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Research Article

Traffic Sign Recognition Using a Customized Convolutional Neural Network

Haseeb Gul[1, *], Moiz Gul[2]

[1] Department of Computer Science, Bahauddin Zakariya University Multan, 60000, Pakistan
[2] Department of Information Technology, Emerson University Multan, 60000, Pakistan
[*]Corresponding Author: Haseeb Gul. Email: haseebcs442@gmail.com
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Abstract: Recognition of traffic signs is fundamentally a multiclass classification problem that is an essential part of autonomous driving system that aid vehicles recognize and obey road regulations. Due to their power to learn and generalize from data, neural networks have become a useful approach for solving complex problems presented by image classification tasks. Such systems are considered as a major component of an intelligent transportation system which enhances road safety and prevents from potential hazards. In the underlying research study, a customized Convolutional Neural Network (CNN) has been exploited for the categorization of traffic signs based on the German Traffic Sign Recognition Benchmark (GTSRB) dataset. The proposed model integrated with data augmentation and a robust architecture of CNN excels with an overwhelming accuracy of approximately 97% and can easily be deployed in real products like intelligent and automated traffic management systems, road safety solutions and self-driven vehicles etc.

Keywords: Traffic Signs Classification; Advance Driving Assistance Systems; Convolutional Neural Network; Deep Learning;

1. Introduction

Deep learning based advanced models, especially neural networks have significantly transformed the landscape of artificial intelligence and machine learning by providing highly efficient as well as optimal solutions to different intricated problems. Convolutional Neural Networks (CNNs) pioneered by LeCun et al. in their seminal work on gradient-based learning [1] represents a specialized architecture that excels at hierarchical feature extraction from visual data. The structure and functioning of human brain serve as a foundation for the development of neural networks [2] which excel at learning representations of sequential data by allowing them to carry out tasks such as speech recognition, image processing, image detection and natural language processing. The specialized network architecture of CNNs' represents an advanced method to image classification because these networks successfully extract hierarchical as well as spatial features from images.

The autonomous driving system utilizes traffic sign recognition as a means for CNNs to have meaningful applications across different fields. Benchmark studies by Stallkamp et al. [3] established the German Traffic Sign Recognition Benchmark (GTSRB) as the standard evaluation framework, while Ciresan et al., [4] demonstrated unprecedented accuracy using multi-column deep neural networks. Autonomous vehicles use traffic sign recognition as a core requirement in intelligent transportation systems because of its complexity. By identifying and classifying traffic signs accurately these systems incorporate in enhancing road safety, improving the traffic flow and aid to support the development of autonomous or self-driving technologies. The integration of traffic sign recognition into real-world applications underwits the potential of neural networks in addressing challenges faced in the society due to traffic and vehicle driving.

By incorporating the German Traffic Sign Recognition Benchmark (GTSRB) dataset, the paper focuses on the recognition of traffic signs. The primary focus is to develop and evaluate a model based on CNN capable of acquiring high classification accuracy to all across 43 distinct classes of traffic signs mentioned in the dataset. The distinctive contributions of this study include the implementation of an augmented training strategy and a robust CNN architecture has been designed to enhance the generalization as well as handling the imbalances in the class efficiently. This study also highlights a wider analysis of the model's performance also demonstrating its practical applications.

2. Literature Review

Traffic Sign Recognition (TSR) is a critical element of an Advanced Driver Assistance Systems (ADAS) and an intelligent traffic management system that focuses on improving road safety and the flow of traffic on the road. It consists of two primary stages; one is the traffic sign detection i.e localization of signs within an image and the other one is the recognition of traffic sign which is the classification of the detected signs. The accuracy obtained by the detection directly impacts the final recognition. Previously used methods for TSR often relied on handcrafted features like shape, color and texture. However, these techniques and methods can affect easily by environmental factors such as weather conditions, illumination changes, occlusions as well as sign aging [5], [6]. Advanced Neural Networks, particularly CNNs are regarded as an authentic tool to tackle with the challenges faced by automatically learning hierarchical and sequential invariant features from raw pixel data [4].

