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Research Article

Understanding the Traffic Sign through a Deep CNN Architecture

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Abstract: Accurate traffic sign classification is essential for intelligent transportation systems and automated vehicles to ensure safety and navigation efficiency. Our research showcases a specialized CNN model focused on achieving precision in traffic sign detection, utilizing the GTSRB dataset for training. The model incorporates advanced methodologies, including skip connections and bilinear interpolation, to mitigate issues like image noise and low resolution. Skip connections preserve vital features across layers to prevent information loss during training, while bilinear interpolation enhances image clarity for improved recognition under various real-world conditions. The architecture consists of multiple convolutional and pooling layers optimized for extracting and maintaining detailed features crucial for accurate classification. With these improvements, the suggested model achieves a remarkable accuracy rate of 99.78%, indicating its competence in identifying traffic signs. Additionally, the model was evaluated on the TT-100K dataset and the Traffic Sign Classification dataset, with accuracies of 99.78% and 98.86%, respectively. This precision showcases the strength and flexibility of the model, confirming its reliability in the development of advanced transportation technologies, while highlighting its practical usefulness in real-world traffic monitoring systems. By enhancing the reliability of traffic sign recognition systems, this research addresses current shortcomings and significantly improves the safety of automated vehicles and road users. The results emphasize the potential of innovative computer vision techniques in traffic sign classification, fostering progress in intelligent transportation systems and automated driving technologies. This investigation represents a crucial advancement toward bridging theoretical research and practical implementation, thereby improving the reliability and safety of contemporary transportation networks.

Keywords: ***Computer Vision; Convolutional neural network; GTSRB; Image Processing; Intelligent transportation systems; Traffic sign***

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1. Introduction

A traffic sign is a visual sign placed beside roads and highways to warn, direct, and provide crucial information to cars and pedestrians. Traffic signs communicate directions, limitations, and warnings to drivers through images, characters, and forms with symbolic color schemes. However, when operating a car, drivers may occasionally misread or ignore these indicators. These misconceptions can have a negative effect on road safety and raise the possibility of collisions [1]. According to the survey, light reflection,

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inattention, unidentified problems, and several other causes of serious collisions result in about 1.24 million fatalities and serious injuries from car crashes each year across all age groups and vehicle types [2]. Therefore, accurately classifying the traffic signs is crucial for keeping the peace and reducing road accidents. When discussing intelligent transportation systems, accurately classifying traffic signs becomes even more critical. Autonomous driving systems, which rely on the ability to interpret and respond to traffic signs, must incorporate advanced traffic sign classification methods to operate safely and effectively. So, a key component of smart city plans is autonomous cars [3]. Automated driving systems use cameras to recognize most items, such as traffic lights, routes, specific cars, and traffic police gestures. Cameras installed on the dashboard are a common feature of driver assistance systems and driverless vehicles. These cameras record traffic sign images or videos in real time, which are then incorporated into the car's system and used to train machine learning models [4].

An integral component of Advanced Driver Assistance Systems (ADAS) is the detection of traffic signs. The growing popularity of ADAS and self-driving cars presents an important issue in real-time and precise object detection from road images [5]. Traffic signs, such as stop signs and speed restrictions, may be precisely identified and interpreted by the system, which then alerts the driver or modifies the vehicle's behavior automatically to comply with traffic laws [6]. When it comes to introducing advanced driving technologies and autonomous driving capabilities into its electric cars, Tesla is leading the way in integrating cutting-edge driving systems. Tesla is creating standard innovative approaches to enhance driving efficiency, security, and accessibility by leveraging cutting-edge software and modern technology [6]. In that sector, one of the biggest obstacles is ensuring that the recognition models are adaptable to the different topographies and traffic sign standards found in different nations. There are significant national differences in traffic sign style, color, placement, context, and symbols [7]. Deep learning encompasses artificial neural networks and related multi-layered machine learning techniques, enhancing the model's ability. In the categorization of traffic signs, these models have shown impressive performance [8]. Convolutional Neural Networks (CNNs) are a type of deep neural network that is comparable to the visual processing of human vision and has the capacity to learn more discriminative characteristics [9].

Even though deep learning techniques have made great strides in traffic sign identification, maintaining consistently high classification accuracy is still a major obstacle for practical implementation. Variations in illumination, reflections, occlusions, motion blur, and environmental changes can all have an impact on traffic signs photographed in actual driving situations. In autonomous driving systems, even minor classification errors might have major repercussions. Therefore, in order to reduce misclassification, extremely dependable classification algorithms are needed. Using an additional verification or double evaluation method, in which a secondary model reassesses the predicted traffic sign to increase dependability, is one possible strategy. Because of their powerful feature learning capabilities, CNN-based models can function as a useful secondary evaluation component in this situation. This drives the creation of a strong CNN architecture that can improve the dependability of intelligent transportation systems and give extremely accurate traffic sign classification. This paper therefore aims to design, validate, and analyze a CNN classifier that can serve as a dependable second-opinion evaluator for traffic sign recognition in autonomous driving. The following are the study's primary contributions:

- We designed a CNN model that achieves an impressive accuracy of 99.78% on the GTSRB dataset by testing 12961 images that are completely unseen by the model.
- An in-depth analysis using a confusion matrix validated the model's performance, highlighting its robustness and precision in accurately classifying various traffic sign classes.
- Our model's skip connection used 1x1 convolutions and bilinear interpolation to match spatial dimensions, ensuring accurate feature map alignment before addition.
- The suggested model was further assessed on additional benchmark datasets including the TT-100k and the traffic sign classification dataset, achieving accuracies of 99.78% and 98.86% respectively.
- To enhance real-world testing, security, and efficacy, work with the automotive sector to implement our classification of traffic signs into intelligent transportation systems. Our results highlight CNNs' potential to improve the dependability and safety of autonomous driving systems. In autonomous driving systems, where high classification accuracy is crucial to reduce errors and enhance system safety, this approach enables the model to execute more dependable feature learning and functions as a potential

supplementary evaluation mechanism for traffic sign recognition. To thoroughly evaluate and measure accuracy, we tested our CNN model at different learning rates. Because of this approach, the model could be fully evaluated across various data splits and hyperparameter settings, providing valuable new insight into the optimal conditions for achieving high classification performance for traffic signs.

