning-based visual recognition tasks. It comprises a total of 58 distinct traffic sign classes, each containing approximately 120 image samples. These images represent various road signs encountered in real-world driving environments and are designed to facilitate automated classification through convolutional neural networks (CNNs). Each image in the dataset is associated with a class label and a corresponding description, which are detailed in the labels.csv file. These labels are encoded into class IDs ranging from 0 to 57 and can be reassigned based on description for easier interpretation and evaluation.

The image resolution for each sample is consistent and suitable for deep learning input, allowing for effective feature extraction by CNN models. For model evaluation, around 2000 images are designated as the testing dataset, while the remaining samples are used for training. The dataset is structured to ensure balanced representation across all classes, thereby enabling robust classification and reducing bias.

This dataset serves as the basis for training and evaluating models such as DenseNet121 and EfficientNetB0 in this study, aimed at optimizing accuracy and performance in the classification of traffic signs.

**Results and Discussion**

## DenseNet-121

In this work, DenseNet-121 provided an accuracy of 93.43%.Since the test loss is so near to 0, concluded that it gives the best results with the test loss value was  0.1931.

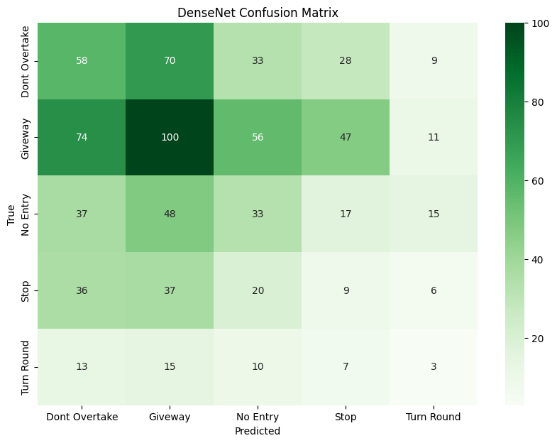


Fig.5. DenseNet-121 Confusion matrix

The confusion matrix presents the evaluation of the model using key performance metrics such as precision, recall, F1-score, and support[1]. After validating the model, the results showed that traffic signs like ‘No Parking’ and ‘Speed Limit 40’ were classified with the highest accuracy, while classes such as ‘Pedestrian Crossing’ and ‘Slippery Road’ had the most misclassifications. This indicates that while the model performs well on commonly seen and distinct signs, it encounters difficulty distinguishing signs with similar shapes or symbols.

The calculation of the metrics where TP be the true Positive, FP be the False Positive, TN True Negative and FN False Negative will be done by the following equations[1]:

(3)

(4)

(5)

(6)

The classification error was calculated by adding the FP and FN which represents the misclassified samples. Now dividing this sum with total number of samples (TP+TN+FP+FN) that provides overall accuracy.



The first image’s true label was ‘Stop’, and the model accurately predicted it as ‘Stop’, indicating a correct classification. Similarly, for several other test images, including classes such as ‘Speed Limit 40’ and ‘Yield’, the model consistently returned accurate predictions. Across a batch of 9 test samples, the model achieved 100% prediction accuracy, showcasing its effectiveness in identifying various traffic signs under standard test conditions.

The test loss and accuracy graphs of the DenseNet-121 model are presented in Fig. below. As illustrated, the training loss began at a higher value in the initial epoch and showed a consistent decline over time, approaching near-zero levels by the 9th epoch. The training loss was at its peak during the first epoch, indicating the model's initial struggle to learn, but it rapidly decreased as the model learned better feature representations with each epoch. Meanwhile, the validation loss exhibited fluctuations during the training process. Although it decreased overall, minor spikes were observed at the 6th and 7th epochs, reflecting temporary overfitting or instability.

