ROAD SIGN DETECTION USING CONVOLUTIONAL NEURAL NETWORK (CNN)

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Abstract - *Automated tasks have simplified practically everything we perform in today's world. Drivers often miss signage on the side of the road in an effort to focus on the road, which can be dangerous for them and others. This issue may be avoided if there was a quick way to alert the driver without requiring them to divert their attention. Road sign detection is critical for autonomous driving, traffic monitoring, and traffic safety. In this paper, we suggest a method for detecting and recognising road signs that uses Convolutional Neural Networks (CNN) for sign recognition. Because CNNs have a high recognition rate, they are ideal for a variety of computer vision tasks. For the CNN's implementation, TensorFlow is employed. In both training and testing, we achieved greater than 95% recognition accuracies for signs on the GTSRB data sets.*

Key Words: **GTSRB, CNN, Tensorflow, Computer vision**

1. INTRODUCTION

Expert systems, such as traffic assistance driving systems and automatic driving systems, rely heavily on traffic sign detection and recognition.

It rapidly aids drivers or automated driving systems in detecting and effectively recognising traffic signs.

The two basic categories of road traffic signs are main signs and auxiliary signs. Warning signs, prohibition signs, mandatory signs, guiding signs, tourist signs, and road construction and safety signs are among the most common types of signage. Prohibition signs were the most common, and they were used to prohibit 43 different types of activity. Near the intersection, mandatory signs identify the function of vehicles that are put in the need to indicate vehicles. The purpose of a warning is to advise vehicles and pedestrians to be aware of potentially harmful situations. There are 45 different categories of targets. In traffic signs,they all play a vital function. The most common speed limit signs, as well as the restriction of left and right turning signals, are extremely important for safe driving and are thus the subject of current traffic sign recognition study. It is a computer vision technique for locating and identifying items in an image or video stream. Despite the fact that the picture of the objects may vary somewhat in different view-points, in many different sizes and scales, or even when they are translated or rotated, humans can recognise a large number of things in photos with minimal effort. Even when partially obscured from view, objects can be recognised. We have presented a more accurate and robust approach for the automatic detection and recognition of traffic signs in a variety of challenging settings and interruptions. The suggested system employs Convolutional Neural Network (CNN) architecture to learn features from traffic sign images automatically. The built system is put to the test with the German Traffic Sign Recognition Dataset (GTSRB), which contains a massive collection of traffic sign images divided into 43 categories.

2. LITERATURE SURVEY

"Evaluation of Robust Spatial Pyramid Pooling Based on Convolutional Neural Network for Traffic Sign Recognition System," by Chirstinedewi et al (2020). Due to the lack of a database or study infrastructure for Taiwanese traffic sign identification, this work concentrates on Taiwan's prohibitory sign. The mean average precision (mAP), workspace size, detection time, intersection over union (IoU), and the number of billion floating-point operations are all important variables to examine while observing and evaluating particular models (BFLOPS).

Hongwei Dong and colleagues (2019) suggested a design for "Densely Connected Convolutional Neural Network Based Polarimetric SAR Image Classification," a revolutionary classification method for polarimetric SAR images based on a new deep learning methodology called Dense Net. To achieve polarimetric SAR image classification, a 20-layer Dense Net (with 3 dense block and 2 transition layers) is created. While automatically extracting high-level features and performing pixel-wise multi-class classification, the suggested method effectively prevents gradient disappear and overfitting by reuse.