Different studies through light on the application of CNNs to traffic sign recognition, demonstrating their ability to achieve high accuracy less calculation of the loss. Existing works involved the use of basic CNN architectures like LeNet-5, often modified or improved for the task of TSR. For example, a few numbers of researchers have performed experiments using Gabor kernels as initial convolutional kernels in LeNet-5 [7]. Some researchers have added layers batch normalization after pooling layers or have used different types of optimizers like Adam [8]. However, standard CNN architectures like LeNet-5 and ResNet exhibit critical limitations in real-world deployment. Despite high accuracy in controlled settings, these models lack robustness to environmental conditions like motion blur, lighting variations and weather induced distortions [9],[10] severely restricting their reliability in autonomous driving systems. This shortfall arises because real-world traffic sign images frequently deviate from idealized dataset conditions due to dynamic occlusions patterns, non-uniform illumination changes and perspective distortions during vehicle motion [6],[11].

To explore and investigates the limitations of basic architectures of CNN, recent studies have demonstrated and explored the use of a deeper and more complex CNN models, such as that of a Multi-Column Deep Neural Networks (MCDNNs), which combine various CNNs trained on differently preprocessed data [4]. Additionally, other studies explored and demonstrates how transfer learning can be beneficial in training a CNN for TSR using a small number of standard traffic training examples [12]. Some researchers have often experimented with other CNN architectures e.g. ResNet and Capsule Networks or even combinations of CNNs with different other machine learning models like SVMs or ELMs and with different types of algorithms such as AdaBoost [13, 14]. The YOLO family architecture family which is also known as (You Only Look Once) includes YOLOv3 and YOLOv4, have commonly been adopted in the field of TSR because of their high efficiency and accuracy. e.g., using YOLOv3 [15] and YOLOv4 [16] for real time TSR. Other work is based on previous studies in which synthetic training data generated by GANs is incorporated to improve YOLO for TSR [17]. A few researchers implementing a lightweight version of YOLO like YOLOv4-tiny for embedded and ensemble systems [16]. Moreover, practical versions of YOLO used with alternate tracking algorithms can also be found [18].

A different perspective of the research involves a customized CNN architecture that contains specific modifications and amendments to TSR. For instance, researchers have explored the use of Mask R-CNN detector both for the recognition and detection and have made suitable improvements that enhances the rate of recall, particularly for the detection of small traffic signs [19]. In addition to some researchers have used a customized CNN with multiple outputs in the final neural network layer. It consists of both a regression output for traffic sign coordinates and a classification output for classifying the type of sign [20]. These types of model architectures that are customized have been found with a high performance and high accuracy on complex and intricated datasets with similar categories and low variability among distinct categories [21].

A crucial and necessary element of TSR based on deep learning is obtaining huge and diverse datasets which can be easily represented. Various researchers incorporate the use of German Traffic Sign Recognition Benchmark (GTSRB) as their foundation because this benchmark serves as a standard benchmark for the analysis and evaluation of TSR algorithms [3], [22]. Researchers modify their self-collected real-world datasets using the techniques like geometric mean and the appearance of distortion to enhance the dataset diversity and validation of its effectiveness [8]. Whereas, most of the studies have used a dataset with static images. The evaluation of the TSR models require video testing using scenarios in the real-world on embedded systems which serves for the practical evaluations [23], [24].

In conclusion, the literature on TSR using customized CNN architectures reflects ongoing advancements toward robust and real-time monitoring systems. Progress has been driven by innovations in network architecture, training strategies, and data augmentation methods. The research activities have significant success in attaining impressive accuracy and speed among different datasets. However, further efforts are required to be made to address the challenges associated with real-time application systems. [11], [25].