This is how the paper is structured. In Section 2, relevant researches on traffic sign classification are reviewed and research gaps are highlighted. The study's materials and methods, such as dataset loading, data preparation, batch loading and visualization, system architecture, skip connection, bilinear interpolation, model parameters, training process, and performance evaluation, are presented in Section 3. The experimental findings and assessment of the suggested model are covered in Section 4. The manuscript is concluded in Section 6 after Section 5 describes possible future directions.

2. Related Works

In recent years, several sophisticated deep-learning models have been developed and employed to improve traffic sign classification. These algorithms recognize and classify different traffic signs with great accuracy and dependability by utilizing the power of neural networks. Hamza and Nawal [10] developed four models for traffic sign classification such as CNN, ResNet50, VGG19, and EfficientNetB7 using the GTSRB dataset. Agrawal *et al.* [11] proposed a system that trains and classifies the signs using a deep learning model based on CNNs, which learn from the training images. A dataset called BTSRB was presented by Sayeed *et al.* [12] and contains images that were gathered from Bangladesh. Here, five distinct models were used to classify traffic signs such as CNN, Inception V3, MobileNetV2, ResNet50, and VGG16. However, their dataset contains a small number of images. Hosseini *et al.* [13] suggested a transfer learning-based method for classifying traffic signs using the GTSRB test dataset and they assessed how well their optimized versions of the VGG-16, VGG-19, ResNet50, and EfficientNetB0 performed. Fang *et al.* [14] employed the deep learning model MicroNet-BF using the GTSRB dataset for short-term traffic flow estimation. Using the GTSRB dataset, Haque *et al.* [15] suggested an effective thin deep CNN architecture for traffic sign identification. A two-level detection framework is presented by Wu *et al.* [16]. It is composed of the classification module (CM), which uses the TT100K dataset to categorize the found items for traffic sign detection, and the region proposal module (RPM), which locates the objects. A CNN-based prior enhancement-focused TSDR framework for traffic sign identification from video sequences is proposed by Ahmed *et al.* [17].

On the other hand, if the road sign and the surrounding area are substantially similar, their system cannot detect the sign. Salam *et al.* [18] used three datasets GTSRB, BTSC, and rMASTIF for their tests using CNN models. The outcomes of the trial showed that their CNN-based method works well for all benchmarks. However, their approach's primary drawback is that, in comparison to other cutting-edge designs, the EndOf and Speed subsets recognition accuracy in the GTSRB benchmark is comparatively lower. In the meanwhile, it may still be challenging for humans to categorize the incorrectly labeled images in these subgroups according to their methodology. By utilizing densely linked deconvolution layers with skip connections and obtaining additional context information, Yuan *et al.* [19] present a multi-resolution feature fusion framework design that can learn more potential characteristics for small-size objects. Additionally, a vertical spatial sequence attention (VSSA) module is suggested. Although their model performance is quite low for detecting the traffic sign. Ahsan *et al.* [20] proposed a CNN network for traffic sign detection and identification that uses a single-shot multibox detector (SSD). In contrast to the suggested research, the dataset in this study is much smaller, with only 16 classifications over 62 classes are available. Kherraki *et al.* [21] introduced LTSNet, a lightweight CNN model for traffic sign classification using the GTSRB dataset but it struggles to categorize images with motion blur and poor lighting. A technique for the automated identification and detection of road signs in Bangladesh was introduced by Shahed *et al.* [22] where candidate areas are identified as maximum stable extremal regions (MSERs), that offer a road sign's physical look in various lighting circumstances, by creating a two-channel chromatic normalized picture. However, their approach has problems in identifying images that are both very old and occluded, despite the system's clear competence. Table 1 presents a summary of previous studies along with the research gaps in each.

Table 1. An overview of deep learning techniques for classifying traffic signs

Reference	Proposed Method	Dataset	Research Limitations
Fang *et al.* [14]	MicroNet-BF	GTSRB	Studying deep learning models is essential for real-world applications since urban road sceneries might differ from benchmark images in several ways.
Haque et al. [15]	DeepThin	GTSRB, BTSC	An item is tracked by an algorithm that gives it a unique ID and keeps it that way even as frames come in and out.
Wu *et al.* [16]	YOLOv3	TT100K	Additionally, while trying to identify traffic signals, incorrect detection or classification results might appear somewhere. Still, they can't quite figure out why that is happening.
Hegde *et al.* [23]	CNN	GTSRB	Models with poor performance and overfitting problems were produced throughout the training procedure.
Wan *et al.* [24]	YOLOv3	TT100K	The model produced poor performance and overfitting.
Jin *et al.* [25]	MF-SSD	GTSRB	A comparable limitation carried over from features-based approaches is the inability to simulate complicated urban road settings.
Liu *et al.* [26]	DR-CNN	TT100K	Since urban environments differ, inadequate-quality images are needed to detect and identify traffic signs on highways.

It is clear from the reviewed papers that deep learning models have greatly enhanced the performance of traffic sign classification. Nevertheless, the current literature still has a number of shortcomings. Feature alignment and effective feature fusion within CNN architectures are not well addressed in many research, which primarily concentrate on increasing classification accuracy. Furthermore, other models rely on intricate deep networks, which raise computing costs while only slightly enhancing robustness. Additionally, a number of methods have problems include overfitting, poor performance in complicated road environments, and trouble identifying or categorizing traffic signs in adverse situations like occlusion, lighting fluctuation, and deteriorating picture quality. Additionally, there are frequently few comprehensive evaluation techniques to confirm categorization reliability. In order to overcome these constraints, this work suggests a CNN-based traffic sign classification model that uses bilinear interpolation and skip connections with 1×1 convolution to guarantee correct spatial alignment during feature fusion. This architecture preserves architectural efficiency while enabling the model to learn additional discriminative features. To guarantee dependable and extremely precise traffic sign classification performance, the suggested model is further assessed through comprehensive experiments, including confusion matrix analysis and numerous learning rate assessments.

