TRAFFIC SIGN RECOGNITION USING CNN

[1] SHARMILA S, [2] SAMYUKTHAA L K, [3] SAMYUKTHA R, [4] CHOZHARAJAN P

[1] [2] [3] UG Scholar, Department of Computer Science and Engineering, Bannari Amman Institute of Technology, Erode, India.

[4] Assistant Professor, Department of Artificial Intelligence and Data Science, Bannari Amman Institute of Technology, Erode, India.

[1] sharmila.cs20@bitsathy.ac.in [2] samyukthaa.cs20@bitsathy.ac.in [3]samyuktha.cs20@bitsathy.ac.in [4] chozharajanp@bitsathy.ac.in

ABSTRACT

Convolutional Neural Networks (CNN) have been used to recognize traffic signs, which is an important development for intelligent transportation systems. This technology, which has its foundations firmly planted in deep learning methodologies, provides a significant resolution to the problems posed by the recognition and categorization of traffic signs, ultimately enhancing traffic management and road safety. CNNs are well equipped to manage a variety of and frequently challenging environmental situations due to their extraordinary capacity to rapidly extract and process vital characteristics from images of traffic signs. The fundamental component of CNN-based traffic sign recognition is the meticulous examination of the geometric patterns, colors, and symbols etched on these significant road markings. CNNs gain a great knowledge of the distinctive qualities that tell one sign apart from another by training on large datasets containing numerous traffic sign variations. The capacity to effectively identify and classify traffic signs in real-time as a result gives them a considerable advantage in a variety of applications. A safer, more effective, and more intelligent era of transportation depends on CNN-based traffic sign recognition, which supports driver assistance systems, improves speed limit enforcement, makes it easier for traffic to flow, and powers the brains of autonomous vehicles. CNNs are positioned to keep at the leading edge of this technological development as our roads become more intricate and interconnected, guaranteeing that we may safely and confidently travel the motorways and backroads.

Keywords: *Traffic sign recognition, image classification, convolutional neural network, road safety, traffic signs.*

---

1. INTRODUCTION:

Traffic sign recognition is an integral part of the modern intelligent traffic framework, which aims to improve traffic efficiency and safety. It plays an important role in helping drivers and autonomous vehicles recognize and understand various traffic signs such as speed limits, stop signs, warning signs and warning signs. These signs must be placed accurately and continuously to ensure proper compliance with traffic rules and prevent accidents. Recently, convolutional neural networks (CNN) have emerged as the dominant method for image recognition tasks, including motion sign detection. CNNs are deep emergent models that can extract many highlights from cinematics and produce exceptionally accurate views. The basic design of CNNs includes various layers, including convolutional layers, convolutional layers, and fully connected layers, which generally enable them to learn colorful descriptions of visual information. This study discusses CNNs as a potential tool for road sign recognition due to their ability to handle complex visual examples and robustness under different lighting conditions, climatic conditions and obstacles. The clear goal is to develop a robust and efficient framework that can correctly recognize and classify road signs over time, which promotes a safer and more reliable driving experience. The following sections discuss the details of the CNN design, dataset design, preparation process and implementation evaluation. After these, potential challenges and future development of road sign recognition systems using CNNs are discussed. The importance of this research lies in its ability to change driving trends and traffic patterns, which improves road safety and lays the foundation for a more efficient and intelligent traffic system.

2. REVIEW OF LITERATURE:

B. A. Vennelakanti, et al. (2019) suggested two-stage systems—detection and recognition—which were analysed and tested using publicly accessible Belgian Dataset and German dataset. Because Hue Saturation Value (HSV) processes images similar to how humans do and because it has a wide spectrum of colours, it is used in the detection phase. The following phase is locating the prospective traffic sign based on colour and determining its shape. Red signs are carefully reviewed in colour-based identification, and if they meet a particular threshold, that area is checked to see if they are traffic signs [1].

C. Sudha S. K, et al. (2016) presented the technique in this research in two stages, Detection and Recognition. It contains layers for image capture, pre-processing, detection, and classification, the author further clarifies. In the detection phase, 720p images are recorded from the moving car's roof at a predetermined frames-per-second rate. The visibility of the traffic sign is impacted by variations in lighting and weather. To reduce noise, the Weiner filter and Gaussian noise are utilised. Convolutional neural network [2].

D. Hasan, et al. (2020) explains in detail how to localise traffic signs using SVM and classify them using CNN. The real-time dataset was initially built by cropping the region around the traffic signs in the video frames. To propose CNN and SVM models, they split the entire dataset into training and validation, each with 1200 images. They have considered 12 different traffic signs and each class has 100 images. Grayscale images are created by first applying a colour transformation to RGB images [3].

