Grenze International Journal of Engineering and Technology, June Issue

Deep Learning Approach for Traffic Sign Recognition

Soumya Bhandari[1], Saurabh K. Suman[2], Md. Altamash[3] and Prof, (Dr.) Alwin Anuse[4]
[1-4]Dr. Vishwanath Karad MIT-WPU, Pune, India
Email: soumyabhandari@mitwpu.org, saurabhsuman@mitwpu.org

***Abstract*—With the advent of driverless car systems, automatic traffic sign recognition is must. The proposed deep learning model performs well in recognising forty-three traffic signs. The model also can be ported on Jetson-Nano device resulting into a portable standby device.**

***Index Terms*— Deep Learning, Jetson-Nano, Traffic Sign Detection, Artificial Intelligence, Computer Vision.**

I. INTRODUCTION

Traffic Signs are an important part of road assistance. Traffic signs are used to show the details of the road that one might miss or not know, which are important to be aware of for self and road safety. To make the driver aware of a narrow road ahead; or of men at work ahead to avoid casualties; to warn the driver of dangers that lie onwards. This is all to give a better chance for safe driving, to protect the personal safety of drivers, pedestrians and all the road users. All the traffic signs play a vital role during using the roads.

Amongst the traffic signs the most common are the prohibition of left and right turning signs and speed-limit signs. These signs are also of great seriousness regarding safe driving. Following this assistance can avoid unnecessary accidents and rash driving, making it safe on the roads. According to analysis more than 400 accidents take place on a daily basis, on Indian roads. Which costs lives and 3% of total annual GDP. Hence it becomes essential to know the importance of road signs.

This paper describes the implementation of a software trained model over a hardware module for prototyping of the concept. Further in this paper one would see deep learning algorithms for traffic sign recognition applied over an IOT (Internet of Things) device. The motivation behind the concept is to spread safety and awareness among people about the importance of road signs, and that how by simply following these signs could avoid a sizeable percentage of accidents and suffering.

The paper also involves in what all ways one can improve the accuracy, real-time performance and response of traffic sign detection model and recognition algorithm. This is the main highlight that the authors have tried to solve from this project. The accuracy of the model is a key element in the working of traffic sign recognition. Wrong recognition would only result in fatal accidents. The real-time aspect of the project depicts the assistance that a driver would get for safer and aware drives. This project considers the accuracy and the real-time problems of traffic sign detection and recognition

II. LITERATURE SURVEY

There has been a wide respect of work done in the concept of traffic sign classification, recognition, and detection [1] [2] [3]. Whereas the implementation of the concept over an IOT is a rear occurrence and specially

Grenze ID: 01.GIJET.8.2.41

with Jetson-Nano as an IOT device as it is a new upcoming technology given to the market by NVIDIA. The implementation of the concept has been seen over a different IOT device, Raspberry-Pi [4] [5] [6] [7]. Still the application of raspberry-pi and Jetson-Nano has a wide difference.

Using the "German Traffic Sign Recognition Benchmark" dataset, the outcomes makes the accuracy of these algorithms shows the talent of traffic sign recognition flawlessly. The achieved accuracy in this area reaches up to 98.98%, this is as same as humans identifying the signs from the dataset [8]. One of such work directs us to HIS colour model, simultaneously after applying the circle detection. Colour detection cannot determine the exact sign. In this method, the edge of region of interest is marked to get the contours after morphologic operations are done on the interested frame. To find the targeted region after that, Hough circle transform is put into application. The object is then detected and extracted. After that next we recognise the sign from the ROI . Image preprocessing is done to remove noise. To gain silhouette with better boundary, the traffic indication symbol edge detection and segmentation are also used to recognise the image. Shape is taken under account on the contour of the object [11].

Though the primary features of these IOT boards are similar [9], they are both single board computers containing ARM Processor and 4G of RAM and various ports for peripheral connectivity. But in terms of GPU, Jetson Nano steps ahead because of its 128- core Maxwell GPU @ 921 Mhz. Whereas Raspberry-Pi 4 GPU is weaker compared to Jetson Nano. If looking into CPU, Raspberry-pi uses the Quad-core ARM cortex-A72 64-bit @ 1.5 GHz, this offers higher performance and faster clocking speed, but for CNN, deep learning, and AI (Artificial Intelligence) it does not provide enough performance benefits. And as this prototype required better performance in deep learning, going forward with Jetson-Nano was the choice.

III. Motivation

The motivation behind this work is to also make the Indian roads safer and spread awareness about the crucial road signs to avoid unnecessary accidents that could be reduced by following the road signs.

IV. Problem Definition

The problem is the negligence of traffic signs which increases accidents and making the roads unsafe for users.
To avoid and reduce such incidences an assistance can help the driver a long way to drive ensuring the safety of oneself and others. To resolve this problem, it is proposed to have a working prototype of traffic sign recognition model applied on an IOT device.

