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Traffic Sign Detection Using Traffic Convolutional Neural

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ABSTRACT

TSD (Traffic Sign Detection) is a key milestone of automated and assisted driving. TSD research has gained much importance in terms of improving road traffic control. In recent years, CNN (Convolutional Neural Networks) has had a lot of success with target detection tasks. It shows higher accuracy or faster execution than the traditional approach. This paper suggests a Convolutional Neural Network (CNN) VGG Net 16-based approach to detecting and classifying traffic signals that is robust to extreme environmental conditions. The IVGG model has 29 layers, as opposed to the original VGG model , which has 16 layers to speed model convergence, capture major features, and minimize training time even further. The classification impact would improve as a result. The investigator in this paper conducted the experiment using the German Traffic Sign Benchmark (GTSRB) dataset.

Keywords: German Traffic sign Benchmark datasets,VGG Net 16

Introduction

The traffic signs engraved on the road these days improve traffic safety by informing drivers of their speed limit or any further hazards, such as deeply curved roads, road works about to be repaired, or any crosswalks. The ADAS (Advanced driving assistance system) system's main concept is to ensure the driver's safety as the traffic sign represents the vehicle's surrounding environment. It is an essential part of ADAS.

The main aspect is to display the content that needs attention in the current road section, such as

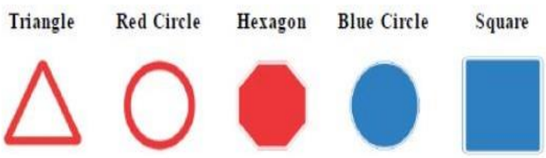
•Warn the driver of the dangers and difficulties ahead on the road,

• Caution the driver to drive at a prescribed speed,

• Guaranty safe driving.

Today traffic sign identification and recognition have become a critical research field. It has turned to be important to avoid road traffic collisions and protect drivers' personal safety. In India, there are various kinds of traffic signs used. In a nutshell, there are warning signals, warning signs, and informative signs. These signs are generally distinguished by their various colours and shapes. In short, the signs are classified as a warning, cautionary signs, and Informative signs. These signs are distinguished primarily by their distinct colour and shape.

Fig 1. Represents the different shapes and colors of traffic signs that are followed in India**.**



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1)Warning Sign A triangle yellow or orange background with black symbols or letters on a diamond-shaped or rectangular sign will frequently be used to display a warning sign.

The yellow pennant-shaped signs on the roads warn motorists driving that there is a danger ahead. Round yellow warning signs alert traffic to the presence of a railroad crossing ahead.

2) Compulsory Sign: Compulsory signs are comprised of a circle with a red border and a white backdrop. The pictogram represented by these signals limits the movement of drivers. Some of the mandatory signs are no left turn or no 'U' turn, and a cross represents a “no parking” warning. . Another exception is an octagon with a white and blue circle with a red border and a cross representing a "no parking" sign.

3) **Regulatory Sign**: These are the **signs** that **modify** driver **moves** on the road. They are used for controlling traffic flow and the movement of vehicles on the route. A regulatory sign is a blue circle with a white line. The arrows inside it reflect the vehicle's activity on the lane.

4) **Information Sign**: This category includes essential details such as local hospitals, phone booths, first aid stations, gas stations, and police stations. This important detail is helpful to a driver in an emergency situation. The pictogram is represented **by using** a white rectangle with a thick blue border. This category additionally consists of parking information

Classification of Traffic Sign in India

Traffic-sign recognition (TSR) is a technology which a vehicle identifies the traffic sign that have been positioned on the lane.e.g. "speed limit" or "children" or "turn ahead." These features are collectively known as ADAS. The main purpose of the Advanced Driver Assistance System (ADAS) in recent days is to provide the driver with important information about the traffic signals and warning signs on the road ahead.

The identification techniques of traffic signs can be broadly divided into two types, namely color-based and shape-based.

