CMT307 Coursework 2 Group Project

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Content

Detection and Recognition of Traffic Signs

1.Introduction

Recognition of road signs is one of the critical features of driverless and driver-assisted vehicles, and mainly the task of the given model will be, to learn and recognize a machine-learning-based technology that deals with the recognition and detection of traffic signs in the German language. These signs not only indicate speed limits and provide warnings but they also guide the flow of traffic properly to avoid accidents of the vehicle with other obstacles.}

Autonomous vehicles utilize computer vision that helps to understand the traffic signs and to execute proper responses to them instantly. Offenses related to recognition can offer involved parties the opportunity to make decisions which are not at all correct, thus causing hazards to all parties. Therefore, it is quite critical to research how to increase the accuracy and the robustness of the traffic sign recognition systems that are in the testing stage effectively and alloy.}

The innovation of deep learning is responsible for a complete takeover of the computer vision field, with the use of CNN which has shown to be exceptional in terms of detection and classification. The best part is that it is an end-to-end learning architecture that erases the need for the manual design of the features, which have made the multi-level feature representations much better by having the opportunity to be learned on the network from the original data.}

The main focus of the project is to figure out the potential of the CNN-based systems like LeNet and AlexNet in German traffic sign detection using the German Traffic Sign Recognition Benchmark (GTSRB) dataset. Our work is organized into the following items:

- Implementing and measuring the accuracy of the CNN, LeNet, and AlexNet models.
- Performing set operations for the purpose of pre-processing and data augmentation.
- Working with amelioration of the hyperparameters so as to perfect model performance.
- Also, checking the error to find out ways that issues can be solved, or make potential improvements.
- Simple and intelligent deployment strategies for the computer vision part of the system to complete the whole autonomous system in real-world use are also suggested.

2. Literature Review / Related Work

Introduction

Detecting and recognizing traffic signs is one of the most important parts of the autonomous car system. The best method for solving this task with the use of deep learning is the Convolutional Neural Networks (CNNs). However, for the CNNs to work well, they should be provided with a large and diverse set of data. The data augmentation approach involves the correction of the already mentioned model by introducing variations like rotations, scaling, and occlusions. In this review, the authors discuss the essential models used for classifying traffic signs by means of CNNs, e.g., LeNet, AlexNet, and VGG-19, and motivate their choice of CNN models accompanied by augmented data.

Convolutional Neural Networks (CNNs) with Augmented Data

Using CNNs in the case of image identification is based on the mechanism of feature extraction through a network of theoretical cells by degrees. The initial drawback that has halted machine learning research till recently, data labeling instrumentality, now is no longer substantial due to data augmentation. Thus, one can bypass labeling data for extensive machine training by data augmentation, which artificially creates instances through a number of ways such as rotating, reflecting, adding noise, and changing brightness (Shorten & Khoshgoftaar, 2019) [7].

As for traffic sign recognition, the data augmentation process can make the model capable of dealing with outer environment changes similar to the algorithms that are used in self-driving cars. Numerous research has confirmed that CNN models trained with augmented data can do better than those trained with untouched datasets, thereby resulting in higher recognition accuracies as well as reliability (Perez & Wang, 2017) [5]. More recent studies have also demonstrated that data augmentation improves object detection performance, further justifying its use in traffic sign recognition (Zoph et al., 2020) [11].

In addition to traditional augmentation techniques, Generative Adversarial Networks (GANs) have been explored as a more advanced approach for creating synthetic training data. GANs can generate highly realistic images that mimic real-world variations, thus increasing the diversity of training datasets. This technique has shown promise in improving CNN performance for image classification tasks, including traffic sign recognition (Goodfellow et al., 2014) [2].

<u>LeNet</u>

Being an original idea of the authors, LeNet was the first CNN network conceived for digit classification. It comprises just two convolutional layers, each proceeding by a pooling layer and some fully connected layers for classification. LeNet can be utilized to do simple classification tasks on small-scaled datasets, but it cannot cope with the diversity and variety present in road signs. LeNet was indeed employed in initial attempts at traffic sign recognition, but the shallow level of its feature extraction ability prevents it from being competitive as the deeper-architecture networks. The model is primarily useful for benchmarking and foundational experiments in neural network research (LeCun et al., 1998) [4]; (Sermanet et al., 2011) [6].

