Seminar Report

on

“Traffic sign detection”

Submitted to the

Savitribai Phule Pune University

In partial fulfilment for the award of the Degree of

Bachelor of Engineering

in

Information Technology

By

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CERTIFICATE

This is to certify that the seminar report entitled **“Traffic sign Detection”** being submitted by **Prathamesh Chaudhari , TI11** is a record of bonafide work carried out by her under the supervision and guidance of **Mrs. Preeti Joshi** in partial fulfillment of the requirement for **TE (Information Technology Engineering) – 2019 course** of Savitribai Phule Pune University, Pune for the academic year 2024- 25

Date: 17 – 10 – 2024

Place: Pune

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This project-based seminar report has been examined by us as per the Savitribai Phule Pune University, Pune, requirements at Marathwada Mitra Mandal's College of Engineering, Pune on 17 – 10 – 2024.

ACKNOWLEDGEMENT

I am extremely grateful to Mrs.Preeti Joshi, Department of Information Technology, for providing all the required resources for the successful completion of my seminar and for her valuable suggestions and guidance in the preparation of the seminar report. I express my thanks to all staff members and friends for all the help and co-ordination extended in bringing out this seminar successfully in time. I will be failing in duty if I do not acknowledge with grateful thanks to the authors of the references and other literatures referred to in this seminar.

Prathamesh Chaudhri (TI11)

Abstract

Automatic detection and recognition of traffic signs plays a crucial role in management of the traffic-sign inventory. It provides an accurate and timely way to manage traffic-sign inventory with a minimal human effort. In the computer vision community, the recognition and detection of traffic signs are a well-researched problem. A vast majority of existing approaches perform well on traffic signs needed for advanced driver-assistance and autonomous systems. However, this represents a relatively small number of all traffic signs (around 50 categories out of several hundred) and performance on the remaining set of traffic signs, which are required to eliminate the manual labor in traffic-sign inventory management, remains an open question. In this paper, we address the issue of detecting and recognizing a large number of traffic-sign categories suitable for automating traffic-sign inventory management. We adopt a convolutional neural network (CNN) approach, the mask R-CNN, to address the full pipeline of detection and recognition with automatic end-to-end learning. We propose several improvements that are evaluated on the detection of traffic signs and result in an improved overall performance. This approach is applied to detection of 200 traffic-sign categories represented in our novel dataset. The results are reported on highly challenging traffic-sign categories that have not yet been considered in previous works.

Table of Contents

List of Figures

CHAPTER 1
Introduction

1.1 Introduction to computer vision.

Computer vision is one of the most vital fields of AI and computer science engineering that enables computer systems to extract meaningful information from visual data like videos and images. This further helps take the proper actions and make suggestions based on the extracted information.

Moreover, Artificial intelligence is the branch of computer science that primarily deals with the development of a smart and intelligent system which can behave and think like the human brain. Thus, if artificial intelligence enables computer systems to think intelligently, computer vision makes them capable of seeing, analyzing, and understanding.

Computer vision applications make use of input from sensing devices, artificial intelligence, machine learning, and deep learning to mimic the nature of a human vision system. Therefore, computer vision applications operate on a large amount of visual data or images in the cloud in order to identify patterns within this visual data to discern the content of other images.

1.2 Introduction to Traffic Sign Detection (Computer Vision).

Proper management of traffic-sign inventory is an essential task to ensure safety and efficiency in the flow of traffic. It is mainly done in manual mode. Traffic signs are captured using a vehicle-mounted camera, and manual localization and recognition occur off-line by the human operator for consistency with the already-existing database. Such manual work can be very time-consuming when applied to thousands of kilometers of roads. Automating this task would significantly reduce the amount of physical work and improve safety by detecting damaged or missing traffic signs much more quickly. A comprehensive way towards the automation of this task is a replacement of the manual localization and recognition of traffic signs with an automatic detection. The problem of traffic-sign recognition already gained substantial attention in the computer-vision community and excellent detection and recognition algorithms have already been proposed. But these solutions have has been designed for only a few types, mainly for traffic signs relates to advanced driver-assistance systems (ADAS) as well as autonomous cars. Detection and identification of a large set of categories of traffic signs are left open. Numerous earlier benchmarks approached the traffic-sign recognition and detection problem. However, a majority of them addressed only TSR and disregarded the much more challenging task of traffic-sign detection (TSD) where the correct location of the traffic sign is to be identified. In existing technology, color information enhancement or shape information enhancement methods are usually used as the preprocess stage of traffic sign detection.