3. Materials and Methods

3.1. Dataset Loading

The GTSRB dataset is a comprehensive and widely used resource for traffic sign recognition research [33]. It contains 51,389 images of traffic signs across 43 different classes, making it ideal for testing traffic sign classification algorithms. The dataset includes both images and corresponding class annotations, facilitating easy categorization. Renowned in the research community for its accurate representation of real-world traffic sign scenarios, the GTSRB is essential for advancing the field of traffic sign recognition. A substantial image classification dataset like this is crucial to improve road safety through better traffic sign classification. A training set of 39,209 photos and a test set of 12,630 images make up the dataset.

We concatenated the training and test sets in our work to create a combined dataset of 51,839 images. After that, the combined dataset was divided into three sections: 60% for training, 15% for validation, and 25% for testing. The model can acquire significant characteristics and patterns connected to several classifications of traffic signs due to the 60% training section, which offers a considerable number of images. A 15% validation set is used during training to monitor the model's performance and modify hyperparameters without overfitting. In the meantime, a more thorough and objective assessment of the trained model on previously unseen data is carried out using a comparatively larger test set of 25%. When applied to real-world traffic sign recognition scenarios, a bigger testing phase helps guarantee that the reported classification accuracy accurately represents the model's reliability and capacity for generalization. Table 2 displays the distribution of this dataset. The GTSRB dataset used in this study consists of 43 traffic sign classes, each represented by a unique integer label ranging from 0 to 42. These labels correspond to various traffic sign categories such as speed limit signs, warning signs, and mandatory direction signs. The labels are encoded as integer class indices, which is compatible with the model training cross-entropy loss function, as it expects class indices instead of one-hot encoded representations.

Table 2. Traffic sign class distribution in training, testing, and validation sets

Class Number	Class Name	Train Samples	Test Samples	Validation Samples
1	Speed limit (70km/h)	1623	644	373
2	Speed limit (80km/h)	1458	663	369
3	End of speed limit (80km/h)	360	143	67
4	Speed limit (100km/h)	1134	480	276
5	Speed limit (20km/h)	156	68	46
6	Speed limit (30km/h)	1738	747	455
7	Speed limit (50km/h)	1800	747	453
8	Speed limit (60km/h)	1124	457	279
9	Priority road	1650	690	450
10	Yield	1757	693	430
11	Stop	618	274	158
12	No vehicles	542	186	112
13	Speed limit (120km/h)	1095	486	279
14	No passing	1162	516	272
15	No passing veh over 3.5 tons	1650	646	374
16	Right-of-way at intersection	1067	420	253
17	Dangerous curve right	289	99	62
18	Double curve	262	100	58
19	Bumpy road	286	149	75
20	Slippery road	392	163	105
21	Veh > 3.5 tons prohibited	336	148	86
22	No entry	887	381	202
23	General caution	926	413	251
24	Dangerous curve left	167	67	36
25	Children crossing	410	175	105
26	Bicycles crossing	205	86	69
27	Beware of ice/snow	355	154	91
28	Wild animals crossing	629	259	162
29	Road narrows on the right	213	95	52
30	Road work	1161	516	303
31	Traffic signals	504	157	119
32	Pedestrians	173	72	55
33	Go straight or right	323	105	82
34	Go straight or left	168	75	27
35	Keep right	1644	684	432
36	Keep left	239	96	55
37	End speed + passing limits	187	66	47
38	Turn right ahead	501	244	154
39	Turn left ahead	325	129	86
40	Ahead only	906	435	249
41	Roundabout mandatory	290	92	68
42	End of no passing	179	72	49
43	End no passing veh > 3.5 tons	212	69	49
	Total	***31103***	***12961***	***7775***

3.2. Data Preprocessing

The GTSRB dataset contains images with varying dimensions ranging from 15×15 to 250×250 pixels, which can create inconsistencies during model training and negatively affect learning performance. All photos were downsized to a fixed resolution of 64 by 64 pixels in order to solve this problem. This scaling lowers computational cost, guarantees consistent input dimensions for the CNN model, and improves the network's ability to learn spatial information. In addition, resizing helps stabilize the training process and improves model convergence by providing consistent feature representations across all samples. After resizing, the images were converted into tensors and the pixel values were scaled to the range 0,1 using the ToTensor() transformation. Furthermore, the images were normalized using the standard deviation values (0.229, 0.224, 0.225) and mean values (0.485, 0.456, 0.406) for each RGB channel. This normalization step standardizes the input distribution, which improves training stability, accelerates convergence, and enhances the overall classification performance of the CNN model.

3.3. Batch Loading and Visualization

Batch size is an important hyperparameter in deep learning that determines the number of training samples processed simultaneously in a single iteration. In this study, the dataset was loaded using the PyTorch data loader utility, which enables efficient batch processing, automatic data shuffling, and optimized memory management during model training. A batch size of 64 was used consistently for the training, validation, and testing phases to maintain uniform data processing across all stages of model evaluation. To improve model generalization and prevent the model from learning order-based patterns in the dataset, the training data were shuffled at the beginning of each epoch (shuffle=True). In contrast, the validation dataset was loaded without shuffling to ensure consistent evaluation during training, while the test dataset was also shuffled to allow unbiased batch evaluation. The DataLoader utility facilitates efficient data loading and batch management, enabling stable training and faster computation. The batch visualization is also an important step for verifying correct dataset loading and preprocessing. By inspecting batches of images, it becomes possible to confirm the integrity of preprocessing operations, verify that all images are correctly resized to 64 × 64 pixels, and observe the diversity of traffic sign classes within the dataset. In this study, Matplotlib was used to visualize the batch samples. Fig. 1 shows a set of traffic sign images from the first batch of the training data loader, demonstrating the variety of traffic sign categories and confirming that the preprocessing and data loading steps were correctly implemented.