Dubey, A.R., Shukla, N., Kumar, D (2020) proposed SVM based classification algorithm to recognize traffic sign. Here, they considered 8 types of road signs. For training purpose they used 600 different images for each signs and for test purpose 120 images was considered. In this paper, they tested individual signs with real data and their accuracy level was 66.6% to 100%. Prashengit Dhar et al. in 2017 proposed a Traffic Sign Recognition (TSR) system. Here, they were used HSV color model and deep CNN for automatic features extraction as a classifier [4].

Pavly Salah Zaki and et al. (2019) worked on traffic sign detection, multiple entity detection system. They used Faster Recurrent CNNs, Single Shot Multi Box Detector along with several feature extractors to detect traffic sign. However, they underpin F-RCNN to get best results. Here, they used the GTSDB dataset. The GTSDB holds complete 900 images, where 800 for training and 100 for testing [5].

Yanmei Jin and et al. (2020) also worked with GTSRB dataset to propose a Single Shot Detector algorithm combine with multi feature fusion and they called it MF-SSD. However, in this time they divided total 900 images into 600 training and 300 as a test data to detect traffic sign [6]. Yassmina Saadna and Ali Behloul (2017) discussed a system to identify and recognize traffic sign. Their main goal was to find out traffic sign detection methods to locate the regions-of-interest that contain traffic sign. They divided the methods into 3 steps focused color, shape, and finally considered learning based methods [7].

Sheikh, M. A. A., Kole, A., Maity, T. (2016) for detecting and classifying the traffic signs they proposed an approach. It has 2 main steps: road sign detection, after that classification with recognition. To classify the traffic sign they used neural network and to complete this work they picked four types of traffic signs: Stop, No Entry, Give Way, and Speed Limit Sign. Considered total 3 hundreds sets images, and they got 90% and 88% accuracy for detection and recognition purpose [8]. So, detection and recognition of traffic sign is necessary to build an autonomous car driving system.

3. OBJECTIVE OF THE PROJECT:

The goal of traffic sign recognition using Convolutional Neural Networks (CNN) is to develop a computer vision system that can automatically identify and classify traffic signs based on images or video streams recorded by cameras placed in vehicles or intersections. This technology plays a crucial role in improving road safety and efficiency of traffic systems. Using CNN, the system can learn and extract important features from road sign images to recognize and interpret different types of road signs, such as speed limits, stop signs, heritage signs and warning signs. This recognition process is critical to assisting autonomous vehicles and human drivers and enabling traffic management systems to make informed decisions, ultimately contributing to safer and more orderly roads. In general, the main goal of traffic sign recognition using CNNs is to improve traffic safety, reduce accidents, and improve the overall efficiency of traffic management and navigation systems.

4. SYSTEM ARCHITECTURE:

In general, classical computer vision methods have been created to detect and recognize road signs, but considerable time-consuming work is required to extract key elements from images. By applying deep learning to this problem, we create a model that effectively classifies photos of road signs and teaches it to figure out on its own which features are most relevant to the problem. In this study, we developed a deep learning architecture that recognizes traffic signs. The model requires a lot of data to run and a huge amount of matrix multiplication, which requires a lot of processing power to handle using the recently announced deep neural network technology. The term "convolutional neural network" refers to this algorithm. For computer vision problems, CNN is more efficient and faster than conventional deep neural network. Convolutional neural networks and regular neural networks are quite similar. They consist of neurons whose weights and biases can be learned. This process is called supervised learning. The basic concepts used or learned in traditional neural networks also apply to CNNs. The only way a CNN differs from a regular neural network is that it assumes an image instead of a vector. As a result, the model has far fewer parameters to adjust. Convolutional Neural Networks, or CNNs, are crucial to the science of computer vision. CNN is more accurate than many deep neural networks and helps to direct neural networks to images. Convolutional Nets models are simpler than conventional models and can be trained faster with photos. We used German Road Sign Database (GTSRB) with more than 50,000 signs to train and test the model. There are 43 different graphic traffic signs, including a stop sign, no trespassing and a 30 km/h speed limit. The size of this dataset allows us to train the model more accurately and provide better results