V. Problem Formulation

To classify traffic signs into forty three classes.

VI. Design Methodology

The software model used in the building of the prototype is Lenet-5. The motive of using this model is that it is one of the lightest models in the market, it is the earliest pre-trained models proposed. LeNet-5 has convolutional and pooling layers in its architecture. Its response time is very less which ultimately results into fast recognition of signs being efficient and valuable in reporting back the results. The hardware model used in the prototype is Jetson-Nano, which is a powerful, small computer. It lets you run multiple neural networks in parallel. It is an NVIDIA product specifically designed for deep learning and convolutional neural network applications.

VII. Algorithm

The domain of the project is deep learning and its application over IOT. Deep learning is a machine learning method that coaches' computers to have an intelligence, to learn by training itself by looking into several examples and learning to identify. Deep learning allows the system to recognise and to distinguish between things after the training.

In deep learning, the system model learns to classify images, text, or sound. Deep learning models have achieved accuracy which sometimes goes beyond the human accuracy. These deep learning models are trained first for impeccable results of an input of large, labelled dataset into a suitable neural network that contains layers for better understanding and accuracy.

The algorithm used in this project is Lenet-5

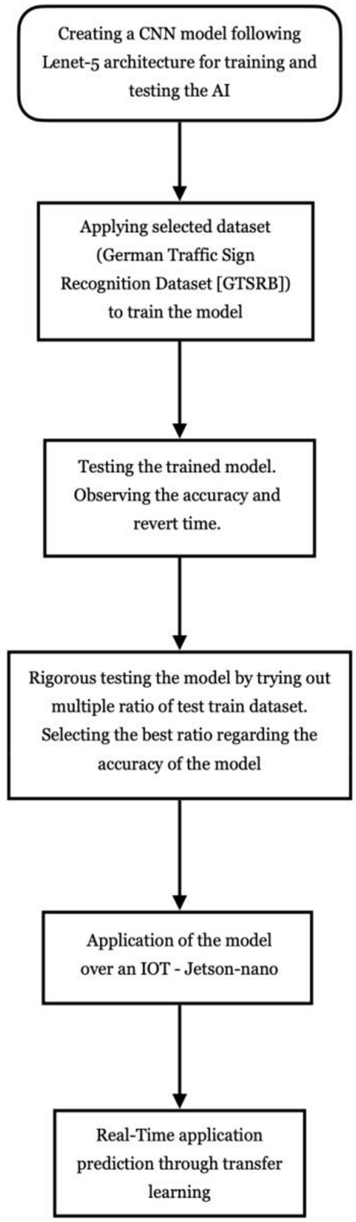

Fig. 1 - Flow Chart of Design Methodology

VIII. Solution Methodologies or Problem Solving

To run the experiment, a CNN model was built to support the modified LeNET model. The GTSRB dataset is used to guide and achieve good accuracy of the model. The experiment is done after adjustment of parameter to see if there is a significant change in the accuracy of the model. Another experiment is then completed using model constructed to detect and traffic sign images using the OpenCV method in real time and with hardware Jetson Nano. The steps for this experiment are:

- Creating a train and test dataset from the images.

- Enhancing image quality by pre-processing images .
- To classify the images, create a CNN model.
- Fine-tuning the parameters to see how much the model's accuracy improves.
- Using OpenCV to categorise images in real-time using this model.

IX. BUILDING THE CNN MODEL

Lenet-5 was a first convolutional neural network, and it was used to classify two-dimensional images Lenet layer structure was very simple there are only seven layers in the structure The size of image is 32 x 32 when we input this image but after applying this convolutional operation the image size become 28 x 28 and the number of channels is also 6 earlier it was 1 but now it is 6. Number of channels always depend upon the number filter which we have used in the image. The image size reduced to twenty-eight into twenty-eight right and then we have max pooling layer. In pooling operations, we are using stripe 2 in pooling operation because when we use try to image will automatically get shrink the image gets reduced. The input of input to first layer is this size of image and in first layer we are saying like we want to have six filter of size five by five, and stride is one right these are the parameters, so we need to use this formula. You can apply the same formula for other layers, and you will see like to you will be getting these sizes of images. The output of this layer will become the input to pooling layer, first we have convolutional layer and after this operation we have this value now we will apply will give this input to max pool layer and we have window size of two by two and stride is two in this case. Lenet was developed to recognise handwritten digits on checks so now we want to perform that classification task recognition task so for that we need to convert our two-dimensional image into a one-dimensional, and we are using stride is equal to 2 and the filter size is 2 by 2 This particular layer every very neurone will process these pixels and then it will pass it to a next fully connected layer. This layer has 120 neurones. For every class we need one neurone so that is why we have 10 neurones over here. The activation function which we are using here is SoftMax activation function and this function will return us a list of probabilities. In final layer we are having 10 neurone just because we are performing traffic sign recognition and we want to recognise sign, every neurone will one neurone will store one kind of output and classify the sign images.

