



TRAFFIC SIGN CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT:

The traffic indicators or signs being present is essential for guaranteeing a safe and efficient flow of traffic. The traffic signs that are visible while we are driving significantly affect our daily lives. They offer fundamental information to clients that approach them on the street. They are consequently gradually being encouraged to alter their driving behaviour and make sure they strictly abide by the current traffic laws without harming other drivers or pedestrians. Therefore, in this project, we suggest a model for classifying traffic signs using deep networks that employs Python as its base language and a number of Python modules to train the CNN model [5]. The interclass samples from the submitted dataset will be accurately classified using this model, which consists of multiple CNN layers.

KEYWORDS: Traffic sign, Deep learning, CNN, Classification.

INTRODUCTION:

In order to alert drivers and forewarn them in advance to avoid infringing the law, traffic signs are classified and identified. Accidents resulting from disregard for traffic regulations and signage have sharply increased. Using integrated preparation information derived from images of street traffic signs, we may circumvent the issues brought on by multiple traffic sign location data sets for different nations and locations.

The value of the traffic and road signs we see on the roads in our day-to-day lives as drivers cannot be emphasised. Insightful information is provided to drivers by them. They must therefore progressively rein in their driving conduct and make sure they strictly follow the traffic laws that are in force at the time without harming other drivers or pedestrians.

It is used to classify and identify traffic signs so that a driver might be forewarned and warned in advance to avoid breaking the law. Road systems for recognising traffic signs are a crucial part of intelligent vehicles.

This system collects and recognises information about traffic signs that appear on the road while a driver is moving, issues prompt instructions or warnings to drivers, and actively regulates moving cars in order to maintain a smooth flow of traffic and prevent accidents.

A variety of data have been successfully classified using CNN, also known as Convolutional neural networks [7], a cutting-edge technology, thanks to its innovative approach that effectively classifies traffic signs. Similar to how people make decisions, neural networks can record the colours and textures of lesions specific to certain traffic signs on the route. With a range of traffic boards as input, the classification abilities of convolutional neural networks were evaluated. Using integrated prepared information generated from street traffic sign images, we can get over the restrictions of traffic sign location data sets, which vary for different nations and locations.

Traffic sign classification is a hard task that requires deep learning methods and a big dataset [3]. To demonstrate the correctness of the classes before they are further acknowledged, the dataset is initially split into a ratio where a certain number of images will undergo one operation and another number of images will undergo a different technique. There are still a number of problems and downsides that need to be fixed despite the lengthy study history and continuous efforts on this topic.

PURPOSE OF THE STUDY:

Our daily lives now depend heavily on our ability to recognise traffic indications. To ensure everyone's safety and prepare for future automated driving, A traffic sign's classification is essential considering the growing traffic.

Advanced Driver Assistance Systems and fully driverless vehicles both benefit greatly from traffic sign classification.

Traffic signs are useful for all drivers who are using motor vehicles on public roads. Traffic signs direct motorists to adhere to all traffic

regulations and minimise disruptions to pedestrians.

Traffic sign prediction and categorization is the process of automatically detecting traffic signs and categorising them according to their appropriate classifications.

Our main goal is to build a deep learning model for classifying traffic signs using convolutional neural networks so that we may compare CNN designs and perhaps classify the results as accurately as possible.

LITERATURE REVIEW:

1. "Mexican traffic sign detection and classification using deep learning", Rben Castruita Rodrguez, Humberto de Jess Ochoa Domnguez, Carlos Mendoza Carlos, Vianey Guadalupe Cruz Sánchez, and Osslan Osiris Vergara Villegas

YEAR: 2022

It is difficult to automatically identify and classify traffic signs in order to support a driver's safety and maybe assist with autonomous driving. This research seeks to develop a deep learning-based system for recognising and classifying traffic signals in Mexico. Two sign detectors—the Region-based Convolutional Neural Network (R-CNN) and the You Only Look Once (YOLO v3)—were trained, tested, and adjusted using a fresh dataset of Mexican traffic signs. Furthermore, even with traffic signs hidden and placed in random places, we were still successful in classifying the image. An ablation was then performed on the data collection and batch size.

2. "Traffic Sign Recognition System based on Belief Functions Theory", Nesrine Triki^{1 a}, Mohamed Ksantini^{1 b}, and Mohamed Karray

YEAR: 2021

For advanced driver assistance systems (ADAS), traffic safety is of utmost importance. This kind of assistance can be very helpful for systems for collision warning, blind spot detection, and track maintenance assistance. We will increase the effectiveness and efficiency of machine learning classifiers on the process of recognising traffic signs in order to meet ADAS reliability and safety requirements. Due to this, we will first use our traffic

sign dataset to train the classifiers MLP, SVM, Random Forest (RF), and KNN. We will then integrate the results using the Dempster-Shafer (DS) theory of belief functions. According to experimental results, using classifiers together rather than separately results in a much higher accuracy rate.