3. Methodology

This section provides a methodological overview adopted for the development and evaluation of CNN model trained on customized model architecture for the recognition of traffic signs. It sheds light on the dataset used, preprocessing techniques applied, the proposed model architecture, training and the evaluation metrices used. By acquiring a systematic approach, this methodology ensures that the model is both accurate and generalized in the recognition of different varieties of traffic signs. A thorough overview of the methodology is demonstrated in the following section.

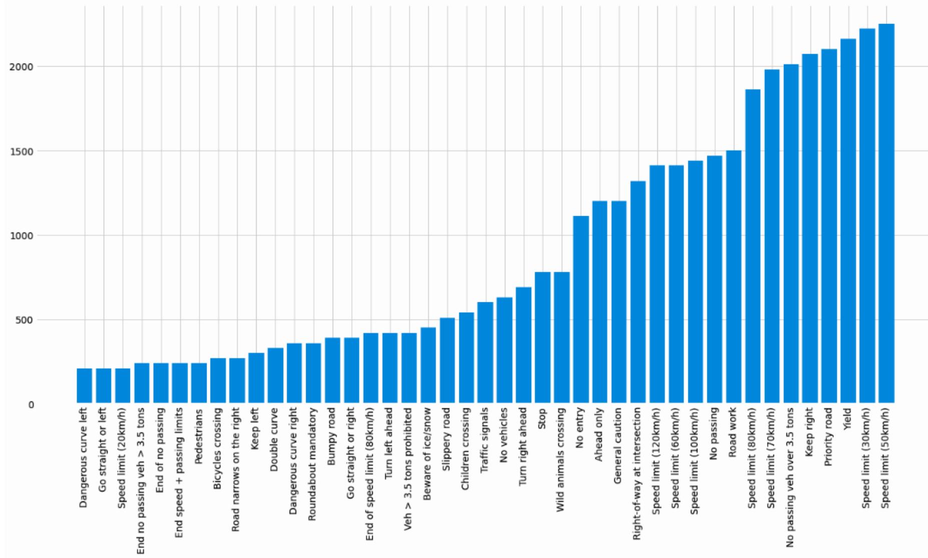
3.1. Dataset and Preprocessing Methods

The dataset used for the study is the German Traffic Sign Recognition Benchmark (GTSRB) [3]. There are 43 distinct classes of traffic signs in the dataset which are comprising a total of 51,839 images. The dataset is splitted into 36,287 training images and 12,630 testing images. The original image dimensions vary between 15 × 15 pixels and 250 × 250 pixels. To ensure the computational efficiency hence preserving important visual features, all images were resized to 30 × 30 pixels with RGB channels, providing compatibility with the model input layer [22]. To overcome the challenges of class imbalance, enhance model generalization and increase the diversity of dataset, different techniques for data augmentation were incorporated. These included zoom (0.2), rotation (±15°), height and width shifts (0.1), shear transformation (0.2) and horizontal and vertical translations. This whole process generates five augmented samples per original image which aid in expanding the effective dataset size to 181,435 samples. Such augmentation mitigates the impact of real-world environmental variations such as illumination shifts, viewpoint changes and partial occlusions that are critical challenges for robust TSR in autonomous driving scenarios [6, 8].

3.2 Dataset Analysis

The dataset encompasses an enormous number of images which are organized into 43 classes in the category of traffic signs. Complex and extensive data augmentation substantially increased the effective dataset size, thereby improving the capacity of the model to generalize with new unseen data. Figure 1 shows the proportion of images distributed across different classes, illustrating the initial imbalance and the manner in which augmentation addressed this disparity.