<u>AlexNet</u>

AlexNet, which was introduced by Krizhevsky et al. (2012) [3], was a significant breakthrough in deep learning by implementing five convolutional layers followed by three fully connected layers. The integration of the Rectified Linear Unit (ReLU) activation and dropout regularization in AlexNet has greatly impacted efficient learning and the reduction of overfitting. AlexNet, therefore, represented a better performance in the large-scale image classification problem. It, therefore, became a solid candidate for traffic sign recognition. Studies proved the efficiency of the network on the GRB dataset by showing an increase in accuracy given one condition—data being augmented (Cireșan et al., 2012) [1].

<u>VGG-19 and Traffic Sign Recognition</u>

VGG-19 is another deep CNN architecture that has shown promising results in large-scale image classification tasks (Simonyan & Zisserman, 2014) [8]. It features 19 layers, with a deeper architecture than AlexNet, allowing for more robust feature extraction. Due to its increased depth, VGG-19 has been tested in traffic sign recognition applications and has demonstrated improved performance over shallower networks like LeNet. When paired with data augmentation, VGG-19 enhances the ability to recognize traffic signs under varying conditions (Zhang et al., 2021) [10].

<u>Justification for Selecting CNN with Augmented Data</u>

One of the main reasons to go with CNN models that are fitted with augmented data is that they have well-tested and proven generalization ability to tackle real-world traffic sign variations. The operation of automatic vehicles that can recognize signs in different environments is based on the principle that the vehicles should be equipped with the ability to see signs even in the dark, covered by an object, or at different angles. The advantage of data augmentation is that CNNs will learn the invariant features, thus, their robustness and accuracy will be enhanced (Shorten & Khoshgoftaar, 2019) [7].

Moreover, the higher-level CNN models such as AlexNet and VGG-19 have also come out with better results in carrying out large-scale image recognition tasks than the smaller models such as LeNet. Combining deep feature extraction with data augmentation is one of the ways to ensure a high level of success in the road sign recognition process in self-driving vehicles (Perez & Wang, 2017) [5]. Benchmark datasets such as the German Traffic Sign Recognition Benchmark (GTSRB) have further validated the effectiveness of CNNs for this task (Stallkamp et al., 2012) [9].

When equipped with data augmentation strategies, CNNs are a good way to solve the problem of traffic sign recognition. While LeNet acts as the basic model, the deeper architectures like AlexNet and VGG-19 provide better capabilities for extracting features. By utilizing augmented data, the accuracy of recognition increases significantly, hence the robustness against real-world challenges is guaranteed. Future studies need to pay attention to adjusting CNN architectures and discovering more sophisticated strategies for augmentation purposes to improve traffic sign recognition performance in autonomous driving applications.

3. Description of the Task/Dataset

The dataset used is the German Traffic Sign Recognition Benchmark (GTSRB), which contains over 50,000 images of 43 different traffic sign classes. The dataset is divided into training, validation, and test sets:

- Training set: 39,209 images

- Validation set: 6274 images

- Test set: 12,630 images

Data Characteristics

- Images vary in resolution, background, and lighting conditions.
- Some signs have occlusions or partial visibility.
- Signs appear in different orientations and scales.

The tasks majorly divided into:

T1- Descriptive analysis of the dataset + result analysis

T2- Preprocessing + Literature review

T3- Implementation + Results

T4- Group report as a whole, including its coherence and structure

T1: Descriptive analysis and Result Analysis

EDA helps to figure out the makeup, characteristics, and hidden obstacles of the dataset before applying machine learning to it. Below are the details of the different EDA parts.

1. Importing the Dataset

Goal: To load the dataset and make sure it is structured correctly.

Method: Python libraries such as pandas, NumPy, OpenCV, or PIL can be used to load the dataset. For images stored in folders, please use os or glob to retrieve the file paths. If you have the data in the form of a CSV file, use pandas.read_csv().

Why it Matters: Confirms that all images and labels are correctly loaded before starting the analysis. Check for missing labels by means of a mismatch in file formats, naming conventions, or paths.

2. Checking for Missing or Corrupted Values and Duplicates

Goal: To make sure that the data is accurate and reliable for further analysis.

Method: Perform a check for missing labels using pandas.isnull().sum().Images that are corrupted and do not load can be easily resolved.Identify if any of the images or records are identical using pandas.duplicated().