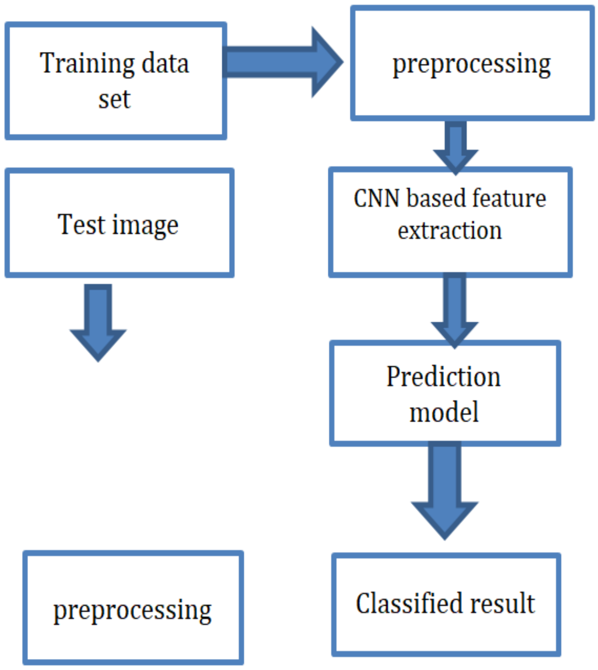
GulcanYildiz and Bekir Dizdaroglu developed a design for "Traffic Sign Recognition through Transfer Learning Using Convolutional Neural Network Models" (2020). The ImageNet database was used to run the processes on pre-trained convolutional neural network models. Then, for 10 classes in the GTSRB database, the recognition process was carried out. VGG19, Res Net, Mobile Net, and Xception are the models employed in this study. When the results are compared, it is clear that the Mobile Net model achieves the highest accuracy value.

Vaibhav Swaminathan and colleagues (2019) suggested a revolutionary "Autonomous Driving System with Road Sign Recognition Using Convolutional Neural Networks." This entails appropriately identifying, classifying, and responding to traffic signs that an automated vehicle may encounter. In this study, an attempt is made to construct such a system by employing image recognition to record traffic signs, correctly classifying them using a Convolutional Neural Network, and responding to them in real-time via an Arduino-controlled autonomous automobile. Various experiments were conducted using the Belgium Traffic Signs dataset to examine the performance of this traffic sign recognition system, and this approach attained an accuracy of 83.7 percent.

Traffic Sign Detection Using Template Matching Technique" was given by Pranjali Pandey and Ramesh Kulkarni (2018).Along the side of the road, there are traffic signs. The system selects and learns the object of interest, a traffic sign board, and then detects where the Region of Interest is in the form of a green-yellow bounding box. The system gets notified when the item reappears, that is, after the current frame has passed. The output is given both in audio as well as in display message format. This mix of outputs allows the driver to maintain vigilance.

3. BLOCK DIAGRAM

Images from a labelled training dataset are first subjected to a series of preprocessing procedures, after which the processed images are sent to a CNN architecture, which learns the features from the images automatically. The learnt model is then saved for testing, during which unlabeled test images are preprocessed and sent to the model for classification.



4. DATASET IDENTIFICATION

We used the GTSRB dataset from Kaggle for our study.

One directory per class containing one CSV file with annotations ("GT-ClassID>.csv") and the training images grouped by tracks containing 30 images of one single physical traffic sign

The German Traffic Sign Recognition Dataset (GTSRB) is an image classification dataset with images of traffic signs containing 43 different traffic sign classes containing 39,209 labeled images and 12,630 unlabeled images.

5. PREPROCESSING

Image preprocessing refers to a set of procedures for formatting images in order to turn them into a format that can be utilized to train the learning model. Both training and test sets are subjected to these preprocessing processes. To prepare picture data for model input, preprocessing is required.

The fully connected layers in a CNN architecture, for example, demand that all of the images be of the same size arrays. The preprocessing phases in our suggested system are as follows:

Splitting the train set for validation and resize the image

Encoding done in single step

6. RESIZING OF IMAGES

Because neural networks receive inputs of the same size, resizing is necessary. As a result, all images must be resized to a consistent size. The time it takes for the learning algorithm to learn can be considerably decreased if the photographs are shrunk to a smaller size. All of the photographs in our system are reduced to a resolution of 30 X 30 pixels.