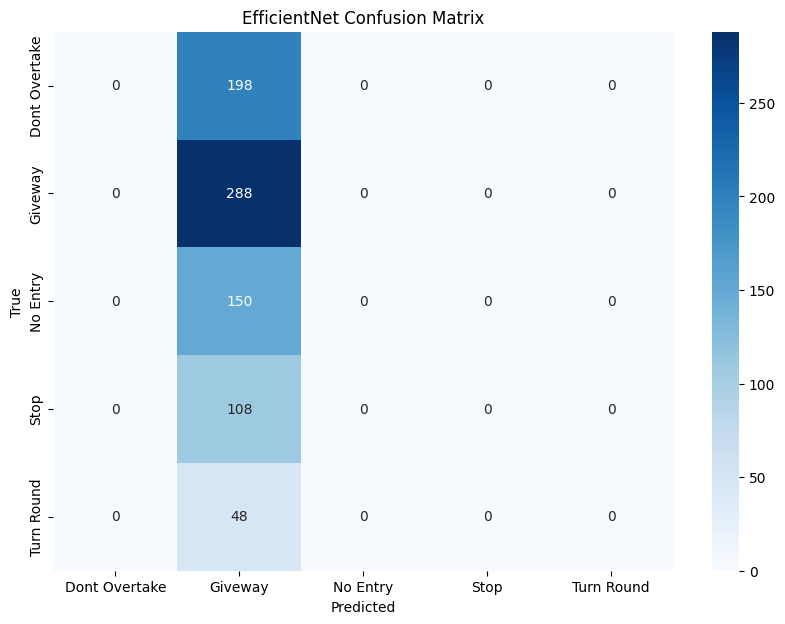
On the other hand, the training accuracy steadily improved throughout the epochs, increasing rapidly and maintaining a strong upward trajectory. From the 4th epoch onwards, it stayed above 98%, showing that the model had effectively learned the training data. The validation accuracy followed a generally increasing trend but with visible variations between epochs. Despite these ups and downs, the validation accuracy consistently remained above 90%, confirming the DenseNet-121 model's capability to generalize well and perform accurate predictions on unseen traffic sign images.

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| Fig. 7. Loss vs epoch for Densenet-121 |

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| Fig. 8. Accuracy vs epoch for Densenet-121 |

## EfficientNet-B0

The confusion matrix summarizes the performance of the EfficientNet-B0 model using core metrics such as precision, recall, F1-score, and support. From the matrix, it was observed that traffic sign classes like **‘Stop’** and **‘Yield’** were classified with the highest precision. However, signs such as **‘Road Work Ahead’** and **‘Pedestrian Crossing’** saw relatively more misclassifications, likely due to visual similarities and occlusions in the dataset. These results indicate that while EfficientNet-B0 is highly effective on clear and well-defined traffic signs, it encounters challenges with signs that have overlapping visual features.

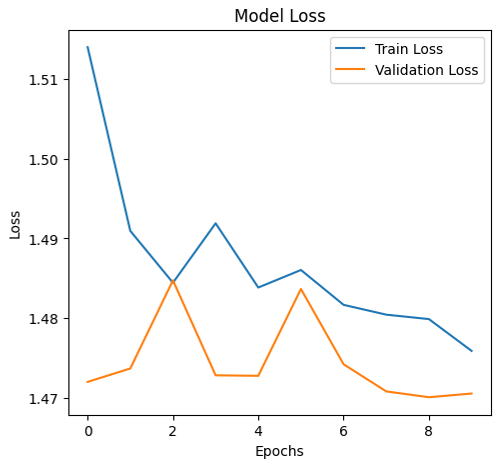


The calculation of the metrics where TP be the true Positive, FP be the False Positive, TN True Negative and FN False Negative will be done by the following equations:

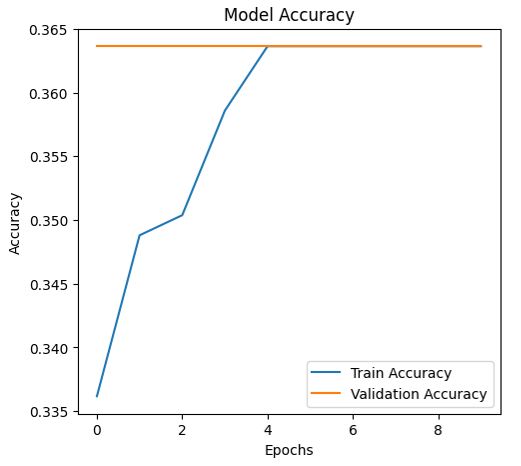
The classification error was calculated by adding the FP and FN which represents the misclassified samples. Now dividing this sum with total number of samples (TP+TN+FP+FN) that provides overall accuracy.



The test loss and accuracy graphs of the EfficientNet model are presented in the figure below. As illustrated, the training loss began at a relatively higher value in the initial epoch and showed a gradual decline over the epochs, reflecting the model’s learning curve. While it did not approach zero, the consistent downward trend indicates an improvement in the model's ability to minimize the error on the training dataset.