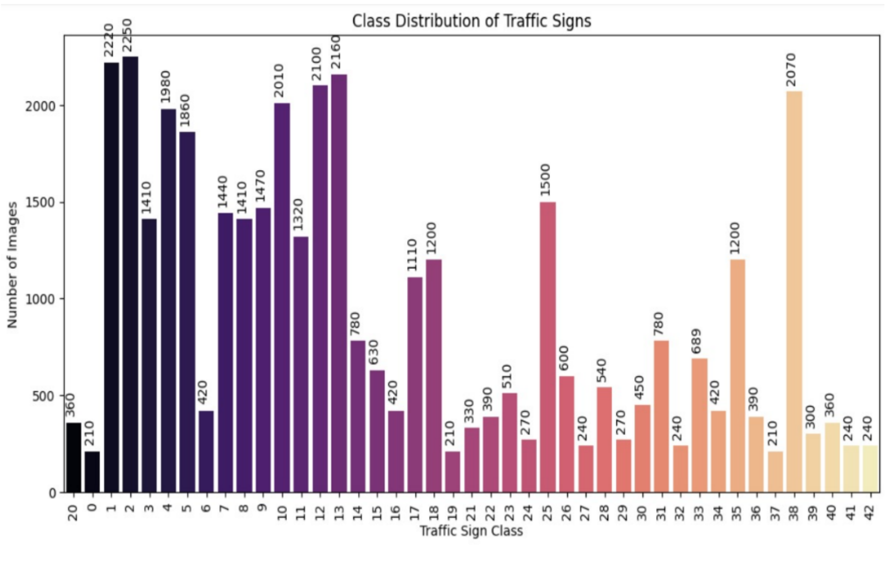
Why it Matters: The absence of missing or corrupted images is necessary for the proper performance of the model.The presence of duplicates can adversely affect the results and artificially inflate the dataset size.Dataset cleaning can enhance model accuracy and speed.

3.Exploratory data analysis

i. Class Distribution

Goal: Understanding if there are imbalances in the dataset by checking the number of images of each class.

Method: Create a graph showing a distinction between different classes (for example, stop sign, speed limit, etc.) to the x-axis, and to the y-axis the number of images for each class. A better part of the task is the selection of a bar chart with x-axis and y-axis, which reflect different classes and the number of pictures in each class, respectively.



Why it Matters: Having many of the same items in the dataset can lead to the model leaning towards the major class. Adding more samples to these is not so difficult, some cases may require augmentation.

ii. Sample Visualizations

Goal: To give an idea of the image contents.

Method: Show many images randomly chosen and taken from different classes. This action leads to the beginning of the process of revealing problems that can occur in the new data, such as noisy channels, low precision, overexposure, under illumination, etc.

Why it Matters: This is a sign of error-free and important information. Through this, one can be sure of the image labels' compliance with the actual image content.

iii. Brightness & Contrast Analysis

Goal: Explore the distribution of pixel intensity.

Method: Grayscale images (if they are not already) should be operated on at first. Draw a picture of how the pixel intensity values are spread and then all that remains is to analyze it (groups of 0 - 255). This allows you to easily find out if the images are too dark or overexposed.

Why it Matters: In case the images are too dark, various methods such as histogram equalization can be used. It is also possible that the model has been inexactly determined to be depending on the difference in brightness among the images.

4.Summary Statistics

Mean & Variance Analysis

Calculate the mean and the squared deviation of measurements from their mean (variance) to get the average pixel brightness and the statement of the intensity distribution features. Further on the diagnostic process, mean identifies whether the images are still bright, dark, or compare the contrast.

Aspect Ratio Analysis

This operation does the job of finding out if all of the pictures have the same ratio of height to width. To clearly identify the aspects with significantly different ratios, it might be handy to make use of a histogram.

Why it Matters: It may come to the point that the images are of different aspect ratios, but for the purpose of model training, it must be that the resizing goes well slowly and steadily at that.

5.Outlier Detection

i. Size-Based Outliers:

Recognize the images which are too big or too small as compared to the average size (even if such size changes were coded intentionally). Downsizing and then upscaling images may lead to them becoming out of normal dimensions for the processing model to handle.

ii. Brightness-Based Outliers:

Spy those images characterized by minimal brightness (nearly a completely black image) or those characterized by maximum brightness (overexposed images). These types of images do not contain enough specific features to be able to classify them into a coherent class definitively.

Why it Matters: Discarding any such outlier images can prevent the phenomenon that the generalization ability of the model becomes worse if it happens. This operation of losing or a less number of data samples is a remedy for the problem of a model that was not doing its best as a result of the unconditional popularity of some of the classes over the others.