Figure 1: Dataset Analysis



3.3. Architecture of Model

The proposed model is a sequential CNN model as shown in figure 2 consisting of the layers given below:

- A max-pooling layer (2 x 2) is placed after two convolutional layers (32 filters, 3 x 3 kernel) using the ReLU activation function.
- A max-pooling layer (2 x 2) with further two convolutional layers (64 filters, 3x3 kernel) with ReLU activation function.
- A dense layer consisting of 512 neurons with ReLU activation is placed after the flattening layer.
- To prevent overfitting dropout layer (0.5 rate) is incorporated.
- The output layer is a dense layer with 43 neurons and Softmax activation function for a multi-class classification.

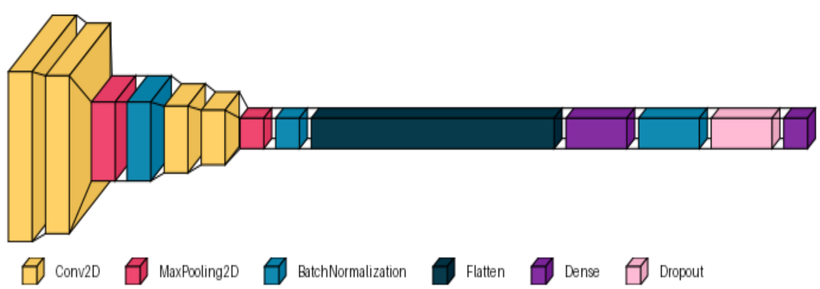


Figure 2: Model Architecture

Adam optimizer is employed in the compilation of the model together with categorical cross-entropy loss with a learning rate of 0.001. Training was conducted on approximately 20 epochs with a batch size of 32 on NVIDIA RTX 3090 GPU (24 GB VRAM), utilizing a total training time of 120 minutes.

The design of this architecture follows the VGG-style convolutional stacking approach [26], but with reduced depth to accommodate low-resolution inputs (30 × 30 pixels), thereby avoiding excessive down-sampling that could degrade small sign features. Alternative architectures, such as ResNet-18 and LeNet-5

[7], were also evaluated but were discarded due to longer computational times and marginal accuracy improvements (<0.5%). The relatively shallow depth of the proposed model ensures computational efficiency for low-resolution inputs while maintaining strong discriminative capability.

3.4. Evaluation Metrics

Standard metrics of classification were used for the performance evaluation of the advocated model, which encompasses the metrices such as Precision, Recall, F1-score and Support, as illustrated in Table 1. A confusion matrix was developed to investigate the possible errors of the model enabling a thorough analysis of the misclassification in the patterns which are shown in Figure 4.

Moreover, the training progress of the undertaken model was evaluated by plotting accuracy, validation accuracy and cross-entropy loss graph over epochs. This graphical representation shows a clear view into the learning dynamics and convergence behavior of the model. The classification reports containing the combined scores of Precision, Recall, and F1-score of all classes is shown in table 1.

Table 1: Classification Report

Class_id	Precision	Recall	F1-score	Support
0	0.79	1.00	0.88	60
1	1.00	1.00	1.00	720
2	0.99	1.00	0.99	750
3	0.96	0.98	0.97	450
4	1.00	1.00	1.00	660
5	0.98	0.99	0.98	630
6	1.00	0.97	0.99	150
7	1.00	1.00	1.00	450
8	1.00	0.97	0.98	450
9	1.00	1.00	1.00	480
10	1.00	1.00	1.00	660
11	0.96	1.00	0.98	420
12	1.00	0.98	0.99	690
13	1.00	1.00	1.00	720
14	1.00	1.00	1.00	270
15	0.99	1.00	0.99	210
16	1.00	1.00	1.00	150
17	1.00	1.00	1.00	360
18	0.99	0.93	0.96	390
19	0.97	1.00	0.98	60
20	0.98	1.00	0.99	90
21	0.83	1.00	0.91	90
22	0.99	0.84	0.91	120
23	0.99	0.99	0.99	150
24	0.97	0.98	0.97	90