Other benchmark challenges that do take TSD into account for the most part focus only on a subset of the traffic-sign categories, the majority of which are ones relevant to ADAS and autonomous vehicles applications. Most categories occurring in such benchmarks have a distinctive appearance with low inter-category variance and can be easily detected by using handcrafted detectors and classifiers. Examples include round mandatory signs or triangular prohibitory signs.

1.3 Motivation

Traffic sign detection is one of the significant sub-components in intelligent transportation and autonomous driving, playing key roles in ensuring road safety and improving efficiency in traffic management. A vehicle should be able to make a timely, informed decision to reduce speed, yield, or stop at an intersection only when it can automatically detect, recognize, and interpret traffic signs. The technology of traffic sign detection has been made an integral part of the design of modern automobiles due to the increased adoption of autonomous vehicles and advanced driver assistance systems. Meanwhile, human drivers often fail to notice traffic signs or read them wrongly due to distractions or poor visibility and then get involved in accidents and commit traffic violations. Such risks can be mitigated through the integration of traffic sign detection systems, as it provides an added layer of safety with constant scanning of the road for critical information. Through advancements in machine learning, deep learning, and computer vision, the accuracy in traffic sign detection, even in bad lighting, adverse weather, or occlusions, became better. This will not only make the vehicle smarter know its environment but also enable intelligent smart cities where traffic flow is efficient, reduces congestion, and emissions. So, the talk for a seminar on the detection of traffic signs emphasizes a high-technology approach that fuses innovation with life-saving devices in the real world, which impacts further development regarding transportable phenomena.

1.4 Aim and Objectives of the work

The overall aim is to build a system that can be used for the inventory of traffic signs.

This will help the local or national authorities to maintain their road and traffic signs up-to-date by automatically detecting and classifying one or more traffic signs from a complex scene when photographed by a camera mounted inside a vehicle.

The main strategy is to find in the scene a right combination of colors such that one colour is placed inside the convex hull of another colour combined with the right shape. If such a candidate is found, the system tries to classify the object following the rimpictogram combination and to give the result of this classification.

Thus, the objectives are:

1. Understand road and traffic signs properties and the implications this has on image processing for the recognition task.

2. Know colour, colour spaces and colour space conversion.

3. Develop robust colour segmentation algorithms for applications in a wide range of environmental conditions.

CHAPTER 2
LITERATURE SURVEY

2.1 STUDY OF LITERATURE SURVEY

Sr No.	Paper Title	Publication & Year	Authors	Findings
1.	Vision-Based Traffic Sign Detection and Recognition using AI	IJRASET, 2021	Albert Keerimolel et al.	AI-driven methods improve accuracy in traffic sign detection.
2.	Traffic Sign Recognition System Based on Machine Learning Techniques	Journal of Traffic and Transportation Engineering, 2020	Sharma et al.	Explored different machine learning algorithms for traffic sign recognition, focusing on classification accuracy.
3.	A Real-Time Traffic Sign Detection System Using Deep Learning	IEEE Access, 2021	Li et al	Introduced a deep learning framework for real-time traffic sign detection, demonstrating high accuracy.

4.	An Automatic Traffic Sign Detection and Recognition System Based on Colour Segmentation, Shape Matching, and SVM	Hindawi Journal, 2019	Safat B. Wali et al.	Proposed a system combining color segmentation and shape matching for effective sign recognition.
5.	Traffic Sign Recognition with Deep Learning: A Review.	IEEE Transactions on Intelligent Transportation Systems, 2020	Shaligram et al.	Reviews various deep learning architectures used for traffic sign recognition.
6.	Traffic Sign Detection and Recognition Using Deep Convolutional Networks.	IEEE ITS, 2018	T. Wu, Z. Chen, Y. Zhang	Introduced a deep CNN model that integrates detection and recognition, achieving high accuracy with real-time performance by optimizing the model's architecture.
7.	Multi-Scale Traffic Sign Detection and Recognition Using Datasets and CNN.	Elsevier, 2017	B. Wang, L. Xiao, K. Li	Utilized multi-scale feature extraction and a customized CNN, significantly improving accuracy across multiple traffic sign datasets, including German and Chinese signs.