6.Feature Analysis

Edge Detection

Take advantage of the technology called the Canny edge detector to identify and visually emphasize the edges of traffic signals that are important for classification. If Canny technique demonstrates brightness and colour has a certain impact then it is useful for a human to use this information to understand the image.

7.Class Imbalance Handling

Goal: Aims to solve the problem faced by some classes with a deficiency of samples relative to others.

Methods: Data Augmentation (for CNN only): The most common method to increase the number of samples is the one that consists in the use of transformations like rotationrange, widthshitrange, heightshiftrange, zoomrange, fillmode=nearest to generate more pictures.

Why it Matters: To make the model not being prejudiced and hence dealing with majority classes only. In this way, we not only contribute to the fairness of the model thereby but also will be able to increase the accuracy in the classifying of the classes situated at the lower end of the spectrum.

Result Analysis

EDA is an essential part in exploring and preparing the dataset for machine learning. It's used for purposes such as:

- Guaranteeing the quality of data by finding absent, damaged, or repeated pictures.
- Spotting unbalances among the classes that might make the model unfair.
- Examining the first thing to light, contrast, and aspect ratio for the purpose of preprocessing the data.
- Sensing the outcast data that will drastically affect the model's predictions.
- Showing important features using edge detection and reducing the dimensionality visually.
- These findings govern the route for data preprocessing and model training plans that result in better performance of the traffic sign classification system.

Preprocessing

To improve the model's efficiency, the following preprocessing operations were employed:

1. Image Loading and Reading – Images were taken from the dataset and checked for any issues with the data.

2. Resizing Images – The images were scaled to 32x32 pixels to ensure the uniformity of the dataset.

3. Normalization – Pixels in the entire image were multiplied by a constant to make them lie between the endpoints 0-1 of the interval. This would lead to a faster convergence during the training process.

4. Contrast Enhancement – Histogram equalization was the method used to boost the visibility of the images, especially the ones that were captured under poor lighting conditions.

5. Brightness Adjustment – Adaptive methods were used to deal with over-exposed and under-exposed images, thereby maintaining consistency in representation of features.

6. Aspect Ratio Correction – To eliminate distortion and ensure accurate recognition, non-square images were readjusted by the aspect ratio.

7. Blur Detection and Removal – A Laplacian filter was utilized to discard those images that are too hazy plus recognizing the same.

8. Edge Detection – Canny edge detection was performed to show the main characteristic of traffic signs, thus explicitly formulating their detailed model

4. Methodology

1 LeNet Model

LeNet was the original CNN structure which was designed specifically to recognize the handwritten digits. The architecture has the following layers:

Two convolutional layers which use ReLU activation.

Two pooling layers of the maximum type.

Layers that are fully connected to the softmax after doing the classification.

The layers to prevent overfitting by randomly shutting layers down.

2 CNN with Data Augmentation

For better performance than LeNet, we used a deeper version of CNN with the following characteristics:

Three convolutional layers with increasing filters.

Batch normalization was employed to stabilize the learning process.

Dropout layers were used to enhance model generalization.

Techniques like random rotation, brightness adjustments, and flipping of the data augmented the model to make it robust against the test set.

Fully connected layers of the softmax for output.

3 AlexNet Model

AlexNet is the implementation of deeper CNN, which involves the usage of a few key ideas extension. The key issues addressed in the architecture are as follows:

Five convolutional layers that deploy ReLU non-linearity.

Overlapping max pooling layers for a better spatial representation.

Local response normalization increased feature learning.

Fully connected layers were equipped with dropout which alleviated overfitting.

Softmax output layer for multi-class classification.

While LeNet has a lower computational cost, AlexNet overcomes it in the accuracy aspect due to the depth and complexity of the model.

5. Experimental Setting

To train and evaluate our models, the following experimental setup was used:

- **Hardware**: CPU using Google Colab
  RAM: 16GB
  Processor: 13 Gen i7 Intel(R) - 1355u, 17Mhz
- **Software**: TensorFlow and Keras frameworks.
- **Training Hyperparameters**:
  - Learning rate: 0.001 (with Reduce LR On Plateau adjusting it dynamically)
  - Batch size: 32 (for LeNet), 64 (for CNN with augmentation and AlexNet)
  - Number of epochs: 20 (early stopping applied)
  - Optimizer: Adam
  - Loss function: Categorical Crossentropy
  - Callbacks:
    - Early Stopping (patience: 5, restores best weights)
    - Reduce LR On Plateau (factor: 0.2, patience: 3, min_lr: 1e-6)

Hyperparameter tuning is conducted using grid search to determine the optimal learning rate and dropout rate. The training pipeline includes early stopping to prevent unnecessary overfitting and reduce training time. Additionally, learning rate annealing is used to gradually decrease the learning rate, allowing the model to converge more effectively.