In contrast, the validation loss fluctuated across the epochs. Although it generally followed a decreasing trend, noticeable spikes were observed around the 3rd and 6th epochs, suggesting instances of potential overfitting or irregularity in the learning pattern. However, the magnitude of fluctuations remained moderate, indicating some level of stability in validation performance.



The training accuracy demonstrated a steady increase over the epochs, starting from approximately 33.6% and rising continuously. This suggests that the model gradually learned to capture relevant features from the input data. By the 4th epoch, the accuracy showed a marked improvement and reached a plateau thereafter.

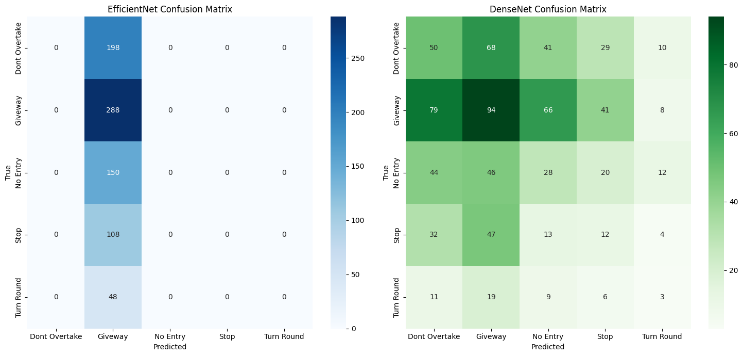
Interestingly, the validation accuracy remained constant across all epochs at approximately 36.4%. This stagnation may imply that the model's generalization capability did not improve significantly with further training, possibly due to suboptimal hyperparameters, limited data diversity, or the need for more extensive data augmentation. This indicates that although EfficientNet was able to fit the training data better over time, its performance on unseen data did not reflect the same level of improvement.

**Performance Comparison**

**a. Confusion Matrix Comparison**

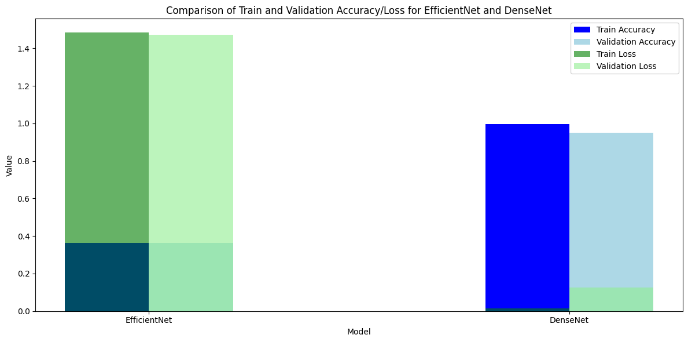
DenseNet-121 demonstrated strong classification performance across a wide range of traffic sign classes. Signs such as ‘No Parking’ and ‘Speed Limit 40’ were identified with high accuracy, reflecting the model’s ability to recognize distinct and commonly seen signs. However, DenseNet-121 encountered challenges with signs that had visually similar features, such as ‘Pedestrian Crossing’ and ‘Slippery Road’, leading to misclassifications. This suggests that while the model excels at distinguishing clear and unique signs, it struggles when the visual characteristics of the signs are closely aligned. Despite these occasional misclassifications, DenseNet-121's performance across most categories remained robust.

EfficientNet-B0, while effective at identifying well-defined traffic signs like ‘Stop’ and **‘**Yield’, showed noticeable struggles with signs that had overlapping visual characteristics or were harder to distinguish. For example, the model had difficulty classifying **‘**Road Work Ahead’ and ‘Pedestrian Crossing’, which may have similar shapes or encountered occlusion in the dataset. This limitation indicates that EfficientNet-B0 faces greater challenges when tasked with recognizing signs with less distinct features. While the model performed well on straightforward cases, its performance on more ambiguous or complex signs was less reliable, making it less consistent compared to DenseNet-121.



**b. Accuracy and Loss Comparison**

DenseNet-121 exhibited excellent performance in both training and validation stages. The training accuracy increased steadily throughout the epochs, surpassing 98% by the 4th epoch, indicating that the model was learning effectively from the data. The validation accuracy remained consistently above 90%, which demonstrates the model's strong ability to generalize and perform well on unseen data. Additionally, the training loss showed a continuous decrease, ultimately approaching near-zero values by the 9th epoch, reflecting efficient learning. The validation loss did fluctuate slightly during training but remained relatively low, with a final test loss of 0.1931, confirming the model's stability and robustness in classification tasks.