8.	Traffic Sign Detection Using Color and Shape-Based Feature Extraction.	IEEE Access, 2016	R. Gupta, A. Bhardwaj, S. Singh	Proposed a hybrid method combining color and shape features for detection, showing efficient processing speed suitable for real-time applications in varying weather conditions.
9.	Improved Road Sign Detection Using HSV Color Segmentation and SVM Classifier.	IEEE ICIP, 2014	C. Wang, M. Zhang, Q. Liu	Employed HSV color space for segmentation combined with SVM for classification, leading to efficient detection with moderate accuracy on various road sign types.
10.	Traffic Sign Detection and Classification Using CNN	IEEE ICCE, 2017	H. Kim, S. Park, J. Lee	Presented a CNN-based approach that integrates detection and classification tasks, achieving improved accuracy over conventional HOG-based methods.

CHAPTER 3

Methodology & Algorithms Used

3.1) Methodology

Recently, the CNN has been adopted in object recognition with high accuracy. Most of these models use raw images rather than hand-coded features, and most of them regard feature extraction and classification as a whole; this is known as end to end classification. Although raw image-based CNN image classification methods have achieved better performance, many scholars have also further researched the performance of CNN classification after feature transformation.

3.1.1 Proposed Solution :

The architecture of the proposed solution is shown in figure 1.

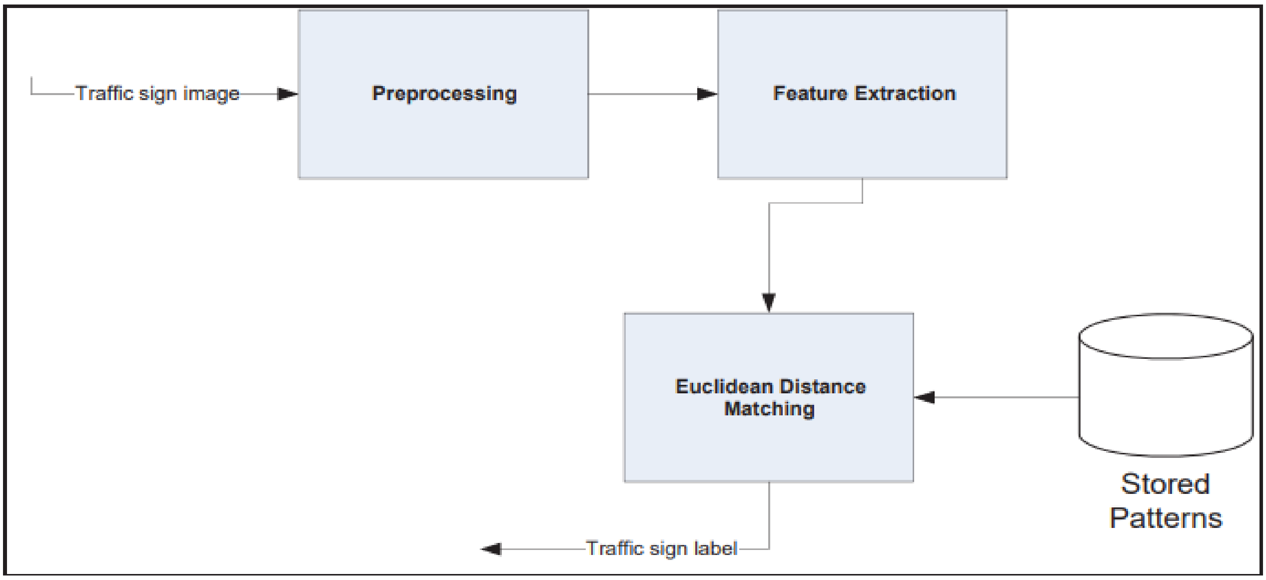

Figure 1 Architecture Diagram

Following are the modules in the above architecture diagram –

Pre-processing: This module processes the image to enhance it and apply thresholding and thinning on image to make suitable for feature extraction.

Image enhancement techniques have been widely used in many applications of image processing where the subjective quality of images is important for human interpretation.

Contrast is an important factor in any subjective evaluation of image quality. Contrast is created by the difference in luminance reflected from two adjacent surfaces. In other words, contrast is the difference in visual properties that makes an object distinguishable from other objects and the background. In visual perception, contrast is determined by the difference in the colour and brightness of the object with other objects. Our visual system is more sensitive to contrast than absolute luminance; therefore, we can perceive the world similarly regardless of the considerable changes in illumination conditions. Many algorithms for accomplishing contrast enhancement have been developed and applied to problems in image processing.

Feature Extraction: This module draws three horizontal lines and three vertical lines and then find the intersection points of traffic sign on these lines and use those intersection as features.