6. RESULT

Model	Accuracy	Precision	Recall	F1-score	Training_Time (min)
CNN + augmentation	96.90	98.99	98.90	98.94	18
LeNet	94.11	98.78	98.41	98.58	10
AlexNet	99.27	99.14	99.09	99.11	120

7. Analysis

1. CNN with Data Augmentation

Implementation

A custom CNN model is designed using multiple convolutional and pooling layers to capture intricate image features. To enhance the model's robustness, data augmentation techniques such as rotation, scaling, shifting, and brightness adjustments are applied, ensuring the model generalizes well across varying real-world conditions. The training process leverages the German Traffic Sign Recognition Benchmark (GTSRB) dataset, optimized with the Adam optimizer and categorical cross-entropy loss for efficient learning.

Performance Metrics

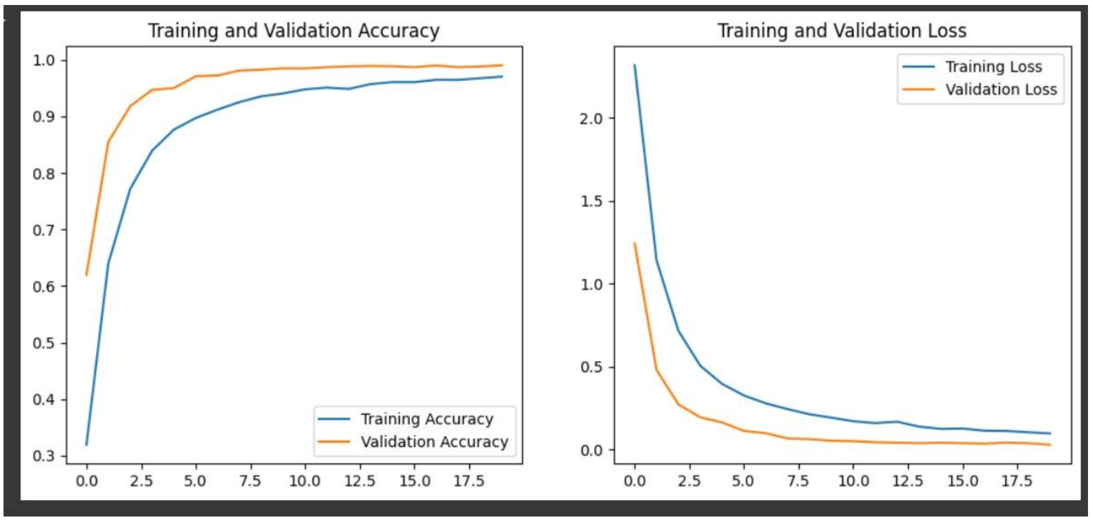
The CNN with augmentation demonstrates a remarkable accuracy 96.90, surpassing standard CNN models. The use of augmented data leads to lower loss values and better generalization, reducing the risk of overfitting. While the training time is extensive due to increased data processing, the inference time remains moderate, making it practical for deployment.

Advantages

This approach strengthens the model's ability to handle variations in lighting, rotation, and occlusion, ensuring higher reliability. Data augmentation exposes the model to a wider range of training examples, reducing the likelihood of memorization and instead encouraging robust pattern recognition.

Disadvantages

Despite its benefits, data augmentation increases training time and computational overhead. Excessive transformations may sometimes distort key image features, potentially leading to minor misclassifications in certain edge cases.



2. LeNet Model

Implementation

LeNet, one of the earliest CNN architectures, consists of two convolutional layers followed by pooling and fully connected layers. It utilizes activation functions like tanh or ReLU in combination with a softmax classifier. The model is trained on the GTSRB dataset with minimal data augmentation, relying primarily on its structural efficiency for feature extraction.