Color-based Method

Color-based segmentation is one of the most frequently used techniques for recognizing or identification signs, as well as removing areas that are unlikely to have signs. Colour is the leading visual feature that portrays the vital information of the traffic sign to the driver. Various methods, such as color thresholding, dynamic pixel aggregation, color indexing area expanding, histogram, and so on, may be used to retrieve color-based information from a visual image or film. The extricate feature of traffic signs that are based on Colour simplifies the process of identification and detection. However, the intensity and Colour varies with lighting. That is the main demerit of the RGB color-based detection method as it is based on the available illumination. Colour space conversion is the widely used method of detection. Unraveling the color details from the brightness information by adapting the RGB color

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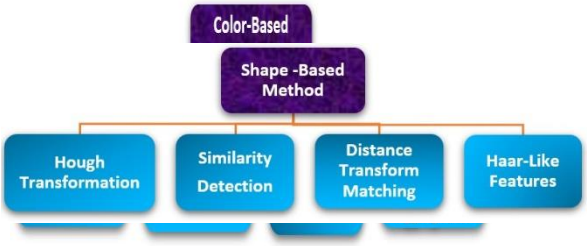
space into other color spaces provides great detection capabilities depending on color cues. There exist various color spaces such as HIS, CIE, RGB, CMYK, HSV, YIQ, YUV, etc.

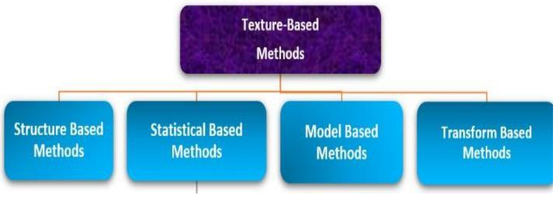
The shape is the second important parameter used in traffic sign recognition. Shape-based detectors might ignore colour information absolutely and find sign with the help of shapes alternatively. This classification of detectors appears a bit outdated on the grounds that all shade detectors additionally use form records for similarly filtering. Mainly, there are different kinds of shapes of different traffic signs



indicating some information in collaboration with Colour and symbol in it. The traffic signs can be of different shapes, such as triangles, circles, octagons, and rectangle. Furthermore, the shape may be confused with numerous other man-made items like commercial signs and building windows. However those strategies are more robust in changing illumination due to the fact they locate shapes using boundary facts. The commonly used shape-based neural network, template matching, and similarity detection, etc. The shape-based features that are used in the identification and detection of traffic signs are canny edge detection, radial symmetry, corner detection, similarity detection, Hough transform Haar-like feature detection, etc.

Texture

Textures are visually graphical and repetitive patterns and have properties such as fineness, coarseness, contrast, entropy, energy regularity, and so on. Texture detail is extracted using methods such as sgldm, glcm, LBP, and glrlm. Texture detection methods are mainly divided into four types on the basis of structure, statistical methods, and models involved in the detection and transform-based methods. Some of them mostly used texture-based methods are given below.



Problems with TSR Traffic

Sign Recognition (TSR) algorithms face three major problems:

i. Due to low resolution, poor image quality, weather conditions that are worse, and over-or under-illumination,
ii. The signs may sometimes rotate in the wrong direction or maybe be covered up by some occlusion and or may even get faded.
iii. The real-world application, such as ADAS, has minimal memory and computing power.

The goals of the systems are as follows:

- ✔ Traffic signs should be able to detect even during unfavorable climatic conditions.
- ✔ Able to classify the captured image of the traffic sign accurately.
- ✔ Should notify the driver of the traffic sign that comes ahead of the road so that he or she can take suitable action on time.

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✔ To compare and evaluate the proposed one with the previous approaches used traffic sign recognition schemes.