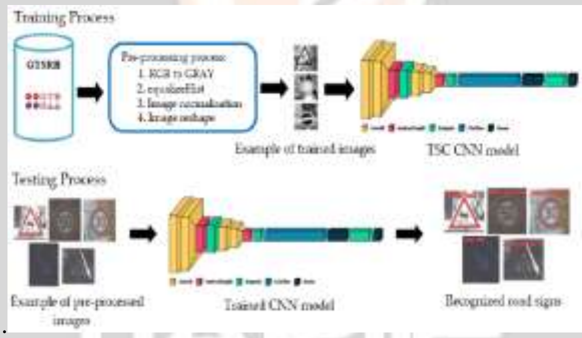

Fig. 1. Architecture Diagram

5. METHODOLOGY:

5.1 Getting data:

The German traffic sign dataset can be obtained from (http://benchmark.ini.rub.de/?section=gtsrbandsubsection=dataset). The following summary statistics are determined using the traffic sign dataset and the NumPy library:

- The size of the training set is 34799.
- The size of the validation dataset is 4410.
- The size of the test set is 12630.
- The image on the traffic sign can be in several forms.
- There are 43 distinct categories in the entire dataset.

Fig. 2. Traffic Sign Dataset

5.2 Dataset exploration and visualization:

We first check the dimensions of all the images in the dataset so that we can process the images at the same size. In this dataset, the images have a variable size from 16 * 16 * 3 to 128 * 128 * 3, so they cannot be directly fed to the CNN model.

Next, we will explore our data by creating a scatterplot that will give us more information about our data and the number of images per category.

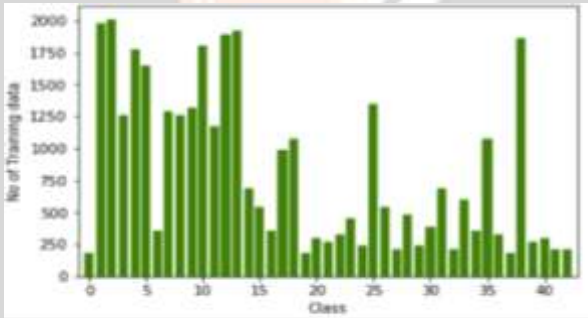

Fig. 3. Distribution of Dataset

As shown in the histogram plot of the data above, there is a significant imbalance between the classes in the training set. Some categories have less than 200 images, while others have more than 2000 images. This means that our model may be overrepresented in certain categories or biased towards more data, especially if it is not confident in its predictions. In fact, these images are samples taken from a real environment. And our model has to withstand all these unusual conditions. So, it is better not to truncate our data set for data balance.

5.3 Data preprocessing:

First, we need to compress or interpolate the images into one dimension. In order not to compress a large part of the data and not to stretch the image too much, we have to decide on an average dimension and keep the right image data. So, we decided to resize each image to 32 x 32 x 3.

Next, we convert these images into composite images, which helps our model find more features in the images. Therefore, preprocessing is a very important step because it reduces the number of functions and thus the execution time.

Fig. 4. Augmented Images

5.4 Model architecture:

Like traditional neural networks, convolutional neural networks are the same as a layered sequence. All layers transform an input image into an output image with some differentiable function that may contain parameters.

The CNN architecture consists of three types of layers: a convolutional layer, a pooling layer, and a fully connected layer.

Layers	Description
Input Layer	32x32x1 images
Convolution-1	Convolution and rectified linear activation (ReLU).
Pool-1	Max pooling.
Convoution-2	Convolution and rectified linear activation.
Pool-2	Max pooling.
Local-3	Fully connected layer with ReLU
Local-4	fully connected layer with ReLU
softmax	Classification result

Fig. 5. Architecture of CNN

1.INPUT layer would store the input image as an array of 3D pixel values.

2. The CONV layer calculates the dot product between the kernel and the kernel-sized subline of the input image. It then collects all the values obtained from the point result and it is the value of one pixel of the resulting image. This process is repeated until the entire input image is covered.

3. The RELU layer applies the activation function max (0, x) to all pixel values of the output image.

4. The POOL layer performs width and height sampling of the image, which reduces the size of the image.

5. The fully connected level calculates class points for each rating category.

6. In this way, the CNN transforms the original image layer by layer from the original pixel values to the final class values. The RELU and POOL layers implement the standard function and no parameters are taught to this layer. FC and Convolutional layer parameters are learned using a gradient descent optimizer.

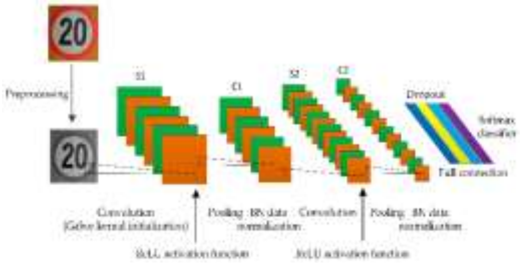

Fig. 6. CNN Model

5.5 Training the model:

We used the Adam optimizer with a batch size of 32 and 20 epochs to train the model. We followed a simple approach and ran only 20 training cycles and encountered a validation error when we tried to set it to a minimum level and also due to the limitation of computing power. It is very important to consider the validation error in most cases when developing a model. Simply reducing the error in the training data can easily lead to unwanted model overconfidence.