Figure 1. Images from the first batch of a train loader.

3.4. System architecture

The suggested technique uses 64 × 64 pixel images from 43 different classes to provide accurate and dependable traffic sign classification utilizing an improved CNN architecture. Because CNNs can automatically learn spatial hierarchies of features, they perform exceptionally well on image identification tasks. The proposed design leverages this capability by incorporating multiple convolutional blocks for robust classification and efficient feature extraction. Initially, the architecture utilizes two convolutional layers with batch normalization, max pooling, and ReLU activations to generate 32 feature channels. The intermediate block incorporates a skip connection, which allows earlier low-level features to be combined with deeper representations, improving gradient flow and preserving important spatial information such as edges, shapes, and color patterns that are essential for identifying traffic signs. To ensure compatibility between feature maps, the number of channels is changed using a 1x1 convolution layer, while bilinear interpolation is employed to align the spatial dimensions of the feature maps before feature fusion. Bilinear interpolation was selected because it provides smooth up-sampling and preserves spatial consistency while maintaining low computational cost compared to more complex up-sampling techniques. Further convolutional layers, along with batch normalization, max pooling, and ReLU activations, are used in the deeper blocks to extract more complex features, increasing the channel count to 128. The final convolutional block expands the number of channels to 256, enabling the network to capture more detailed and discriminative features before classification. To reduce overfitting and enhance model generalization, the resultant feature maps are flattened and run through fully connected layers with ReLU activation and dropout regularization (dropout rate = 0.5). The final output layer produces logits corresponding to the 43 traffic sign classes, enabling accurate classification. The suggested architecture's scalability and flexibility make it simple to adapt to other traffic sign datasets or image resolutions by modifying the input dimensions and the number of output classes in the final layer. The structural processing steps of the suggested CNN architecture are illustrated in Fig. 2.

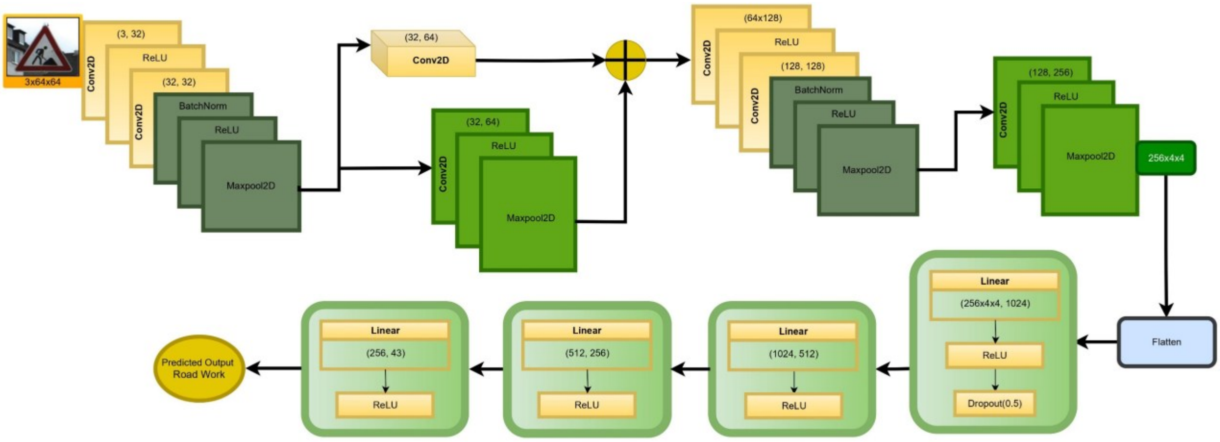

Figure 2. Proposed CNN-based system architecture for traffic sign classification incorporating skip connections and bilinear interpolation.

3.5. Skip Connection

The training dynamics and gradient flow are improved by implementing a skip connection. After a 1x1 convolution to match the number of channels, the output of the first block is upsampled to fit the dimensions of the output of the second block. Bilinear interpolation is used during the upsampling process to align the spatial dimensions (height and width) of the feature maps before they are combined through the skip connection. To improve information flow and model performance, this converted and upsampled feature map is subsequently incorporated into the output of the second block. That is fed into the third block and the equation is given by

$$y_{output} = MaxPool\left(ReLU\left(BatchNorm\left(Conv_{128\to128}\left(ReLU\left(Conv_{64\to128}(y_{combined})\right)\right)\right)\right)\right) \quad (1)$$

Where,

$y_{combined} = y_{second} + y_{upsample}$

$y_{upsample}$ = upsampled output of the first block.

y_{second} = output of the second block.

In a neural network, the output of one layer acts as the input for the subsequent layer without skipping connections. On the other hand, a skip connection allows the input of one layer to be added straight to the output of a different layer. This facilitates the preservation of the data and helps the network understand the identification function.

3.6. Bilinear Interpolation

Bilinear interpolation is a method for two-dimensional interpolation on a rectangle. If you know the value of a function at each of the rectangle's four corners, you may use an interpolation approach to estimate the function's value at any point inside the rectangle. The average of the data at each corner of the rectangle is used in the bilinear interpolation method. For a (x, y) position inside the rectangle, the weights are determined by measuring the distance between the point and the corners. The corner's weight increases as it reaches its peak**.** In image processing, bilinear interpolation is commonly used for image resizing or feature map scaling because it produces smooth transitions between neighboring pixels and avoids abrupt changes in pixel intensity. In this study, bilinear interpolation is used to modify feature map's spatial dimensions before combining them through the skip connection. This helps preserve the spatial structure of the features and reduces distortion that may occur during scaling, thereby improving the quality of the model input and supporting more accurate feature learning in the CNN architecture. Specifically, it is used to upsample feature maps from deeper layers so that their spatial dimensions match those of the corresponding feature maps from earlier layers. This alignment enables effective fusion of feature maps through the skip connection mechanism, allowing the model to combine low-level spatial information with high-level semantic features during the learning process.