25	1.00	0.97	0.98	480
26	0.83	1.00	0.91	180
27	0.86	0.50	0.63	60
28	0.99	0.99	0.99	150
29	0.85	1.00	0.92	90
30	0.99	0.83	0.90	150
31	1.00	1.00	1.00	270
32	1.00	1.00	1.00	60
33	0.99	1.00	1.00	210
34	1.00	1.00	1.00	120
35	0.99	0.98	0.99	390
36	0.98	1.00	0.99	120
37	1.00	0.98	0.99	60
38	1.00	1.00	1.00	690
39	0.99	0.98	0.98	90
40	0.96	0.98	0.97	90
41	1.00	1.00	1.00	60
42	0.99	1.00	0.99	90
Accuracy			**0.98**	**12630**
Macro Avg	0.97	0.97	0.97	12630
Weighted avg	0.99	0.98	0.98	12630

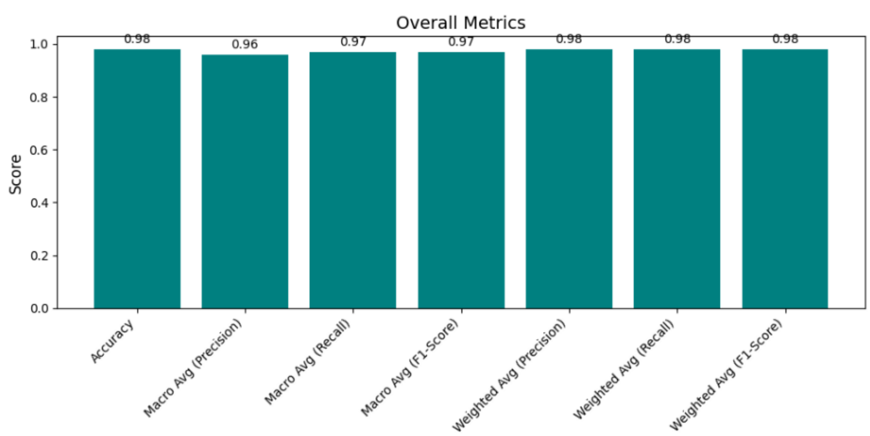


Figure 3: Aggregate performance on metrices (Precision, Recall, F1-score)