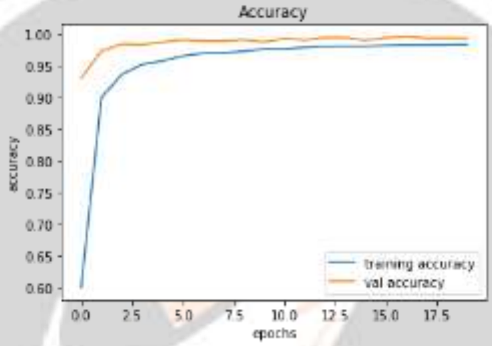

Fig. 7. Accuracy Graph

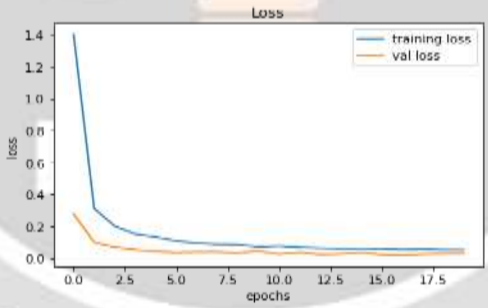

Fig. 8. Loss Graph

After training the model for up to 10 epochs, with each epoch containing 2000 set sizes, we get an accuracy of about 95% and a small loss.

5. 6 Testing the model:

Finally, we test our road sign recognition system on unseen traffic images. Certainly, the accuracy obtained by the test set is also a very good sign of the good performance of the model.

We can see that the results are very good. We also collected random images from Google to further test the model.

Fig. 9. Testing Model on new Images

Fig. 10. Traffic sign image

Here we test our model with live video captured by a handheld webcam or any external desktop camera. For better and clearer images, we recommend using a camera with a higher resolution, which will ultimately give us better results.

After receiving the traffic signal images, we process each frame of the video (up to 30 frames per second) and preprocess it first, then feed each image into our pickled model.

Our model prints the predictions and shows us the name of the class the image belongs to. Our system also shows the probability that the prediction is correct.

6. CONCLUSION:

We have successfully implemented a convolutional neural network with an average accuracy of more than 90% for the task of traffic sign recognition. We discussed how deep learning can be used to classify road signs with high accuracy, using different pre-processing and visualization techniques and experimenting with different model architectures. We built a simple and easy-to-understand CNN model for accurate traffic sign recognition. Our model achieved an accuracy of almost 90 on the test set, which is good considering the limits of computing power and fairly simple architecture. Much remains to be done, linking, including modern deep learning systems using newer and more complex architectures such as Google Net or ResNet. But obviously this comes at the cost of computing on the other hand.

7. REFERENCES:

[1] A. Vennelakanti, et al. (ICCE, 2019), "Traffic sign detection and recognition using a CNN Ensemble".

[2] Sudha S. K, et al. (IJERT, 2016). "A Real-Time System for Detection and Recognition of Traffic Signs".

[3] Hasan, et al. (ICICCT, 2020). “Traffic Sign Recognition System (TSRS): SVM and Convolutional neural Network”.

[4] Dubey, A.R., Shukla, N., Kumar, D.: Detection and Classification of Road Signs Using HOG-SVM Method. Smart Computing Paradigms: New Progresses and Challenges. Advances in Intelligent Systems and Computing, vol 766. Springer, 11 Singapore (2020).

[5] Zaki, P. S., et al.: Traffic Signs Detection and Recognition System using Deep Learning. In: Conference on Intelligent Computing and Information Systems (ICICIS) (2019).

[6] Jin, Y., Fu, Y., Wang, W., Guo, J., Ren, C., Xiang, X.: Multi-Feature Fusion and Enhancement Single Shot Detector for Traffic Sign Recognition. in IEEE Access, vol. 8, pp. 38931-38940, (2020).

[7] Saadna, Y., Behloul, A.: An overview of traffic sign detection and classification methods. In: J Multimed Info Retr 6, 193–210(2017).

[8] Sheikh , M. A. A., Kole , A., Maity, T.: Traffic sign detection and classification using colour feature and neural network. In: Conference on Intelligent Control Power and Instrumentation (ICICPI), Kolkata, pp. 307-311. (2016).