Difficulties faced in detecting the traffic sign

- **Video source (video camera)** – Recognition of a video source (video camera) is dependent on the accuracy of the image sensor (CMOS/CCD chips) and the image output format. Colour or greyscale cameras with different resolutions, configurations, compression speeds, and so on can be used. Issues may occur not only as a result of camera settings but also as a result of the camera being incorrectly installed in a car, causing distortion and blurring of video sequences.
- A moving vehicle consists of blurring and vibration effects, so the camera should be fixed properly.
- The picture captured can additionally be influenced by using rain, snow, or the occurrence of fog, e.g., Traffic signs , for example, may be obscured by snow or become difficult to see in fog.
- **Lighting Condition**: Images captured during the day and at night influence the source of the Difficulty of the Traffic Sign Identification light. As a result, when the lighting varies, the hue on the colors of things will be viewed differently. Reflection from any light , like sun during the day or street lights at the night , often causes problems in the detection of traffic signs
- **Occlusion-**It is a kind of object that obstructs the traffic sign on the road for e.g. trees, vehicles, pedestrians, poles, or any other roadside object. Shadows can also induce a different type of occlusion. The interpretation of a traffic sign will change its meaning, A shadow from a power line on a priority road sign, for example, can be seen as the end of the priority road.
- **Fading Colour** – The sun's and weather's impact can also fade the Colour on traffic signs over time.
- **Damage-** Traffic signs can be affected not only by the heat
  But also by devastation or natural disasters such as (strong breeze, storm, raining). They'll get dusty, scribbled over, tilted, and rusted, and so on.
- **Scene complexity** – The presence of several road signs on a traffic scene to be identified in an image increases computational complexity and thereby slows down real-time processing.
- **Cascade of traffic signs-**.This is an issue that is similar to a complex scene. Furthermore, in the case of lower image quality, a pair of traffic signs and are very closely placed as a result, they would have appeared as one traffic sign.
- **Similarity-** Some objects in the traffic scene resemble traffic signs, especially advertisements displayed along the route.
- **Incorrect placement or signs similar to real traffic signs**. Traffic signals are sometimes located incorrectly, such as inverted or twisted. As a result, their meanings are either contradictory or incomplete. Signals that tend to be road signs but are not valid for a driver are considered special cases.
- **Variable size of traffic signs** – The size of traffic signs varies. Furthermore, the height of traffic signals varies as they get closer to a moving vehicle's traffic sign.
- **Multiple appearances of sign**s: Multiple appearances of signs of signs at the same time that are identical to man-made can cause symbol overlapping and contribute to false detection. The detection technique can be affected by Rotation, translation, scaling, and partial occlusion
- **Motion artifacts**: when images are taken from a moving vehicle, motion artifacts kick in, resulting in distorted images. Using a low-resolution camera can result in images that are noisy and blurry.
- **Chaotic background and viewing angle problem**: Chaotic background and foreground scenery, as well as constant changes in viewing angle when running on the highway, make identification impossible.

A shape-based approach to traffic sign identification appears to be an effective solution for this problem.

Literature Survey

Zhongyu Wang et al. proposed a method using CNN with the YOLO method. The author significantly enhanced the model's accuracy in the traffic sign detection, as well as the detection speed and hardware specifications of the detection system.

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Prabu et al. proposed a method using Colour based method for detecting traffic sign detection. Here the author had used Artificial Neural Network, and the results obtained were found to be better compared with the Convolutional Neural Network.

Currently, traffic signs classification is generally classified into color-based [**Jung, Lee, Jung et al. (2016**)] and shape-based [**Mohammadi and Makui et al. (2016)],** On the other hand, the deep learning method CNN model is most effective in obtaining feature expression and holds the aspects of scaling invariance, rotation, and translation and is able to recognize weight sharing using local receptive fields. It is frequently used in image classification **[Krizhevsky et al.,(2012)]** ,face recognition**[Li et al. (2015)]** and target recognition [**Schmidhuber et al (.2012)].** In CNN, traffic sign recognition is performed by feature subspace and SIFT features. However, SIFT relies on the point of object appearance and disdain basic information of the full image **[Skoczylas et al. (, 2016)].**
Deng et al. (2015) suggested a method by training the probabilistic neural network-based upon the core projection features to identify the traffic signs and correlate with SIFT feature identification. The experiment results show that the projection feature displays a high recognition rate, whereas; the center projection depicts only shapes of traffic signs.
Maity et al. (2017) presented a color normalized traffic sign recognition method that simplifies composite color details within five classes.
According to **Yan et al. (2009)**, the SVM method detects traffic signs which yield better results in the coarse classification and displays the least performance in the sub-classification.
Liu, et **al. (2015)** offered a novel approach for detecting traffic signs by circulating invariable pattern features depending upon specific traffic signs. This invariant pattern feature is applied as an input for training the artificial neural network; the detection rate was 98.62%.