3.7. Model Parameters

The proposed CNN architecture involves extensive use of parameters to ensure that the network can extract complicated features from the input data. Convolutional layers, batch normalization, fully connected layers, and skip connections work together to give the model high precision in the classification of traffic signs. Reliable training and avoiding overfitting may be achieved by carefully controlling these parameters using methods like batch normalization and dropout. By normalizing the feature distributions across mini-batches, batch normalization speeds up convergence and enhances training stability, which aids in stabilizing the learning process. Additionally, by periodically turning off a subset of neurons during training, dropout serves as a regularization strategy that lowers the danger of overfitting by preventing the network from depending too much on certain characteristics. The overall internal parameters value of our proposed model is 5410187. Table 3 shows our suggested CNN architecture's thorough parameter analysis.

Table 3. Comprehensive parameter analysis of the proposed CNN model

Layer Name	Shape	Parameters
Convolutional 2D	(input channels=3, filter size=32, kernel size=(3, 3))	896
Convolutional 2D	(input channels=32, filter size=32, kernel size=(3, 3))	9248
Batch Normalization	(filter size=32)	64
MaxPooling 2D	(filter size=2)	0
Convolutional 2D	(input channels=32, filter size=64, kernel size=(3, 3))	18496
MaxPooling 2D	(filter size=2)	0
Convolutional 2D	(input channels=32, filter size=64, kernel size=(1, 1))	2112
Convolutional 2D	(input channels=64, filter size=128, kernel size=(3, 3))	73856
Convolutional 2D	(input channels=128, filter size=128, kernel size=(3, 3))	147584
Batch Normalization	(filter size=128)	256
MaxPooling 2D	(filter size=2)	0
Convolutional 2D	(input channels=128, filter size=256, kernel size=(3, 3))	295168
MaxPooling 2D	(filter size=2)	0
Fully Connected	(filter size=1024)	4195328
Dropout Layer (p=0.5)	(filter size=1024)	0
Fully Connected	(filter size=512)	524800
Fully Connected	(filter size=256)	131328
Fully Connected	(filter size=43)	11051

3.8. Training

For image classification problems, our suggested CNN model's training procedure is specially developed. As a result, this model is composed of many convolutional blocks and a fully linked classifier. The two primary stages of the training loop are validation and training. The model uses the Adam optimizer to adjust its parameters as iteratively goes through batches of training data, making predictions and backpropagating the error. Training loss and accuracy metrics are monitored and kept a record of. Similarly, generalization skills are assessed during validation by analyzing the model's performance on a different dataset. During training, a model check pointing strategy is employed, where the model with the highest validation accuracy is saved to prevent performance degradation and reduce the risk of overfitting. This approach ensures that the best-performing model is retained for final evaluation. A history object captures important metrics during training, making performance monitoring and visualization easier. These metrics include training and validation accuracy as well as loss. The visual representation of accuracy and loss to the 50 epochs is displayed in Fig. 3.

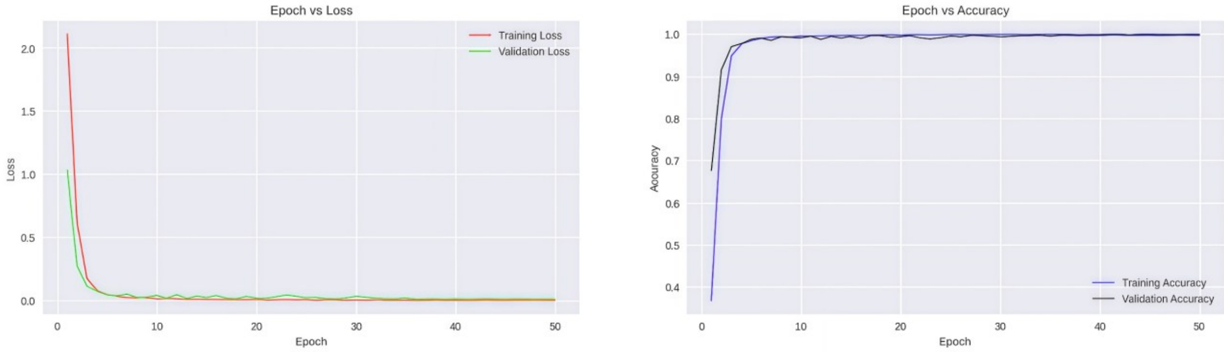

Figure 3. Visualization of loss and accuracy through training epochs.

3.9. Assessment of Performance

A range of metrics are used to evaluate the trained models' performance to make sure they are efficient at identifying traffic signs. This section describes the primary metrics used in the assessment process.

Accuracy: The proportion of accurate predictions the model generates among all forecasts is known as accuracy. It provides a straightforward yet thorough statistic for determining how well the model performs in the categorization job. The expression of accuracy is:

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \quad (2)$$

F1-Score: The F1-Score, which is the harmonic mean of recall and accuracy, is a statistic that offers a balance between the two. When evaluating models on imbalanced datasets, when accuracy and recall by themselves might not provide a clear picture, it is very helpful. The expression of F1 score is:

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} \quad (3)$$

Precision: Precision indicates the percentage of accurate positive predictions out of all the positive predictions the model makes. It shows how well the model predicts a certain class. The expression of precision is:

$$Precision = \frac{True\ Positives(TP)}{True\ Positives(TP) + False\ Positives(FP)} \quad (4)$$

Recall: The percentage of real positive cases that the model accurately detects is known as recall. It indicates the model's capacity to capture all pertinent instances of a certain class and is sometimes referred to as sensitivity or the true positive rate. The expression of recall is:

$$Recall = \frac{True\ Positives(TP)}{True\ Positives(TP) + False\ Negatives(FN)} \quad (5)$$

4. Results and Discussion

4.1. Results

Computer vision and deep learning methods such as traffic sign classification are vital to recognizing and classifying traffic signs from images or video streams in real-time. The potential of advanced driver assistance systems (ADAS) and autonomous vehicles to comprehend and react correctly to traffic signs is made possible by this technology, improving road safety and adherence to traffic laws. Our research uses the GTSRB dataset, which includes over 50,000 images categorized into 43 classes, to identify traffic signs.