TABLE I - ARCHITECTURE OF LENET-5

Type of layer	Output shape
conv2d (Conv2D)	(None, 28, 28, 60)
conv2d_1 (Conv2D)	(None, 24, 24, 60)
max_pooling2d (MaxPooling2D)	(None, 12, 12, 60)
conv2d_2 (Conv2D)	(None, 10, 10, 30)
conv2d_3 (Conv2D)	(None, 8, 8, 30)
max_pooling2d_1 (MaxPooling2)	(None, 4, 4, 30)
dropout (Dropout)	(None, 4, 4, 30)
flatten (Flatten)	(None, 480)
dense (Dense)	(None, 500)
dropout1(*Dropout*)	(None, 500)
dense1(*Dense*)	(None, 43)

X. RESULTS AND SENSITIVITY ANALYSIS

For Learning Rate 0.001

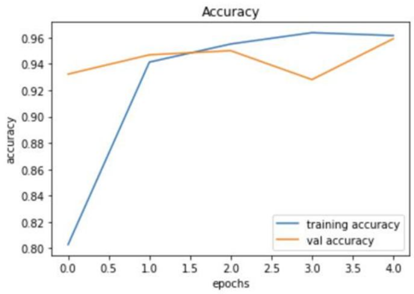

Fig. 2 - For Learning Rate 0.001 as epochs increase the validate accuracy increases

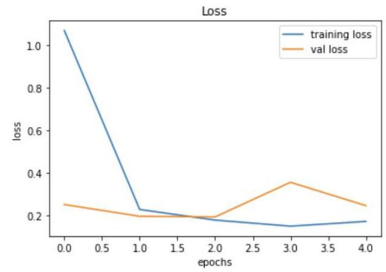

Fig 3 - For Learning Rate 0.001 as epochs increase the validate loss decreases

For Learning Rate 0.002

Fig. 4 - For Learning Rate 0.002 as epochs increase the validate accuracy increases

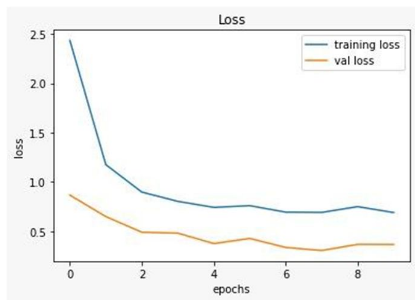

Fig. 5 - For Learning Rate 0.002 as epochs increase the validate loss decreases

For Learning Rate 0.002

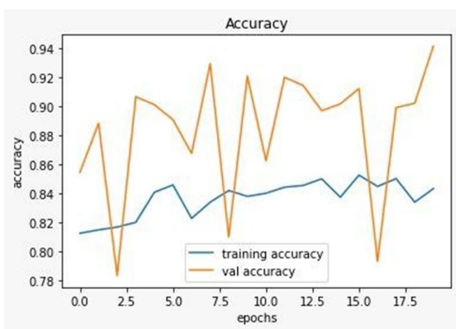

Fig. 6 - For Learning Rate 0.002 as epochs increase the validate accuracy increases

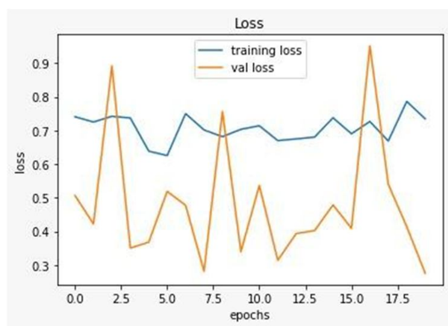

Fig. 7 - Learning Rate 0.002 as epochs increase the validate loss decreases

When the learning rate is tweaked, the model's accuracy is discovered. The number of weights updated while training the model is referred to as the learning rate or step size. We can see that increasing the learning rate over the default optimum value of 0.001 reduces the model's accuracy. This can happen because the learning rate determines how quickly a model adapts to a challenge. As a result, a high learning rate allows the model to learn more quickly but results in a sub-optimal set of weights. The training dataset loses accuracy because to the diverging weight. A lower learning rate helps the model to learn the best set of weights, but this can take a long period. The model could be stuck on a less-than-ideal solution. As a result, altering the learning rate from the default reduces model accuracy.

XI. DATASET

The data model used is German Traffic Sign Recognition Dataset (GTSRB) which is a dataset of German roads that contain 43 different classes of traffic signs.

XII. CONCLUSION

The accuracy of the overall system is 95.1% which may be further improved by using transfer learning approach.