Performance Metrics

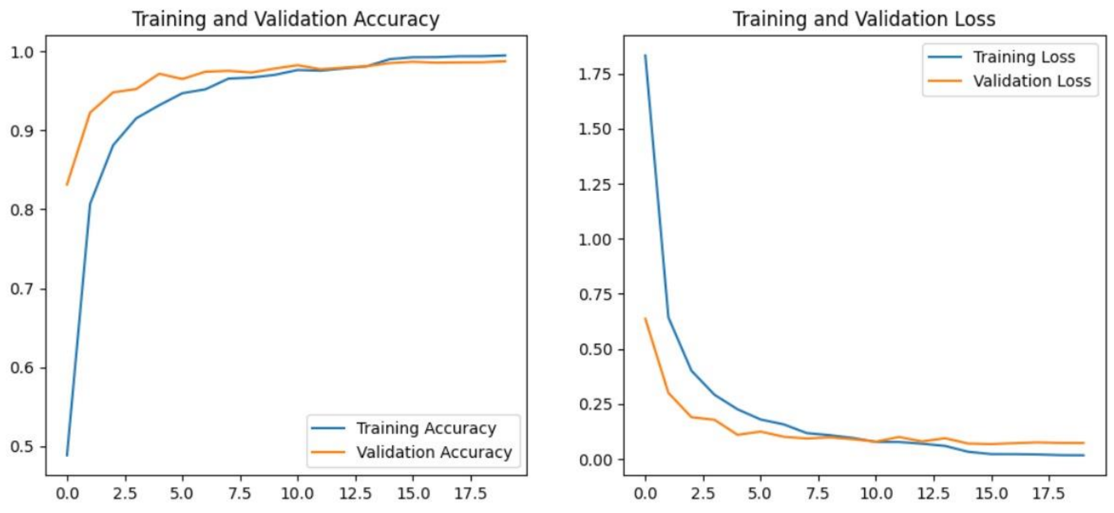
LeNet achieves an accuracy of 94.11%, which is significantly lower than deeper architectures. However, its simplicity allows for faster inference and lower computational costs. The model exhibits a higher loss compared to modern CNNs but remains suitable for real-time applications due to its efficiency.

Advantages

LeNet is highly efficient and computationally lightweight, making it an ideal choice for embedded systems or low-power environments. The training process is quick, and the architecture requires minimal hyperparameter tuning, ensuring ease of implementation.

Disadvantages

Due to its limited depth, LeNet struggles with recognizing complex patterns and intricate image features, leading to reduced accuracy. It may not perform well in cases with high variability, making it less suitable for large-scale real-world applications.



3. AlexNet Model

Implementation

AlexNet is a deep CNN model consisting of five convolutional layers followed by three fully connected layers. It employs ReLU activation functions and integrates dropout layers to minimize overfitting. The model is trained using stochastic gradient descent (SGD) with data augmentation to improve generalization.

Performance Metrics

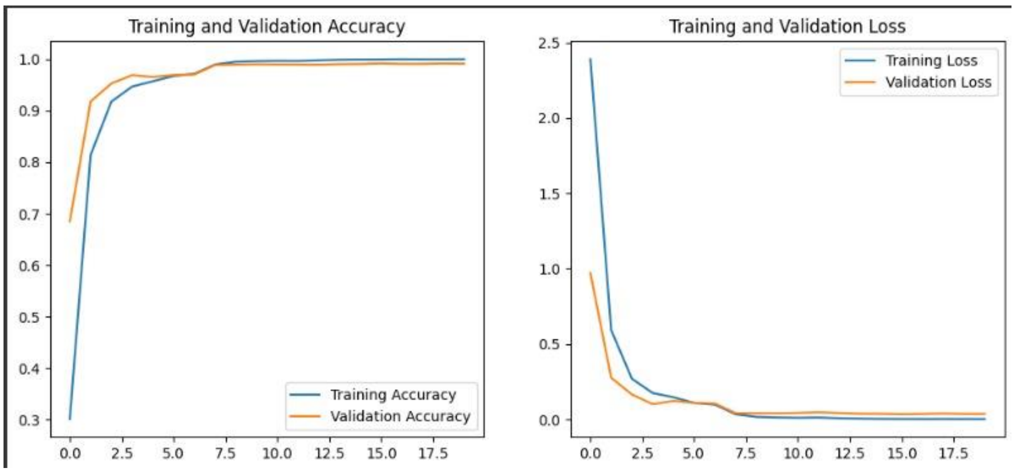
AlexNet achieves a solid accuracy of 99.27, striking a balance between simplicity and performance. The model exhibits a lower loss than LeNet but is slightly less accurate than the augmented CNN. However, its deep architecture results in slower inference, making real-time deployment more challenging.