To extract and analyze data hierarchically, we used a CNN architecture with convolutional layers, batch normalization, max-pooling, and ReLU activations. Furthermore, robust performance is ensured by classifier layers with dropout that avoid overfitting and skip connections that enhance feature maps by upsampling. The model encounters completely unseen data during testing. That's why the model achieved high accuracy during the traffic sign classification task. To evaluate the performance of our proposed model, we conducted experiments with variations in the learning rate parameter. The initial configuration yielded an accuracy of 99.78%. Subsequently, upon adjusting the learning rate, we observed a little decline in accuracy, with the model achieving 99.71%. The tabulated results below in Table 4 illustrate the comparative performance of our model under these distinct learning rate settings. This analysis provides insights into the sensitivity of the model's performance to variations in hyperparameters, thereby informing potential optimization strategies for enhancing classification accuracy in traffic sign recognition tasks.

Table 4. Evaluation of model performance with different learning rates

	Learning rate	**Accuracy**	**Precision**	**Recall**	**F1 score**
Proposed model	0.0001	0.9978	0.9978	0.9978	0.9978
	0.001	0.9971	0.9972	0.9971	0.9971

The TT100K dataset, which comprises 63,185 images across 50 classes, and the Traffic Sign Dataset - Classification, which comprises 6,164 images across 58 classes, are two more benchmarks available on Kaggle that were used in a thorough evaluation to further validate the efficacy of the proposed architecture. To evaluate the trained model's ability for generalization, it was first tested directly on these datasets. However, direct evaluation was unable to produce trustworthy results because of variances in class definitions and differences across the dataset's label sets. As a result, the suggested architecture was retrained independently for every dataset before being assessed on the corresponding test sets. The model demonstrated good performance and robust feature learning across datasets with diverse distributions and class structures, achieving accuracies of 99.78% on the TT100K dataset and 98.86% on the Traffic Sign Dataset - Classification.

4.2. Discussion

The effectiveness of several models on traffic sign classification tasks has been thoroughly studied in recent research, which has shown substantial variance in dataset sizes and accuracy levels. On the GTSRB dataset, Prakash and Sruthy [27] utilized DenseNet-121 and obtained an accuracy of 98.32%, whereas Krishna *et al.* [7] used a CNN and obtained an accuracy of 97.3%. Malhotra *et al.* [29] achieved 98.2% accuracy using a CNN on GTSRB. The best accuracy on GTSRB was obtained by Bhatt *et al.* [31] using a CNN at 99.85%, and Bangquan and Xiong [32] with an accuracy of 98.6% using E-Net. Conversely, Zaibi *et al.* [28] used LeNet-5 on BTSD with an accuracy of 98.37%, while Rani *et al.* [30] created the DLHR-TSDR model on the CURE-TSD dataset, achieving 99.01%. Utilizing the COCO dataset, Hegde *et al.* [23] attained 90% accuracy with a CNN. By comparison, our suggested approach achieves an impressive 99.68% accuracy using a CNN architecture that has been optimized for the GTSRB dataset. By beating earlier models and creating a new standard in the area, this much better performance demonstrates the stability and effectiveness of our method for correctly categorizing traffic signs. Our findings show not only how good our model is, but also how crucial it is to optimize neural network designs and hyperparameters for certain datasets to get the best results. The difference in traffic sign classification performance between our suggested CNN model and current approaches is seen in the following Table 5.

Table 5. Comparative performance of traffic sign classification methods

Reference	Model	Dataset	Accuracy
Krishna *et al.* [7]	CNN	GTSRB	97.3%
Hegde *et al.* [23]	CNN	COCO	90%
Prakash *et al.* [27]	DenseNet-121	GTSRB	98.32%
Zaibi *et al.* [28]	LeNet-5	BTSD	98.37%
Malhotra *et al.* [29]	CNN	GTSRB	98.2%
Rani *et al.* [30]	DLHR-TSDR	CURE-TSD	99.01%
Bhatt *et al.* [31]	CNN	GTSRB	99.85%
Bangquan and Xiong [32]	E-Net	GTSRB	98.6%
Proposed method	**CNN**	**GTSRB**	**99.78%**

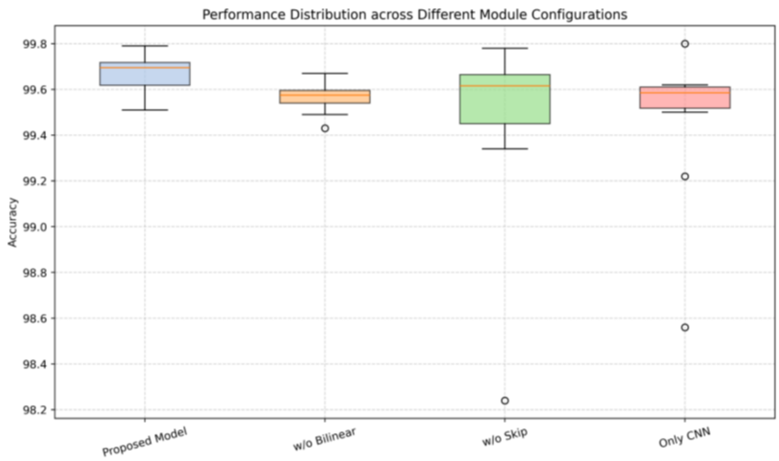

Figure 4. Box plot–based statistical analysis of classification performance across different CNN module configurations, highlighting the impact of skip connections and bilinear interpolation on model accuracy and stability.

The better robustness of the suggested model over the ablated variations is demonstrated by the statistical distribution of the accuracy across 10 independent runs, as shown in Fig. 4. However, there are a number of outlier data points in the ablated designs that perform noticeably worse than average. The suggested model keeps the distribution compact and free of outliers. In particular, the 'w/o Skip' and 'Only CNN' variations exhibit performance deterioration as low as 98.24% and 98.56%, indicating that these architectures are more vulnerable to training instability. On the other hand, the lack of outliers in the suggested model shows that the combination of CNN, skip Connections, and bilinear interpolation successfully stabilizes the learning process, guaranteeing consistently high accuracy and reducing the possibility of suboptimal convergence.