3. "Traffic Sign Detection and Recognition using Image Processing", Karthikeyan D, Enitha C, Bharathi S, Durga Devi K

YEAR: 2020

The focus of this essay is on detection and recognition accuracy and high efficacy. It is advised to train traffic sign training sets using a deep convolutional neural network algorithm using the open-source Caffe[3] framework in order to create a model that can classify traffic signs as well as learn and recognise their key features, with the end goal of recognising them in real-world scenes.

4. "Traffic sign detection and recognition based on convolutional neural networks.", M. T. Islam

YEAR: 2019

This work differs from other studies in that it uses symbols that are generally understood rather than being limited to a few, as many other articles are. 28 signs that are in use all around the world are used in this study to classify signs. Two separate neural networks have been implemented for detection and recognition; one classifies signs and the other shapes. Using image augmentation, the training and validation datasets were produced. A total of 40,000 pictures were used to train the first classifier, of which 28,000 were positive (included traffic signs) and 12,800 were negative (lacked any such signals). 3,600 photos, 1,200 of which were negative and 2,400 of which were positive, were used to train the second classifier.

5. "A traffic sign image recognition and classification approach based on convolutional neural network", L. Shangzheng

YEAR: 2019

In this project, feature categorization is implemented using convolutional neural networks in order to outperform the precision and effectiveness of a conventional model. The image is converted to grayscale before being divided into three layers by

the algorithm. They are concurrently assigned to the proper courses using an experienced convolutional neural network that incorporates crucial knowledge about traffic signs and images. The system's effectiveness has been shown by the results.

6. "Traffic sign recognition and classification with modified residual networks", Kang-Hyun Jo and Lihua

YEAR: 2017

In this study, we present a novel methodology for classifying traffic signs in order to enhance classification accuracy. Modified residual networks (mResNets) and image data preprocessing make up our model's two main parts. The picture data preparation includes data normalisation, data augmentation, and colour space conversion.

Competitive performance is produced by the improved Residual Networks. The experimental findings show the robustness and superiority of our model. With a 99.66% accuracy rate, our performance on the German Traffic Sign Recognition Benchmark (GTSRB) dataset was outstanding.

7. "Traffic sign detection — a new approach and recognition using convolution neural network", P. Dhar, M. Z. Abedin, T. Biswas, and A. Datta.

YEAR: 2017

This project uses colour cues and convolution neural networks (CNNs) as feature extractors and classifiers, respectively, to build and develop a TSR system for Bangladeshi traffic signs. The first stage involves some pre-processing after the acquisition of the photos. The HSV colour model's colour information is then used to segment the image. After that, morphological closure is used to adjust the segmented image. After filtering the image using region attributes and shape signature, the suitable region is then cut. Then, utilising automatic features extraction from deep CNN, the obtained sign region is classified. The experimental results show that the proposed method functions similarly and precisely.

METHODOLOGY:

Data Collection

The dataset used in this model is the GTSRB, or German Traffic Sign Recognition Benchmark. The International Joint Conference On Neural Networks (IJCNN) initially included this dataset in 2011.

Data Preprocessing:



50000 images make up the German Traffic Sign Recognition Benchmark, or GTSRB, which includes traffic sign photos that have been rotated completely, partially, at a specific degree, or even left or right. The photos utilised in this model may be found in this dataset, GTSRB. From among those images, 43 different types of traffic sign shots were picked. Using the supplied dataset, training and testing datasets have been produced. Pre-processing methods are applied to the training datasets and testing datasets by repeatedly iterating through the images. At first, the image is divided up into its component pixels. CNN receives the collection of pixels as input.

Implementation of Model

A CNN model with a modified LeNet model is used in this experiment. The model's assessment metric determines the model's accuracy. Additionally supplied are live camera class information and an example of image classification.

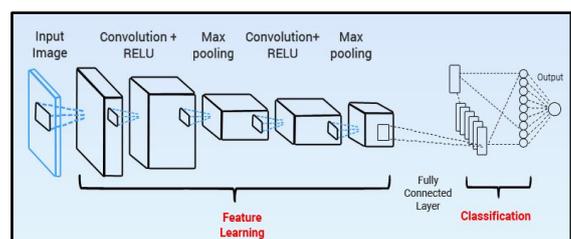
Convolutional Neural Network:

Convolutional neural networks, sometimes referred to as CNNs or convnets. It is one of many distinct artificial neural network models that are used for various tasks and data sets.