Matching: This module matches the features of traffic sign image with stored pattern and gives the matching label of the stored patter to whom the features of traffic sign is maximally matching.

The matching is based on maximal matching criteria. In this work it is the smallest distance between two feature vectors. Say, a feature vector of traffic sign image A is <x1, x2, x3, x4, …, xn> and the feature vector of traffic sign image B is <y1,y2,y3,y4….yn> . The matching distance between A and B is calculated.

3.1.2 OOPS Design :

Object oriented design of the project is described below. A use case diagram shown in figure 2 is a type of behavioural diagram created from a use case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases.

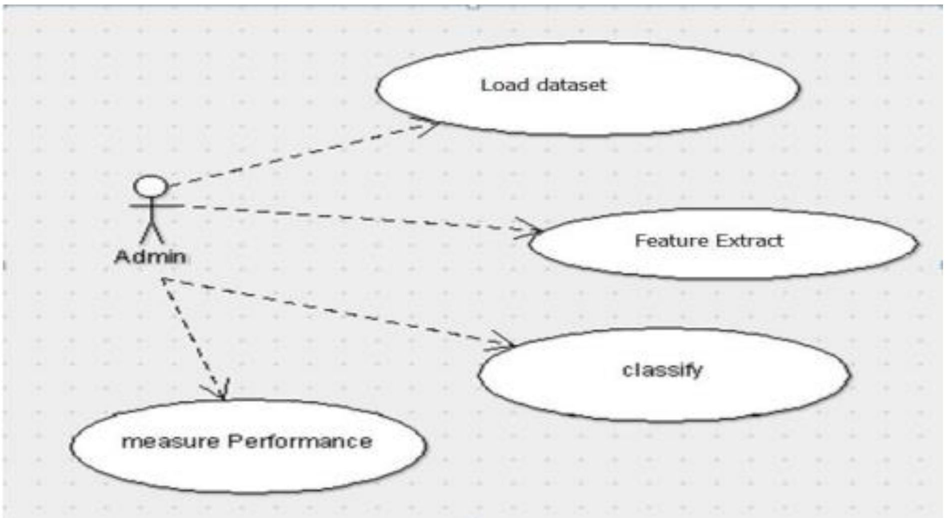

Figure 2 Use Case Diagram

Admin is the user who can do the following functions:

1. Load data set
2. Extract features
3. Classify any given input symbol.

11

4. Measure the performance.

3.1.3 Data Flow Diagram :

The input, output and the process flow in the system is shown in figure 3.