7. TRAIN-TEST SPLIT

The separation of the training data set into train and validation data sets is the second stage in the preprocessing. The accuracy of the learning algorithm can be validated before moving on to the real testing phase by using a fraction of the training data for validation. This stage is primarily used to check for data overfitting. In our approach, we examine 20% of the training dataset for validation

8. ONE-HOT ENCODING

Categorical data consists of variables with label values rather than numeric values. Many machine learning algorithms are unable to operate directly on label data. They demand that all input and output variables be numeric. One-hot encoding is a common technique that works well unless the category values include a significant number of variables. One hot encoding generates new binary columns, one for each potential value from the original data. One-shot encoding in action

Label Encoding	
Label	**Category**
Red	1
Blue	2
Green	3
Yellow	4
Yellow	4

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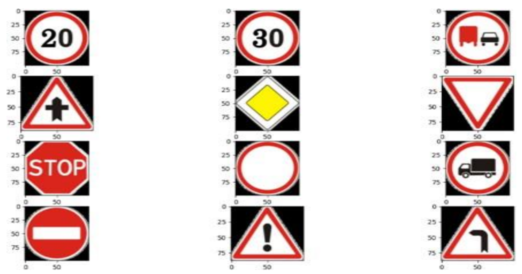
One-Hot Encoding			
Red	**Blue**	**Green**	**Yellow**
1	0	0	0
0	1	0	0
0	0	1	0
0	0	0	1

9. RESULTS AND DISCUSSION

In our project preprocessing is important role in the dataset. Preprocessing is used to read and resize the image to improve the quality of the image We have a GTSRB dataset in this data set we have 39209 images in these images are in different dimensions. So, we resize the dataset images dimension of 30x30x3 for our convenience.

Resizing image	Dimension 30x30
Total images	39209
Training validation images	80%=26579
Testing validation images	20%=12630

RESIZED IMAGES



LAYER(TYPE)	OUTPUT SHAPE	PARAM#
conv2d (Conv2D)	(None,26,26,32)	2432
conv2d_1(Conv2D)	None,22,22,32)	25632
(MaxPooling2D)	(None,11,11,32)	0
dropout_1(Dropout)	(None,3,3,64)	0
flatten(Flatten)	(None, 576)	0
dense(Dense)	(None, 256)	147712
dropout_2(Dropout)	(None, 256)	0
dense_1(Dense)	(None, 43)	11051

Neural Network Output

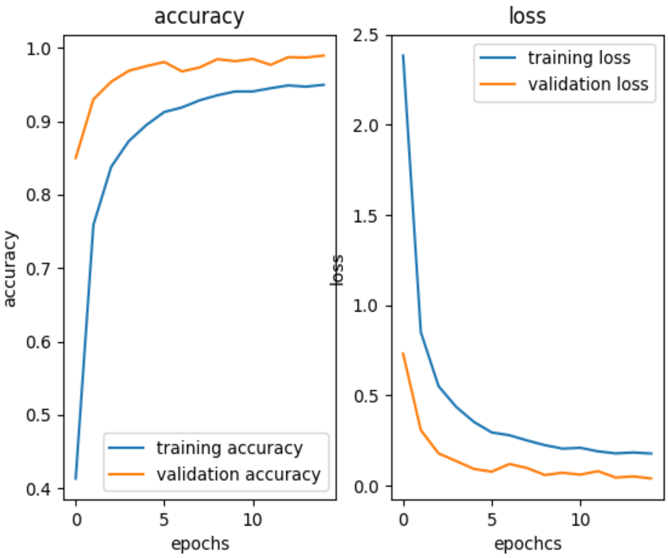
Total params: 242,251

Trainable params: 242,251

Non-trainable params: 0

After data preprocessing is to read and resize the image the second step is to split the training data set for train and testing data set for test. We have taken 80% for training and 20% for testing in our project road sign detection and we get accuracy from training and validation loss.

S.NO	TOTAL IMAGES (39209)	ACCURACY	LOSS
1	Training images (80%=26579)	98.93	0.1776
2	Testing images (20%=12630)	94.32	0.1296



Finally, we get the output of Training accuracy and Validation accuracy is 98.93% and 94.32% with loss , when we increase the training and validation accuracy and loss will be decreased.

10. CONCLUSION

In the proposed work we use to know about convolutional neural networks and how they can be used in neural image recognition. We made a traffic sign recognizer with the use of convolutional neural networks by splitting up images into two categories as testing and training validations. In this implementation, we fixed 15 epocs for execution and got an accuracy of 94.32% in testing validation (20%) and98.93% in training validation (80%). This type of road sign detection is advisable for future use in autonomic self-driving cars systems.

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