A CNN is a specific kind of network architecture for deep learning algorithms that is used for processing pixel input and image recognition, among other things [5]. Among the several kinds of neural networks, CNNs are the one most commonly used for object recognition in deep learning. As a result, they are ideal for computer vision tasks and applications where accurate object recognition is crucial, such as facial recognition and self-driving automobiles.

CNN Model:

The ConvNet architecture is designed to mirror the linked network of neuronal cells in the human brain and is modelled after how the Visual Cortex is arranged. In the constrained Receptive Field of the visual field, only individual neurons are activated. Time series and picture data may both be used to discover significant information using a particular type of neural network called the CNN. As a result, it is highly beneficial for tasks involving images, such as pattern recognition, object categorization, and picture identification. CNNs give remarkably accurate outcomes, especially when a lot of data is involved, which makes them very useful for image recognition, image classification, and computer vision (CV) applications.



- Input Layer:

Input Image is contained in the CNN input layer. The dimensional matrices are used to represent the input image. It must be reconfigured to become a single column.

- Convolutional layer:

It is known as the central component of the convolutional neural network. Most of the calculations happen in the convolutional layer. One further convolutional layer could be added after the first. In this layer, a kernel or filter travels over the image's receptive fields during the convolution process to look for the presence of a feature.

Through a series of iterations, the kernel progressively explores the entire scene. Every iteration ends with the calculation of a dot product between the input pixels and the filter. When the dots are joined in a particular way, it creates a feature map. The picture is finally converted to numerical values in this layer so that the CNN can recognise them and identify the necessary patterns.

- Max - Pooling layer:

Like the convolutional layer, the pooling layer enhances the input image that uses a kernel or filter. The pooling layer has less input values than the convolutional layer, but it also causes some information to be lost. CNN is made more user-friendly and effective because of this layer.

- Flatten layer:

A completely connected layer receives a pooled feature map that has been flattened into a single column. This is a frequent process that occurs while moving from completely connected layers to convolutional layers.

- Fully connected or Dense layer:

The classification of images using the features acquired from the previous layers happens in the Fully Connected layer of CNN. In this context, the term "fully connected" refers to the connection of all inputs and nodes from one layer to all activation units and nodes in the following layer.

Not all the layers in the CNN are fully linked since doing so would result in an extremely thick network. Additionally, it would be computationally expensive, increase losses, and have an impact on the output quality. ReLU and SoftMax are the two activation procedures.

- Dropout:

Dropout includes placing some nodes into layers at random in order to stop them from being modified during back-propagation. So, overfitting is prevented. After the model has been trained successfully, the application can identify the images from the dataset that match to the Traffic Signs Classification. The test image and trained model are compared after efficient training and pre-processing, in order to forecast the traffic sign.

- Output Layer:

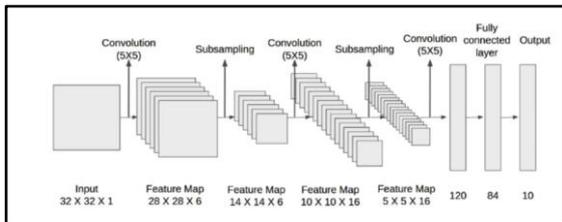
The intended predictions are in the output layer. One of a neural network's output layers creates the final prediction. It uses its own set of weights and biases to decide the outcome.

In order to support our thesis, we used the experimental approach. The experiment was carried out using a CNN model that was based on the modified LeNET model [3].

LeNet-5:

In 1990, the LeNet network—one of the earliest convolutional neural networks—was trained to detect handwritten numbers in the MNIST dataset. It has only 5 layers (counting a convolutional layer and a pooling as one layer—have been trained to classify grayscale images

of size 32x32. Due to its simple architecture and limited number of parameters, it is the ideal place to start when learning convolutional neural networks intuitively.



As there are five learnable layers in this network, it is known as LeNet-5. The convolution and the pooling layers are followed by two entirely linked layers. Images are then classified properly by a SoftMax classifier.

We also have an output layer with ten neurons because the data is divided into ten classes.