Zhang et al. (2014) proposed a model based upon the CNN algorithm and Stochastic Gradient Descent, and the traffic signs recognition rate was 99.65%. However, the training period for this method took up to 50 hrs.

Krizhevsky et al. (2012) had suggested a VGG network method that has been extensively used because of its multilayer structure and outstanding performance in the target recognition field.

Sutskever, et al. (2012) VGG model is evolved by AlexNet. It has two significant attributes. The first one is that convolution kernels are compact, generally of size is 3*3, and very few are 1*1. The convolution operation is coupled with an activation function, which can recognize numerous features; the second is the compact pooling kernel in comparison with AlexNet's of 3*3 pooling kernel, VGG has the pooling size of 2*2, which makes the feature map wider and layers deeper. As the convolution kernel emphasis enlarging the number of channels, where pooling layers lays their importance on making the model framework wider

Proposed Scheme:
Traffic Sign Datasets:
The Training image data are taken from **GTSRB** (The German Traffic Sign Recognition Benchmark). It is one of the best repositories for traffic sign videos. Here 39,209 traffic sign images were taken for the training purpose, and 12,630 were taken for the testing purpose.

Traffic Sign Image Detection Process
The Assessment of CNN is carried out on the GTSRB dataset. CNN model is executed using Python on a PC with an a3.4 GHz CPU and 64-bit Windows 7 operating system, and a server with 2.4 GHz CPU and Windows Server., Intel I5 CPU, Tensor Flow frame was endorsed. It took approximately 23h to train the network.

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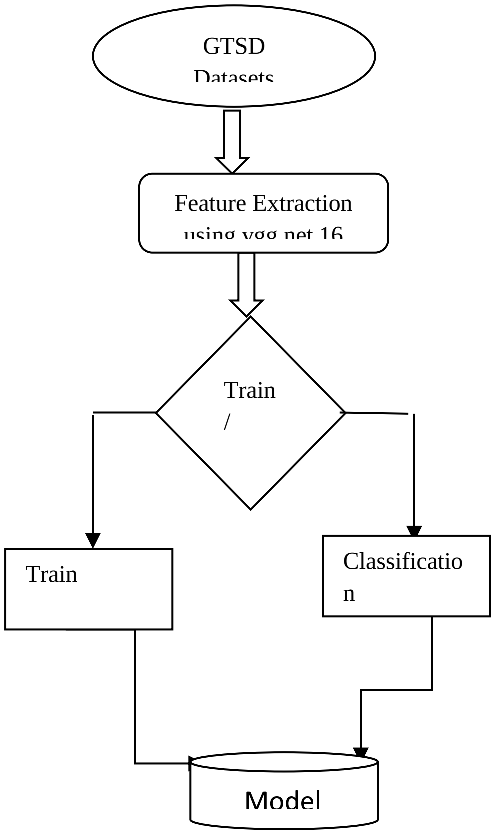

Step1: Data

To undertake a traffic sign recognition experiment, 51,630 images are obtained from the German Traffic sign Recognition Benchmark (GTSRB) dataset, where 39,000 images are used for training and 12,000 images for testing. A total of 43 classes are used for this experiment.

Feature Extraction Using Improved VGG 16 Net

In the existing VGG 16 Net

In this proposed methodology, the VGG16 model is a CNN architecture that has been designed with 29 layers, which is the most peculiar feature of VGG16. Rather than having a huge amount of hyperparameters, it highlights featuring convolution layers of 3*3 filter with stride 1. It has two fully connected layers at the end, followed by a softmax function that performs multiclass classification for the output layer. It includes dropout and max-pooling functions.