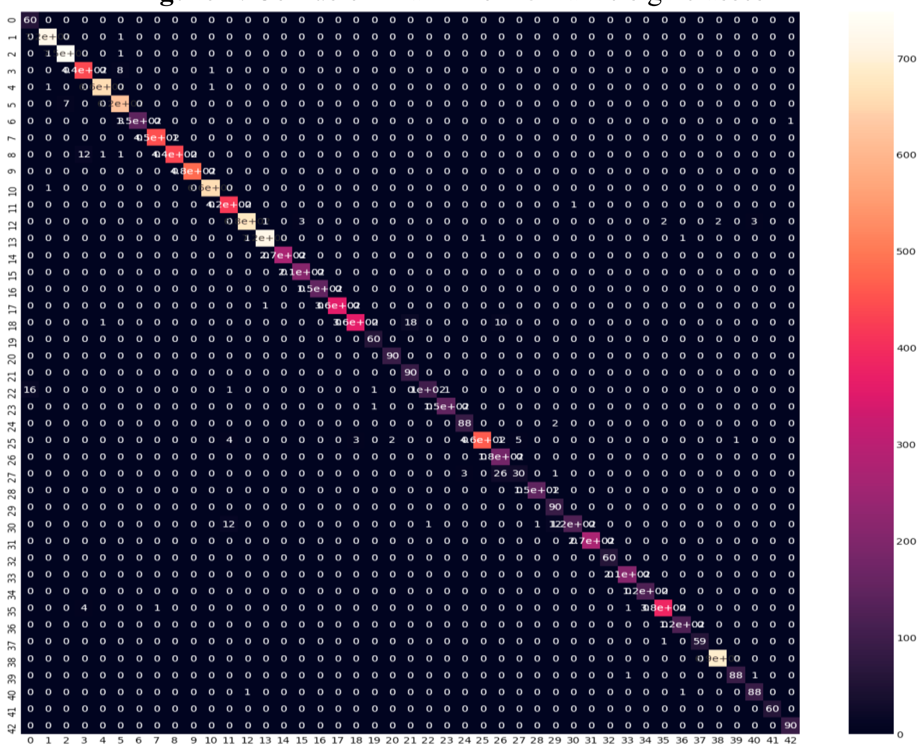
4. Findings and Analysis

In this section, they exhibit the analysis and application of the outcomes of the operations of the CNN model to be outlined in the research they propose to understand different traffic signs. The current section will demonstrate a description of the dataset and its details. It also gives the assessment of the model efficiency with various statistical metrices: precision, recall and F1-score. The accuracy and loss of the model, confusion matrix and comparative analysis to explain effectiveness of model are also displayed in this chapter.

4.1 Model Performance

The proposed model has achieved a maximum accuracy of about 97%. Evaluation metrics are summarized displaying the high recall and precision score across in many of the classes. A confusion matrix analysis as shown in figure 4 reveals that the misclassifications primarily occurred among visually similar signs, like as signs of speed limit with minor variation in numerical values. The confusion matrix as developed after the model training and evaluation and is showed below:

Figure 4: Confusion Matrix for 43 traffic sign classes



4.2. Comparative Analysis

When compared with the existing approaches and techniques, the proposed model exhibits high generalization capabilities and accuracy gains. It outperforms baseline models such as ResNet-34 and YOLOv4-tiny in both accuracy and F1-score. These improvements are largely attributed to the integration of different techniques of data augmentation and the design of a compact yet robust CNN architecture optimized for the task.

The quantitative comparison between the model proposed and existing approaches is illustrated in Table 2 which are provided below:

Table 2: Quantitative Comparative Analysis

Model	Accuracy (%)	F1-Score	Reference
Proposed CNN	97.0	0.96	-
ResNet-34	95.2	0.94	[21]
YOLOv4-tiny	93.5	0.92	[16]

4.3. Visualization

The accuracy and loss curves, as shown in figure 5, demonstrate a consistent improvement across the training epochs, with minimum chances of overfitting. The gradual convergence of both training and validation metrics shows that the model has learned effectively without significant performance degradation on unseen data.

In addition to the performance curves, visualizations of predictions on test images further confirms the capability of the model to correctly distinguishes a huge range of traffic sign categories, including those with challenging visual variations such as illumination changes, occlusions, and scale differences.