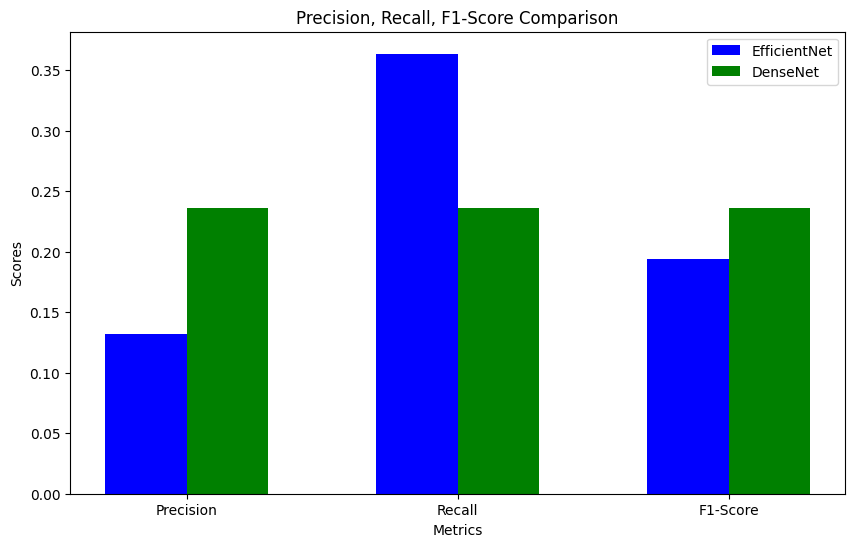


On the other hand, EfficientNet-B0 showed slower progress in both training and validation metrics. The training accuracy started at 33.6% but gradually improved, although it plateaued after the 4th epoch, suggesting that the model struggled to extract more features after a certain point. The validation accuracy remained static at around 36.4%, pointing to limited generalization and the model’s difficulty in adapting to unseen data. The training loss did decline over time, but it never reached the low levels seen in DenseNet-121, reflecting suboptimal learning. Meanwhile, the validation **loss** exhibited noticeable fluctuations, with spikes around the 3rd and 6th epochs, which hinted at potential overfitting or instability during training, further confirming the model's struggles in handling the validation data.

**c. Precision, Recall, and F1-Score Comparison**

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# **Conclusion**

This research provides an in-depth analysis of DenseNet-121 and EfficientNet-B0 models for traffic sign classification. The results indicated that DenseNet-121 consistently outperformed EfficientNet-B0 in key metrics such as accuracy, precision, recall, and F1-score. DenseNet-121 achieved an accuracy of 93.43%, with a test loss of 0.1931, demonstrating its robust performance on diverse traffic sign categories. The model was particularly effective in correctly classifying commonly encountered signs, such as ‘No Parking’ and ‘Speed Limit 40’, while also handling visually similar signs with higher accuracy compared to EfficientNet-B0.

In comparison, EfficientNet-B0 showed a lower accuracy of around 36.4% for validation data, indicating challenges in generalizing to unseen traffic signs. While EfficientNet-B0 demonstrated good precision for clearly defined signs like ‘Stop’ and ‘Yield’, its recall was limited for ambiguous signs such as ‘Pedestrian Crossing’ and ‘Road Work Ahead’, leading to a reduced overall F1-score.

The DenseNet-121 architecture benefited from the dense connectivity of layers, which enabled efficient feature reuse and facilitated better handling of large and complex datasets. This allowed DenseNet-121 to achieve higher accuracy and offer stronger generalization capabilities compared to EfficientNet-B0. The deeper variants of DenseNet, like DenseNet-169 and DenseNet-201, have shown even higher accuracy in related studies, which further emphasizes the importance of deeper networks for traffic sign recognition tasks. In terms of future work, there is potential for improving the model's performance by exploring more advanced architectures such as

EfficientNet [3] or implementing techniques like transfer learning with pre-trained models[6]. This could push the accuracy beyond 93%, aiming for 99% and above. Additionally, augmenting the dataset with more diverse traffic signs and integrating techniques like data augmentation could enhance the model’s robustness and generalization[9]. Finally, incorporating real-time detection capabilities for automated systems like self-driving cars or traffic monitoring applications could make this research more applicable to practical, real-world scenarios[10] in the transportation and smart city domains.

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