The primary objective of using this drop-out operation is to regulate the network while training. This method is composed of dropping neurons randomly with certain probabilities. Overfitting issues are impeded through arbitrary modifications of the network framework, which is believed to disdain co-adaptation of neurons by making it unfeasible for two subsequent neurons to depend on each other. Max pooling operations are able to spill the images into various blocks of similar size; this could only obtain the highest value in every block. It holds to the unmodified plane structure invariance after deserting other nodes, and it depletes computing time which improves CNN training greatly. Batch Normalization (BN) and Dropout are added to each and every fully connected layer to enhance the image classification effect and to further speed up the model convergence. Training CNN is a laborious task regarding the fact that dispersion of each layer's inputs alters in the middle of training because the parameters of the preceding layers also get changed. BN resolves these issues by normalizing the input of each layer and make sure the dissemination of data is constant in each layer, therefore achieved the goal of speeding the training process. The improved model is illustrated in Figure2, and the information of the layers are mentioned below:

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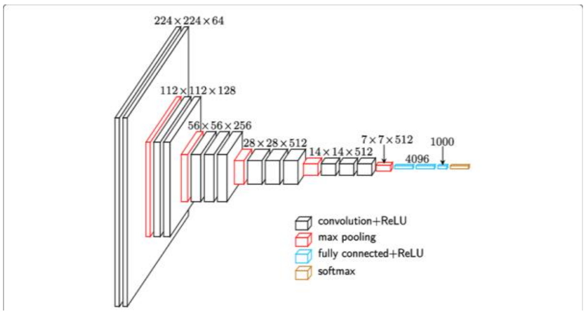

Figure 2: Architecture of VGG16 model

Input layer: Image is loaded into the network model. The output vector is an input to the convolution layer. To fit into the convolutional layer, the loaded traffic sign images are systematically placed to a size of 224*224.

Convolutional layer: This layer plays a significant role in feature learning that comprises a feature map that contributes to a convolution kernel. The main function of the convolution kernel is to convolute with various preceding maps and conjoins interrelated bias and feature, followed by transferring it to a non-sequential activation function. To acquire a feature map and to perform feature extraction ReLU function has been used in this model. This model comprises 7 convolution kernels of range 3*3; the first 2 convolutional layers include 32 feature maps, followed up by a pooling function.

We add dropout and Batch Normalization (BN) after each fully connected layer in order to improve model convergence and classification effect. Convolutional neural network training is complicated because it makes use of the fact that the distribution of each layer's inputs varies at some point during training as the parameters of the previous layers shift. This slows down teaching by lowering the learn rate .It is notoriously difficult to train models with saturating nonlinearities without proper parameter initialization. BN is in charge of resolving this problem. By normalizing the input of each layer, it guarantees that the distribution of input data in each layer is constant, fulfilling the goal of accelerated training. Data augmentation and transition learning can also help to speed up network model.

Fully-connected layer: This layer measures the probability values for classification into the various groups based on the previous layer's output (Convolutional, ReLU, or Pooling).

Batch Normalization (BN Batch Normalization (BN) Batch normalization is a layer that allows each layer of the network to learn independently. In order to maximize the neural network's stability, it normalizes the previous activation layer's output by subtracting the batch mean and splitting the batch standard deviation. It is sometimes placed immediately after the convolution and pooling layers.

Loss Function: The input sample is subjected to a soft-max function in this layer. This layer **is** in charge of final prediction.

Dropout Layer: One of the most widely used regularization techniques for reducing over fitting in deep learning models is the Dropout Layer.

Over fitting occurs in the process where the model performs well on training data but poorly on measurement or unseen data. The dropout mechanism involves randomly dropping or omitting neurons in hidden or visible layers..

Training Strategeries :: The data is arbitrarily split into three sets: the training set contains 50% of the data, the testing set contains 25% of the data, and the verification set contains 25% of the data. The training set is used to study and understand the model's parameters. The validation array is used to refine the model, which is then evaluated during the model training phase. followed by network fine-tuning based on the results of the model tests. The test set is used to put the model's recognition and generalization abilities to the test. Meanwhile, we have the IVGG to test the efficacy of data augmentation and transfer learning techniques which further proves this model is scientific.