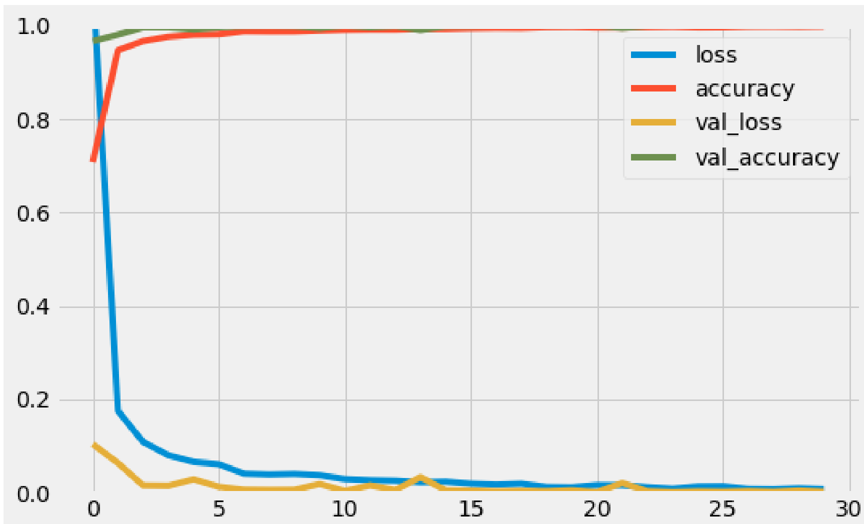
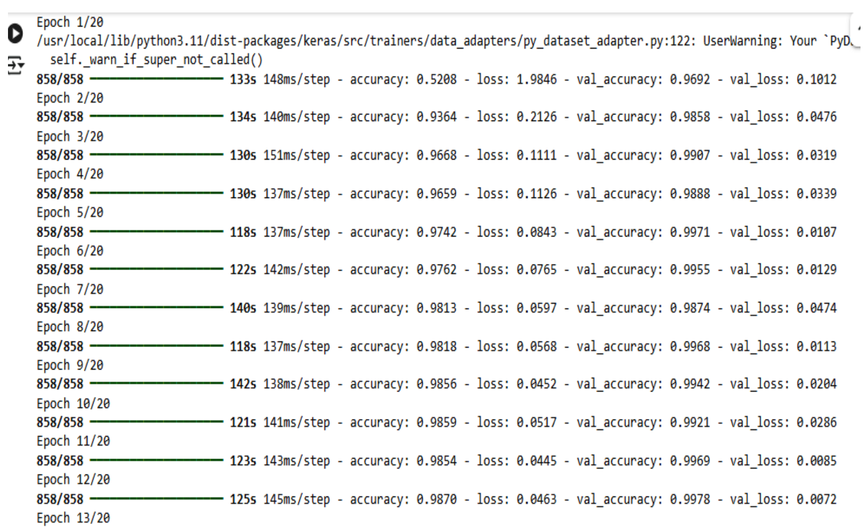


Figure 5: Training and Validation Accuracy and Loss Curves

The variation of validation accuracy and loss over the epochs as presented in Figure 6, providing further evidence of the stable training process and capability of the model for the generalization of the new data.



```
Epoch 1/20
/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:122: UserWarning: Your `PyD
  self._warn_if_super_not_called()
858/858 ━━━━━━━━━━━━━━━━━━━━ 133s 148ms/step - accuracy: 0.5208 - loss: 1.9846 - val_accuracy: 0.9692 - val_loss: 0.1012
Epoch 2/20
858/858 ━━━━━━━━━━━━━━━━━━━━ 134s 140ms/step - accuracy: 0.9364 - loss: 0.2126 - val_accuracy: 0.9858 - val_loss: 0.0476
Epoch 3/20
858/858 ━━━━━━━━━━━━━━━━━━━━ 130s 151ms/step - accuracy: 0.9668 - loss: 0.1111 - val_accuracy: 0.9907 - val_loss: 0.0319
Epoch 4/20
858/858 ━━━━━━━━━━━━━━━━━━━━ 130s 137ms/step - accuracy: 0.9659 - loss: 0.1126 - val_accuracy: 0.9888 - val_loss: 0.0339
Epoch 5/20
858/858 ━━━━━━━━━━━━━━━━━━━━ 118s 137ms/step - accuracy: 0.9742 - loss: 0.0843 - val_accuracy: 0.9971 - val_loss: 0.0107
Epoch 6/20
858/858 ━━━━━━━━━━━━━━━━━━━━ 122s 142ms/step - accuracy: 0.9762 - loss: 0.0765 - val_accuracy: 0.9955 - val_loss: 0.0129
Epoch 7/20
858/858 ━━━━━━━━━━━━━━━━━━━━ 140s 139ms/step - accuracy: 0.9813 - loss: 0.0597 - val_accuracy: 0.9874 - val_loss: 0.0474
Epoch 8/20
858/858 ━━━━━━━━━━━━━━━━━━━━ 118s 137ms/step - accuracy: 0.9818 - loss: 0.0568 - val_accuracy: 0.9968 - val_loss: 0.0113
Epoch 9/20
858/858 ━━━━━━━━━━━━━━━━━━━━ 142s 138ms/step - accuracy: 0.9856 - loss: 0.0452 - val_accuracy: 0.9942 - val_loss: 0.0204
Epoch 10/20
858/858 ━━━━━━━━━━━━━━━━━━━━ 121s 141ms/step - accuracy: 0.9859 - loss: 0.0517 - val_accuracy: 0.9921 - val_loss: 0.0286
Epoch 11/20
858/858 ━━━━━━━━━━━━━━━━━━━━ 123s 143ms/step - accuracy: 0.9854 - loss: 0.0445 - val_accuracy: 0.9969 - val_loss: 0.0085
Epoch 12/20
858/858 ━━━━━━━━━━━━━━━━━━━━ 125s 145ms/step - accuracy: 0.9870 - loss: 0.0463 - val_accuracy: 0.9978 - val_loss: 0.0072
Epoch 13/20
```