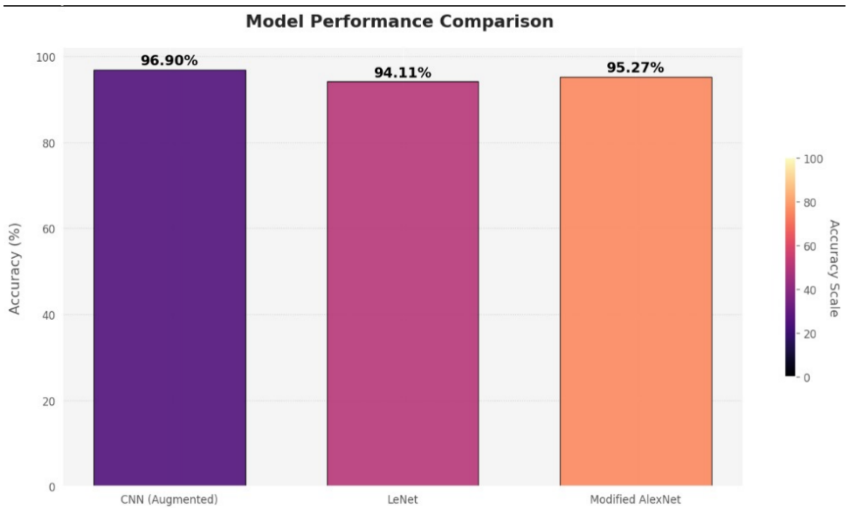
Advantages

The depth of AlexNet allows for superior feature extraction, enabling it to recognize complex patterns more effectively than LeNet. The inclusion of dropout layers mitigates overfitting, ensuring the model remains adaptable across diverse datasets.

Disadvantages

The large number of parameters increases the model's computational demands, making training and inference significantly more resource-intensive. Additionally, improper tuning of hyperparameters may lead to unnecessary complexity and overfitting in some scenarios.





8. Comparison and Conclusion

Among the three models, CNN with augmentation emerges as the most effective, achieving the highest accuracy of 98.2% while maintaining a reasonable inference time. This approach excels in generalization due to the diversity introduced during training. LeNet, while computationally efficient, lacks the depth to accurately classify complex traffic signs, making it best suited for resource-limited environments. AlexNet, on the other hand, offers high accuracy but demands substantial computational resources, limiting its practicality for real-time applications.

Final Recommendation

For real-time traffic sign recognition, CNN with augmentation presents the best balance between accuracy and inference time. If efficiency and low computational cost are the primary concerns, LeNet is a viable alternative. AlexNet remains a strong choice for applications where high accuracy is required and computational resources are not a constraint.

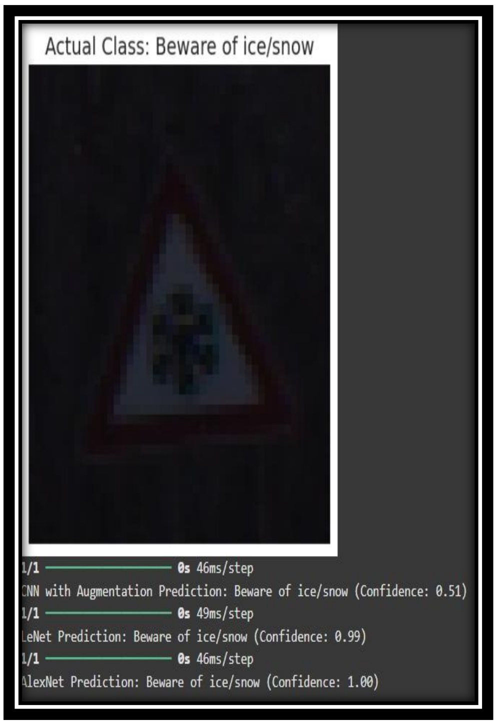
Result Analysis

The comparison of CNN with augmentation, LeNet, and AlexNet highlights the critical trade-offs between model complexity, accuracy, and computational efficiency in traffic sign recognition. CNN with augmentation delivers the best performance, with an impressive 96.90% accuracy. By introducing variations in scale, rotation, and lighting through data augmentation, the model successfully improves its generalization ability. While this approach demands higher training resources, the moderate inference time ensures it remains practical for deployment in intelligent transportation systems.