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Performance Metrics

The performance metrics adopted are:

Accuracy (ACC) = $TP + TN$ **/ n (1)**

Precision (P) = T P /T P + F P (2)

Recall (Sensitivity) = T P/ T P + F N (3)

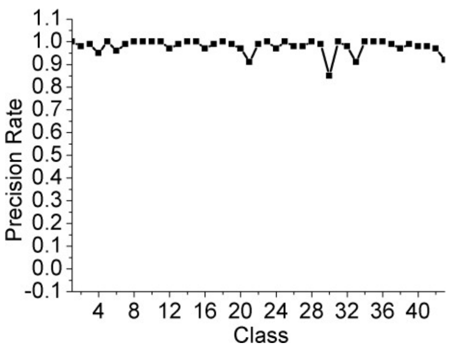
F1 − score = 2(P recision × Recall /Precision + Recall) (4)

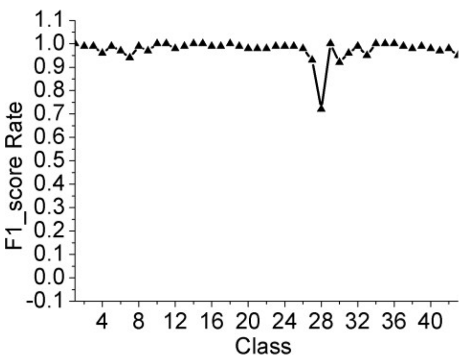
Specificity = T N/ T N + F P (5)

For each class, true positive, true negative, false positive, and false negative samples are denoted by TP, TN, FP, and FN (Traffic sign, Not). After that, the macro-average results were computed and shown to demonstrate classification performance. The ratio of estimated correct labels to overall labels is used to calculate precision (predicted and actual). In this study, accuracy defined as the predicted correct label to total label ratio (predicted and actual). In this study, accuracy relates to the total accuracy of the model. (Equation 3)Recall is defined as the proportion of predicted correct labels to total predicted labels (Eq 3) Sensitivity is referred to as recall. Another word for sensitivity is recall (also called true positive rate). Furthermore, the F1 score (Eq 4) is the harmonic mean of Precision and Recall,

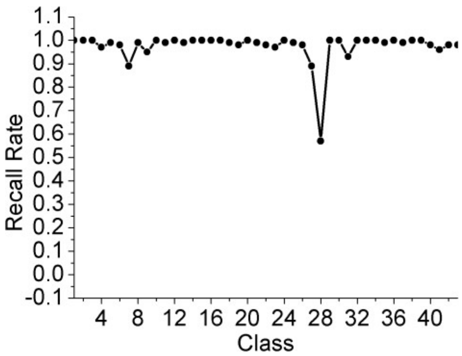
4 **Experimental evaluations**

In this research work, the effectiveness of several state-of-the-art pre-trained convolutional neural





networks was evaluated regarding the detection of Traffic signs.



Output of the proposed System

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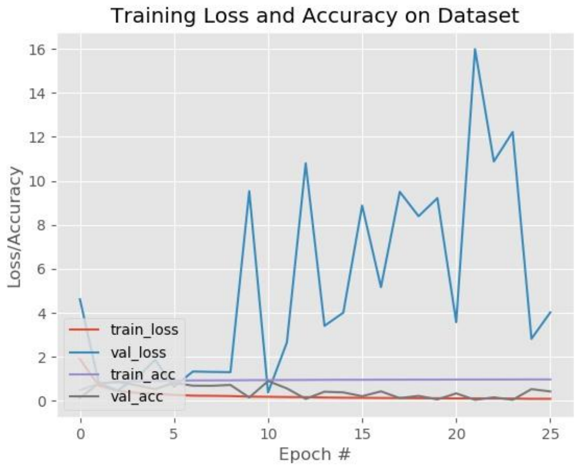

Conclusion

The primary goal of automating a traffic sign image recognition system is to categorize into several traffic signs, which enables driver safety. This recognition system is designed and trained using CNN architecture to identify the traffic signs from the renowned German Traffic Sign Recognition Benchmark database. CNN is considered a good fit for image classification due to its ability to make correct speculation about the image features such as locality of dependencies and stationery of statistics. The use of these applications yields better performance and accuracy. Even though this proposed model has provided outstanding performance, progress is still to be made. In the future, CNN will be trained to recognize many more traffic sign images, possibly even at the time of bad weather conditions. There are plans to amplify the capacity of this system not merely for classifying images but also for object detection.