FUTURE WORK

This system can be used for driverless and autonomous cars making them smart cars which assist the drivers while driving with these signs which usually people tend to miss. As it is a portable device which can be used as a standalone device it could be installed into two wheeler vehicles as well.

REFERENCES

[1] T. Zhao, Q. Liu, and Y. Zhang, "A Traffic Sign Detection Method based on Saliency Detection," 2019 1st International Conference on Industrial Artificial Intelligence (IAI), 2019, pp. 1-6, doi: 10.1109/ICIAI.2019.8850782.

[2] Y. Zhu, M. Liao, M. Yang and W. Liu, "Cascaded Segmentation-Detection Networks for Text-Based Traffic Sign Detection," in IEEE Transactions on Intelligent Transportation Systems, vol. 19, no. 1, pp.2 0 9 - 2 1 9 , J a n . 2 0 1 8 , d o i : 1 0 . 1 1 0 9 / TITS.2017.2768827.

[3] H. S. Lee and K. Kim, "Simultaneous Traffic Sign Detection and Boundary Estimation Using Convolutional Neural Network," in IEEE Transactions on Intelligent Transportation Systems, vol. 19, no. 5, pp. 1652-1663, May 2018, doi: 10.1109/TITS.2018.2801560.

[4] D. M. Filatov, K. V. Ignatiev and E. V. Serykh, "Neural network system of traffic signs recognition," 2017 XX IEEE International Conference on SoftComputing and Measurements (SCM), 2017,pp.422-423, doi: 10.1109/SCM.2017.7970605.

[5] M. M. William et al., "Traffic Signs Detection and Recognition System using Deep Learning," 2019 Ninth International Conference on Intelligent Computing and Information Systems (ICICIS), 2019, p p .160-166, d o i :10.1109/ICICIS46948.2019.9014763.

[6] K. Vinothini and S. Jayanthy, "Road Sign Recognition System for Autonomous Vehicle using Raspberry Pi," 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS), 2019, pp. 78-83, doi: 10.1109/ ICACCS.2019.8728463.

[7] D. Priyanka, K. Dharani, C. Anirudh, K. Akshay, M. P. Sunil, and S. A. Hariprasad, "Traffic light and sign detection for autonomous land vehicle using Raspberry Pi," 2017 International Conference on Inventive Computing and Informatics (ICICI), 2017, pp. 160-164, doi: 10.1109/ICICI.2017.8365328.

[8] J. Stallkamp, M. Schlipsing, J. Salmen, and C. Igel, “The German traffic sign recognition benchmark: a multi-class classification competition,” in Proc. IEEE IJCNN, 2011, pp. 1453–1460.

[9] A. A. Süzen, B. Duman and B. Şen, "Benchmark Analysis of Jetson TX2, Jetson Nano and Raspberry PI using Deep-CNN," 2020 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA), 2020, pp. 1-5, doi: 10.1109/HORA49412.2020.9152915.

[10] S. Houben, J. Stallkamp, J. Salmen,M. Schlipsing, and C. Igel, “Detection of traffic signs in real-world images: The German traffic sign detection benchmark,” in Proc. IEEE IJCNN, 2013, pp. 1–8.

[11] Kai Li, Weiyao Lan, “Traffic indication symbols recognition with shape context,” IEEE ,2011.

[12] Yi Yang, Hengliang Luo, Huarong Xu and Fuchao Wu, “Towards Real-Time Traffic Sign Detection and Classification,” IEEE,2014.

[13] J. Greenhalgh and M. Mirmehdi, “Real-time detection and recognition of road traffic signs,” IEEE Trans. Int. Transp. Syst., vol. 13, no. 4, pp. 1498– 1506, Dec. 2012. e-ISSN: 2395 -0056 p-ISSN: 2395-0072

[14] L. Jia, X. Shi and L. Wei, "Design of Traffic Sign Detection and Recognition Algorithm Based on Template Matching," 2020 IEEE 2nd International Conference on Civil Aviation Safety and Information Technology (ICCASIT, 2020, pp. 237-240, doi: 10.1109/ICCASIT50869.2020.9368750.

[15] A. Suriya Prakash, D. Vigneshwaran, R. Seenivasaga Ayyalu and S. Jayanthi Sree, "Traffic Sign Recognition using Deeplearning for Autonomous Driverless Vehicles d o i : 1 0 . 1 1 0 9 /ICCMC51019.2021.9418437

[16] C. Liu, F. Chang, Z. Chen and D. Liu, "Fast Traffic Sign Recognition via High-Contrast Region Extraction and Extended Sparse Representation," in IEEE Transactions on Intelligent Transportation Systems, vol. 17, no. 1, pp. 79-92, Jan. 2016, doi: 10.1109/TITS.2015.2459594.