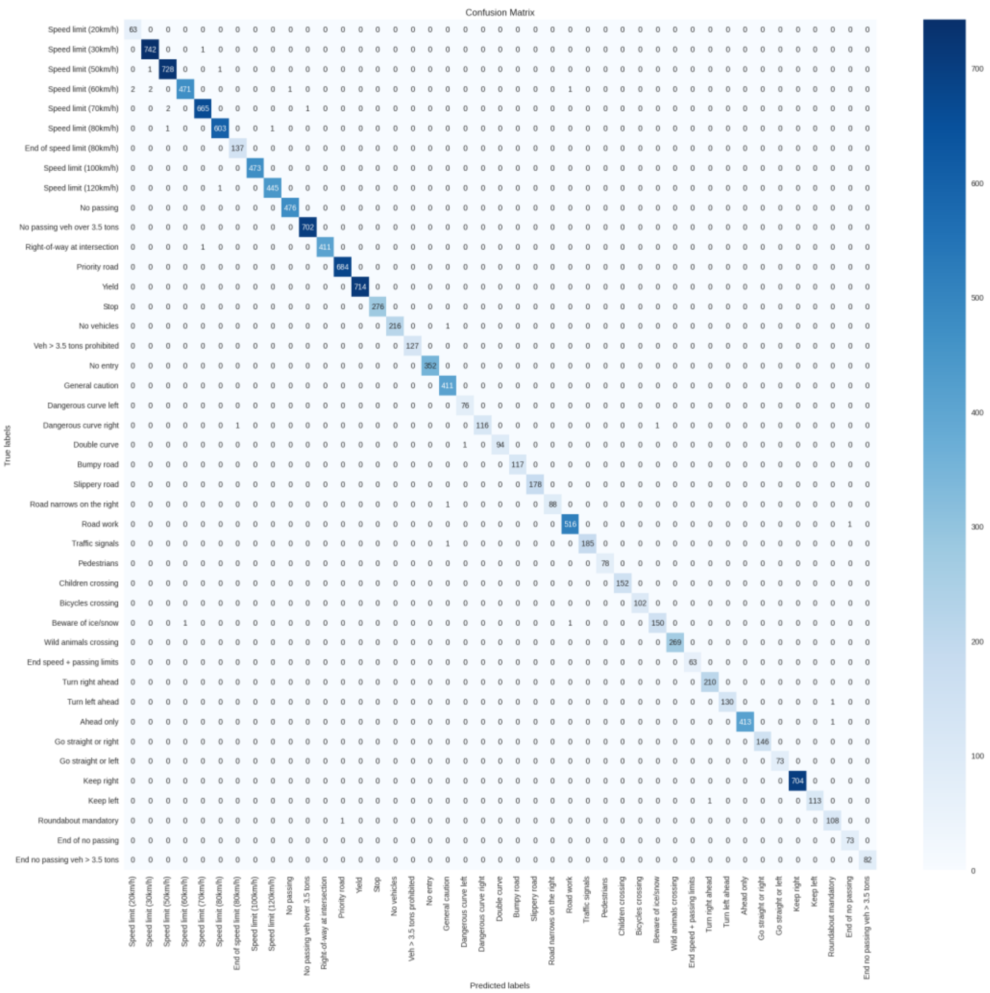

Figure 5. GTSRB dataset confusion matrix using CNN.

When the suggested model was first trained and assessed on the German Traffic Sign Recognition Benchmark, it demonstrated a strong capacity to classify traffic signs with a high accuracy of 99.78%. The model was further assessed on two other datasets, TT100K and Traffic Sign Dataset-Classification, to further investigate the architecture's resilience and capacity for generalization. With 99.78% accuracy on TT100K and 98.86% accuracy on the Traffic Sign Dataset-Classification, the suggested method continued to perform exceptionally well. The model's ability to manage differences in traffic sign distributions, image circumstances, and class structures is demonstrated by its consistently excellent performance across several datasets. This illustrates the suggested architecture's robustness and excellent generalizability. Moreover, because of its effective CNN architecture, the model may be used in conditions with low computational resources, like embedded devices or TinyML-based applications, where obtaining high accuracy is crucial.

We used a confusion matrix to examine the performance of our suggested model in addition to reporting overall accuracy. This matrix offers a comprehensive evaluation of the model's predictions across various traffic sign classes, allowing us to evaluate both accurate and inaccurate classifications. The diagonal elements of the matrix represent correct predictions, whereas the off-diagonal elements indicate misclassifications. To analyse these elements that enable us to understand the model's strengths and limitations in differentiating between different traffic sign categories. Identifying such patterns is helpful to enhance the model and enhancing its accuracy and robustness in real-world applications, as illustrated by the confusion matrix presented in Fig. 5. Furthermore, the interpretability of the suggested model is demonstrated through Grad-CAM analysis on the GTSRB dataset, as shown in Fig. 6, which highlights the specific regions of traffic signs that most influence the classification decisions. The generated heat maps reveal that the model consistently focuses on fundamental semantic features, such as geometric boundaries and numerical values, ensuring that predictions rely on relevant visual cues even under challenging conditions such as low visibility or fog.

Figure 6. Grad-CAM interpretability analysis on the GTSRB dataset, highlighting the important regions of traffic sign images that contribute to the model's predictions.

As a result, we used the GTSRB dataset, which has over 50,000 images in 43 distinct categories. The images vary in quality, which can sometimes cause our methodology to make inaccurate predictions. Despite this difficulty, the model showed remarkable accuracy. Enhancing the dataset's quality may also improve the model's performance by reducing the likelihood of incorrect classifications. Fig. 7 illustrates how our model's predictions are affected by image quality.