Model Evaluation:

```

Model: "model_1"
Layer (type)                Output Shape          Param #
-----
input_1 (InputLayer)        (None, None, None, 3) 0
conv2d_1 (Conv2D)           (None, None, None, 32) 2432
dropout_1 (Dropout)         (None, None, None, 32) 0
max_pooling2d_1 (MaxPooling2D) (None, None, None, 32) 0
conv2d_2 (Conv2D)           (None, None, None, 64) 51264
dropout_2 (Dropout)         (None, None, None, 64) 0
max_pooling2d_2 (MaxPooling2D) (None, None, None, 64) 0
conv2d_3 (Conv2D)           (None, None, None, 128) 264928
dropout_3 (Dropout)         (None, None, None, 128) 0
global_max_pooling2d_1 (GlobalMaxPooling2D) (None, 128) 0
dense_1 (Dense)             (None, 84)            10836
dense_2 (Dense)             (None, 43)            3655
-----
Total params: 273,115
Trainable params: 273,115
Non-trainable params: 0
    
```

Model Accuracy:

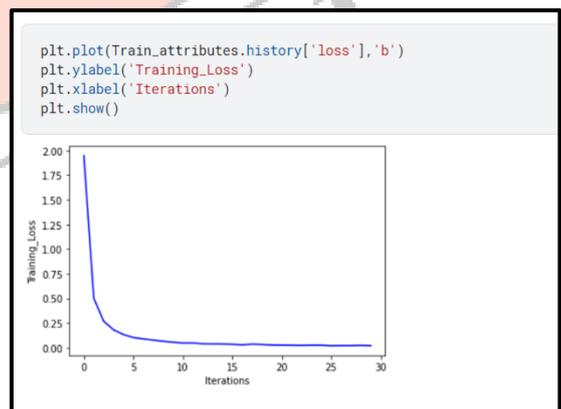
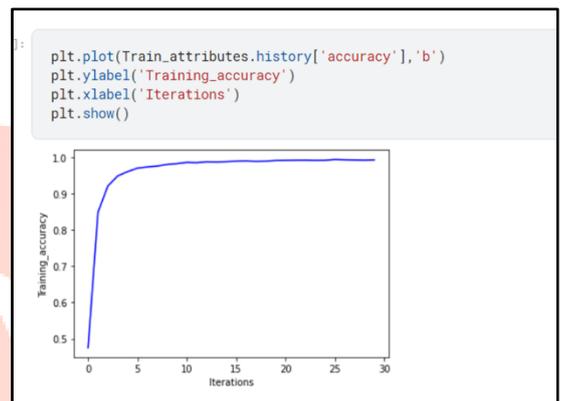
Accuracy, loss, and value accuracy are all clear concepts. With a classification accuracy of about 0.95, it classifies the photos.

The accuracy and loss of the model are then determined by plotting the graph, and the outcomes are often positive.

Loss values for the CNN model-trained dataset
Accuracy of trained dataset for CNN model

There is just one channel because the model takes a grayscale image as input. We then have 6 such filters after applying the first convolution operation to the filter. As a result, we are given a size feature map. When pooling is used after the initial pooling procedure, The feature map has been reduced in size by half. The following layer is a convolution layer with sixteen filters.

Another change was made to the feature map. Similar math is used to determine the output size. The feature map was then again reduced in size by half using a pooling layer. After that, there is another convolution layer with filters. Then, the result values are flattened. After these convolution layers, we have a layer that is entirely coupled and has 84 neurons.



Model Deployment:

OpenCV is used to display the real-time classification of the traffic signs together with the labels and classes after the training is finished.

Algorithm:

The backpropagation method for convolutional neural networks (CNNs) is a supervised learning technique used to train neural networks. Its foundation is the idea of backpropagation, a technique for training neural networks that involves sending mistakes from the output layer back to the input layer.

Minimises error by varying the weights of the connections between the neurons in the network. The mistakes are propagated back to the input layer in order to do this.

Calculating the difference between the actual and expected outputs is how the algorithm operates. The weights of the connections connecting the neurons are then modified as a result of the mistake being transmitted back through the network. Until the error is reduced and the network can precisely anticipate the intended output, this procedure is repeated. A key tool for deep learning is the Convolutional Neural Network Backpropagation Algorithm.

It frequently serves as an image recognition tool. It has the capacity to learn from its errors and perform better. Additionally, because it is a supervised learning technique, neural networks may be trained using labelled data. The algorithm is also quick and effective, which makes it perfect for use in large-scale applications.

DEPLOYMENT:

Deploying the model and predicting the output: After the training is complete, Flask API is used to display the real-time classification of the traffic signs together with the labels and classes.

OUTPUT:**Conclusion:**

It focused on utilising CNN model in the field and with historical data to recognise Traffic Signs in images from a given dataset (a training dataset). We compared the accuracy of different CNN models using different datasets, and we found that they produced better classifications and were deployed in Flask, a web application framework utilising Python to create a better user interface.

We infer from the provided system that, after building a useful CNN model and properly preparing the training dataset, it gets accurate classification results and also generates results with good accuracy.

To begin with, obtaining an effective training distribution necessitates the use of very large data sets. The data sets our system has employed, however, will also yield effective outcomes.

Future Work:

- AI model integration for traffic sign prediction.
- This process can be made automated by displaying the prediction outcome in a desktop or web application.

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