Figure 6: Validation Accuracy and Loss by Epochs

4.4. Prediction on Test Data

Sample test predictions as demonstrated in Figure 7, presents a comparison between the actual and predicted labels for the selected test images. These visualizations confirm the ability of the model to correctly distinguishes different traffic signs across multiple categories.

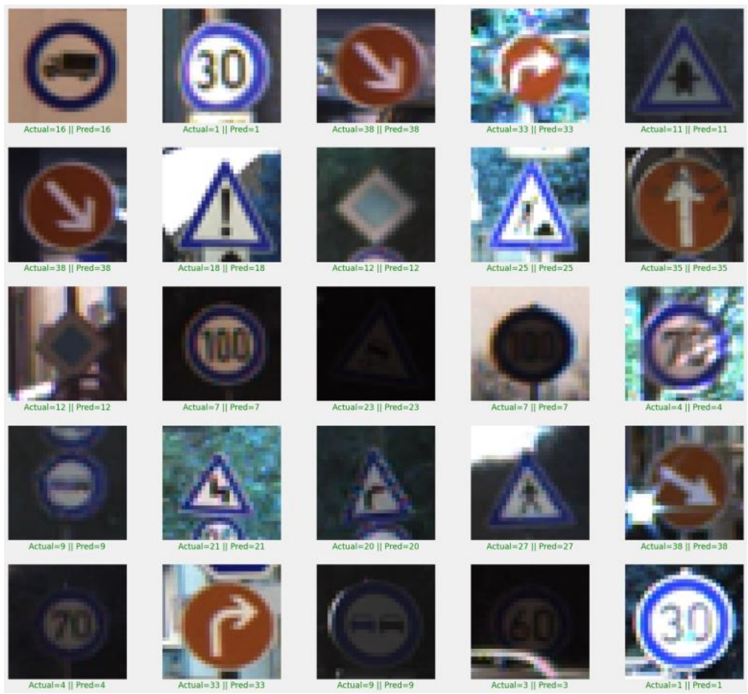


Figure 7: Sample Test Predictions

5. Conclusion

This study demonstrates how effectively Convolutional Neural Networks (CNNs) can act as a robust approach for Traffic Sign Recognition (TSR) using the German Traffic Sign Recognition Benchmark (GTSRB) dataset. The proposed model has achieved a maximum accuracy of approximately 97%, showing its practical potential for deployment in Intelligent Transportation System applications. The research addressed different challenges such as misclassification of visually similar signs by incorporating and class imbalance by incorporating a carefully designed CNN architecture in conjunction with extensive data augmentation techniques. These measures significantly boost the generalization capabilities of model and robustness to real-world conditions. The future research will concentrate on integrating attention mechanisms to further enhance the model's discriminative power and to address persistent misclassification issues in visually similar traffic sign categories. This enhancement is expected to further strengthen the model's applicability in advanced autonomous driving and smart transportation systems.

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Conflicts of Interest: No conflicts of interest are associated with this study.

Data Availability: The data used in this study are publicly available from the German Traffic Sign Recognition Benchmark (GTSRB) dataset.

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