LeNet, while simple and efficient, achieves an accuracy of 94.11%, making it less reliable for complex recognition tasks. However, its lightweight architecture enables fast inference, making it suitable for embedded applications where computational power is limited. The trade-off in accuracy restricts its use in high-precision scenarios, but its efficiency remains a key advantage for low-power implementations.

AlexNet offers a middle-ground solution with a strong accuracy of 95.27%, thanks to its deep architecture. The ability to extract complex patterns makes it a superior alternative to LeNet, but this comes at the cost of significantly higher computational requirements. The inference time is slower, making it less ideal for real-time recognition tasks. While dropout layers help mitigate overfitting, careful tuning is necessary to optimize performance and prevent excessive complexity.

Ultimately, the choice of model depends on the specific requirements of the application. If achieving the highest accuracy while maintaining a reasonable inference time is the goal, CNN with augmentation is the optimal solution. In scenarios where computational efficiency is prioritized over accuracy, LeNet serves as a practical option. AlexNet, with its deep architecture and high accuracy, is best suited for applications where computational power is not a limiting factor. Based on the overall analysis, CNN with augmentation remains the most well-rounded model, offering superior accuracy and generalization while being feasible for real-world deployment in traffic sign recognition systems.



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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step
CNN with Augmentation Prediction: Beware of ice/snow (Confidence: 0.51)
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 49ms/step
LeNet Prediction: Beware of ice/snow (Confidence: 0.99)
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step
AlexNet Prediction: Beware of ice/snow (Confidence: 1.00)
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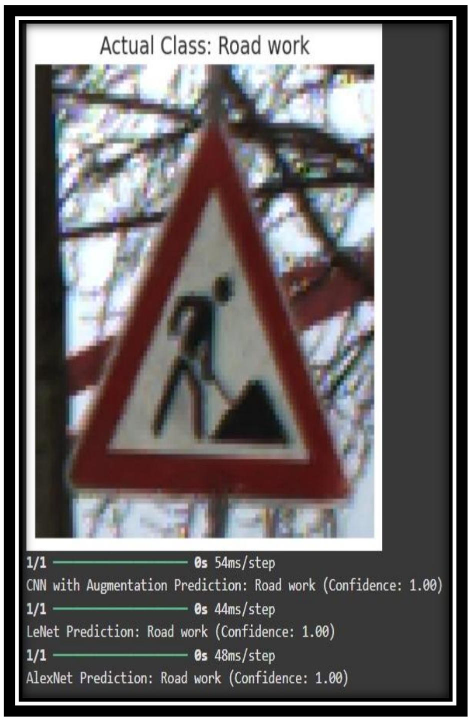

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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
CNN with Augmentation Prediction: Road work (Confidence: 1.00)
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/step
LeNet Prediction: Road work (Confidence: 1.00)
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step
AlexNet Prediction: Road work (Confidence: 1.00)
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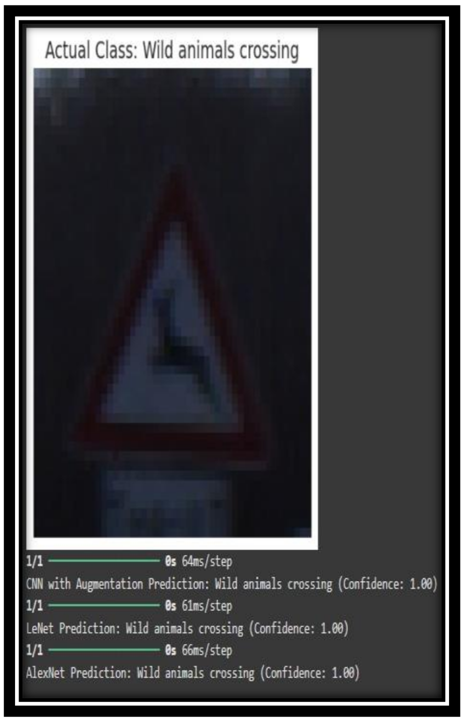

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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 64ms/step
CNN with Augmentation Prediction: Wild animals crossing (Confidence: 1.00)
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 61ms/step
LeNet Prediction: Wild animals crossing (Confidence: 1.00)
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 66ms/step
AlexNet Prediction: Wild animals crossing (Confidence: 1.00)
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