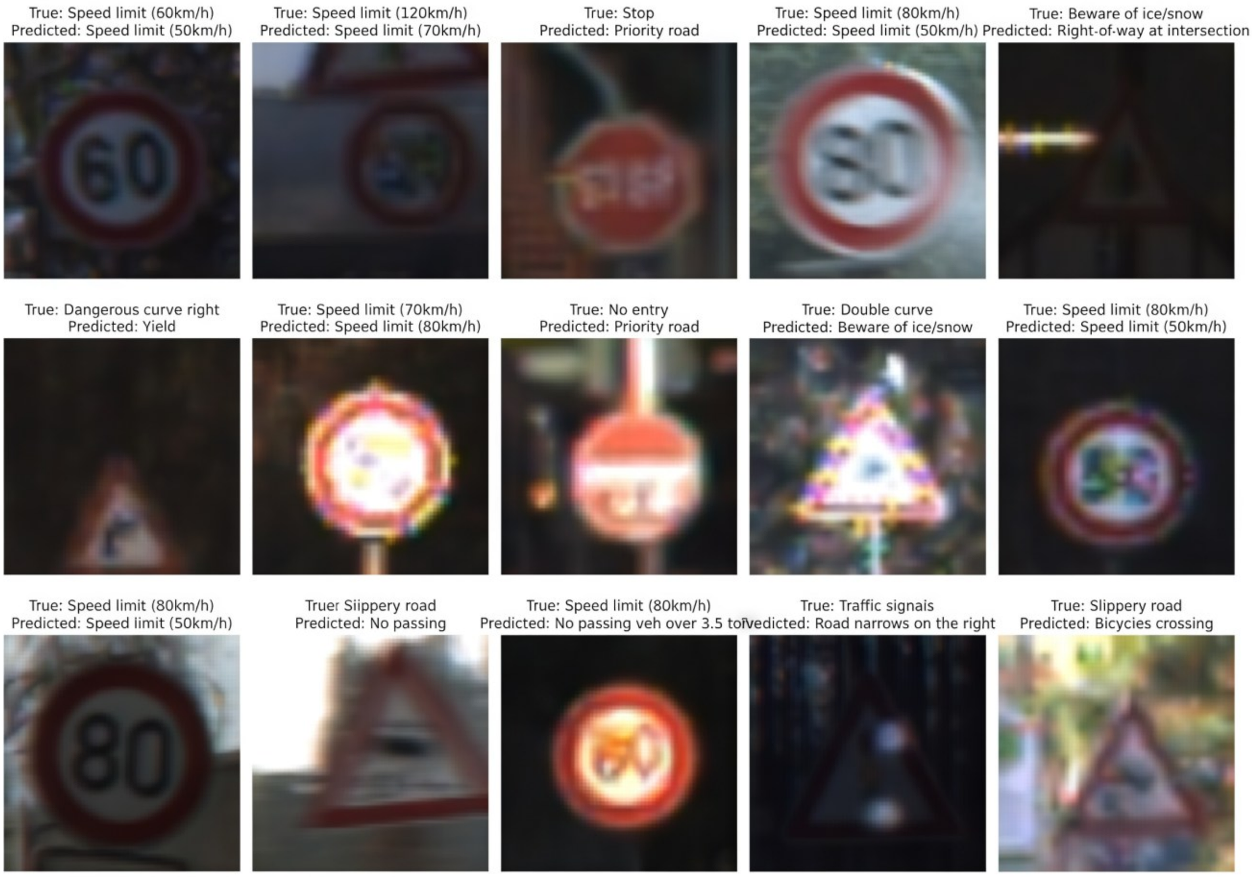

Figure 7. Analysis of misclassification based on our model's predictions.

5. Future Work

Future advancements in traffic sign classification are likely to focus on enhancing dataset quality by addressing issues such as noise, blur, and low resolution through advanced preprocessing techniques, which can significantly improve model performance. Additionally, employing sophisticated data augmentation strategies will enable the model to generalize more effectively to varied real-world conditions. To ensure robustness and generalizability, it is essential to validate the model on external traffic sign datasets from different countries or regions, evaluating its effectiveness across diverse traffic sign designs and standards. Collaborating with automotive industry partners to integrate the traffic sign classification system into intelligent transportation systems will facilitate real-world testing and validation, ultimately improving overall vehicle safety and navigation efficiency.

6. Conclusion

This study concluded by proposing an effective framework for classifying traffic signs using convolutional neural networks (CNNs). In order to optimize feature propagation and increase network stability during training, the model incorporates skip connections with bilinear interpolation. With an accuracy of 99.78% on the GTSRB dataset, the suggested design proved to be very capable of reliably identifying different types of traffic signs. The model can manage fluctuations in traffic sign images and maintain consistent performance because to the combination of the intended CNN structure and suitable preprocessing procedures. Additionally, the use of skip connections in conjunction with bilinear interpolation enhances model robustness and consistent feature learning, both of which are critical for obtaining accurate classification outcomes. The suggested model's efficacy indicates that it can be incorporated into Advanced Driver Assistance Systems (ADAS), where safe vehicle operation depends on precise traffic sign recognition. To enhance the dependability of traffic sign identification in intelligent transportation environments, the suggested method can specifically assist double evaluation procedures in ADAS systems, offering an extra layer of verification.

CRediT Author Contribution Statement

Naima Islam: Conceptualization, Methodology, Software, Data curation, Visualization, Writing – original draft, Writing – review & editing; Sajeeb Kumar Ray: Methodology, Software, Formal analysis, Visualization, Project administration, Writing – review & editing; Md Mynoddin: Methodology, Investigation, Validation, Writing – review & editing; Md. Tofael Ahmed: Methodology, Investigation, Validation, Writing – review & editing; Md. Zahid Hasan: Methodology, Validation, Visualization, Writing – review & editing; Sheikh Mohammad Jawad: Methodology, Validation, Visualization, Writing – review & editing; Md. Anwar Hossain: Methodology, Investigation, Supervision, Writing – review & editing.

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Conflicts of Interest

The authors declare no conflict of interest.

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