References:

1. Zhongyu Wang, Hui Guo" **Research on Traffic Sign Detection Based on Convolutional Neural Network",** [ACM Press the 12th International Symposium - Shanghai, China (2019.09.20-2019.09.22)] Proceedings of the 12th International Symposium on Visual Information Communication and Interaction - VINCI'2019
2. M. Prabu, Pooja Patil, Mallika Yadav, Nidhi Ranjan" **Automated Traffic Sign Recognition System using Computer Vision**", International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-1, November 2019
3. Jung, S.; Lee, U.; Jung, J.; Shim, D. H. (2016): "**Real-time traffic sign recognition system with deep convolutional neural network**". IEEE International Conference on Ubiquitous Robots and Ambient Intelligence, pp. 31-34.
4. Mohammadi, S. E.; Makui, A. (2016): "**Multi-attribute group decision making approach based on interval-valued intuitionistic fuzzy sets and evidential reasoning methodology".** Soft Computing, vol. 21, no. 17, pp. 5061-5080.

ISSN: 2233-7853 IJFGCN

5. Krizhevsky, A.; Sutskever, I.; Hinton, G. E. (2012): "I**mageNet classification with deep convolutional neural networks"**. International Conference on Neural Information Processing Systems, vol. 60, pp. 1097-1105.
6. Li H, Lin Z, Shen X, Brandt J, Hua G (2015) ,"**A convolutional neural network cascade for face detection**". In: IEEE conference on computer vision and pattern recognition, CVPR 2015, Boston, MA, USA, 7–12 June 2015, pp 5325–5334
7. Schmidhuber, J. (2012)." **Multi-column deep neural networks for image classification"**. Computer Vision and Pattern Recognition, 157(10):3642–3649.
8. Lasota, M; Skoczylas, M. (2016): "**Recognition of multiple traffic signs using keypoints feature detectors"**. IEEE International Conference and Exposition on Electrical and Power Engineering, pp. 535-540.
9. Wang, Q.; Yu, H.; Deng, D. (2015): "**Automatic recognition for mechanical images based on sparse non-negative matrix factorization and probabilistic neural networks"**. IEEE International Conference on Mechatronics and Automation, pp. 2408-2413.
10. Sheikh, M. A. A.; Kole, A.; Maity, T. (2017): "**Traffic sign detection and classification using colour feature and neural network"**. IEEE International Conference on Intelligent Control Power and Instrumentation, pp. 307-311.
11. Yan, Z.; Du, P. (2009): **Generalization performance analysis of M-SVMs**. Journal of Data Acquisition & Processing, vol. 24, no. 4, pp. 469-475
12. Yin, S.; Peng, O.; Liu, L.; Guo, Y.; Wei, S. (2015): **Fast traffic sign recognition with a rotation invariant binary pattern based feature**. Sensors, vol. 15, no. 1, pp. 2161-2180.
13. Jin, J.; Fu, K.; Zhang, C. (2014): **Traffic sign recognition with hinge loss trained convolutional neural networks**. IEEE Transactions on Intelligent Transportation Systems, vol. 15, no. 5, pp. 1991-2000.
14. Krizhevsky, A.; Sutskever, I.; Hinton, G. E. (2012**): ImageNet classification with deep convolutional neural networks**. International Conference on Neural Information Processing Systems, vol. 60, pp. 1097-1105
15. Rubina Sarki, Khandakar Ahmed, , Hua Wang, Yanchun Zhang, and Kate Wang" **Automated Detection of COVID-19 through Convolutional Neural Network using Chest x-ray images**", medRxiv preprint Feb 2021

ISSN: 2233-7853 IJFGCN