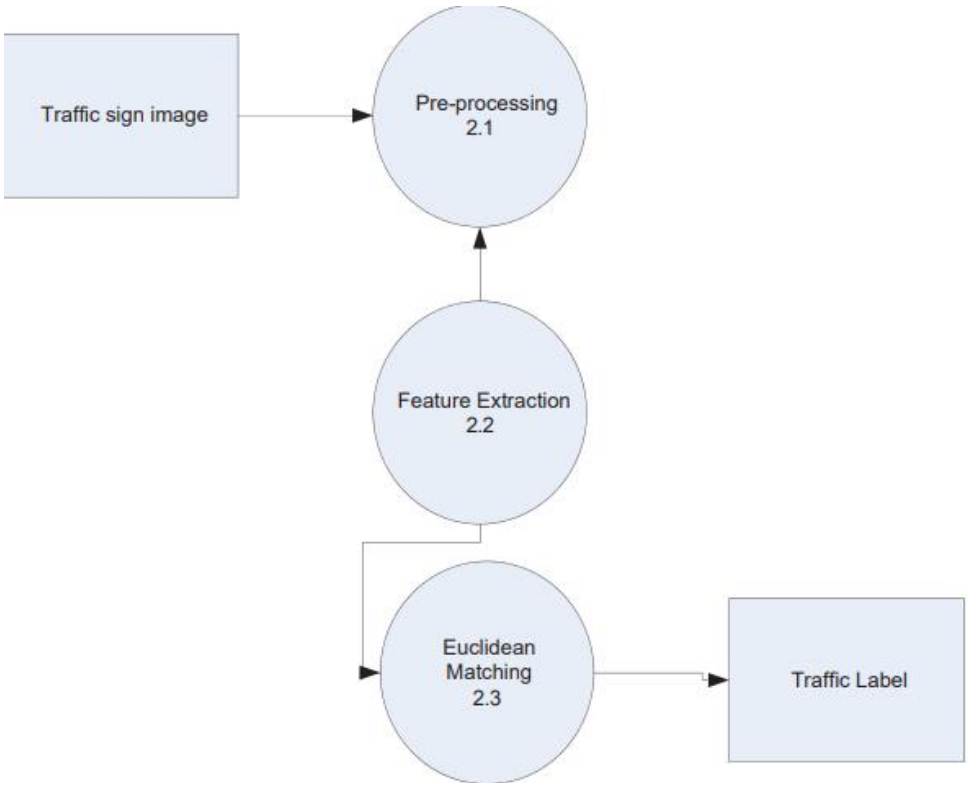

Figure 3. Classification Flow diagram

The classification process is split to sub process as shown in figure 9. The input image is preprocessed, features are extracted from it and matching to features of image stored in repository is done. The closest matching image‘s label is given as output.

3.2) Algorithms Used

In image classification fields, the Gabor feature has been widely used as the input of classifiers. In References the Gabor feature was used for face recognition, mostly obtaining the performance of state-of-the-art methods. Many researchers have used the Gabor feature as an input of CNN and achieved better results. In the fingerprint image recognition area, Reference used the Gabor filter to preprocess the raw image and made it the input of the CNN. In Reference the speech signal was filtered by the Gabor filter, and then recognized by the CNN. In Reference the Gabor filter was used as the first layer

of the neural network and experiments regarding the open database in the area of face detection, digit recognition, and objection recognition, where it obtained a comparable performance with energy efficiency and fast learning during the training of the CNN. Therefore, the use of the special parameters of Gabor-based preprocessed images as the input of the CNN for image classification is very valuable research.
Convolutional Neural Networks (CNNs) are deep learning models that have been widely applied to a lot of computer vision tasks: such as classification, object detection, and image segmentation. In this field of study area, CNNs showed much effectiveness due to the ability of the networks to automatically learn and extract meaningful features from images.

The basic steps for the construction of a CNN can be summarized in the following:

1. Preprocessing: The first step to building a CNN is preprocessed images to be used as an input. All images must be resized to a fixed size, normalized pixel values, and, depending on the dataset, augmented. Increasing preprocessing helps reduce the complexity of computations involved and improves performance by the model.

2. Convolutional Layers: These are the basic building blocks of a CNN.
These layers perform convolution, or a small filter known as the kernel slid over the input image, and compute the dot product between the filter and the local receptive field of the image. The outcome is a feature map that represents the presence of certain features in the input image.
Stacking several convolutional layers together can learn more complex and hierarchical features.

3. Activation Function: After a convolution operation, an activation function is applied element-wise to the output of every convolutional layer. ReLU is the most common activation function in CNNs: the Rectified Linear Unit, that introduces non-linearity into the model and helps learn complex patterns.

4. Pooling Layers: A pooling layer reduces the spatial dimensions of the feature maps while retaining the most important information. The most common pooling operation used is max pooling, which chooses the max value from a local neighborhood in the

feature map. Pooling reduces the computational complexity and helps to make the model more robust to small translations and distortions in the input images.

5. Fully Connected Layers: After many convolutional and pooling layers, feature maps are flattened into a one-dimensional vector and then passed through one or more fully connected layers. In this layer, it connects every neuron in one layer to every neuron in the next layer, just like a traditional neural network. The fully connected layers, therefore learn these high-level features and make the final predictions.

6. Output Layer: The output layer of a CNN depends on the type of task being specified. In classification, say in an image classification output layer would most probably comprise a softmax activation function that produces a probability distribution over the different classes. An output layer in object detection can consist of multiple neurons which represent presence or absence of different objects in the image. Loss Function: The loss function is the difference between the predicted output of the CNN and the ground truth labels. This will depend upon what task the model is built for. For instance, cross entropy loss when the images are to be classified. Optimization: The aim of optimization is to learn the parameters of the CNN to minimize the loss function. This is usually done with some optimization algorithm such as stochastic gradient descent (SGD) or Adam. The parameters of the CNN are updated iteratively by computing the gradients of the loss function with respect to the parameters and adjusting them appropriately. Training and Testing: The CNN gets trained on the labeled dataset by passing input images to the network and optimized parameters using the optimization algorithm. Thus, training is developed by undergoing many iterations or epochs, out of which each epoch represents the passing of the complete dataset forward through the network. The performance of the CNN is tested over another validation set to check its generalization capability. Once the CNN has been trained, it can then make predictions on new, unseen images.

CHAPTER 4
Performance Analysis

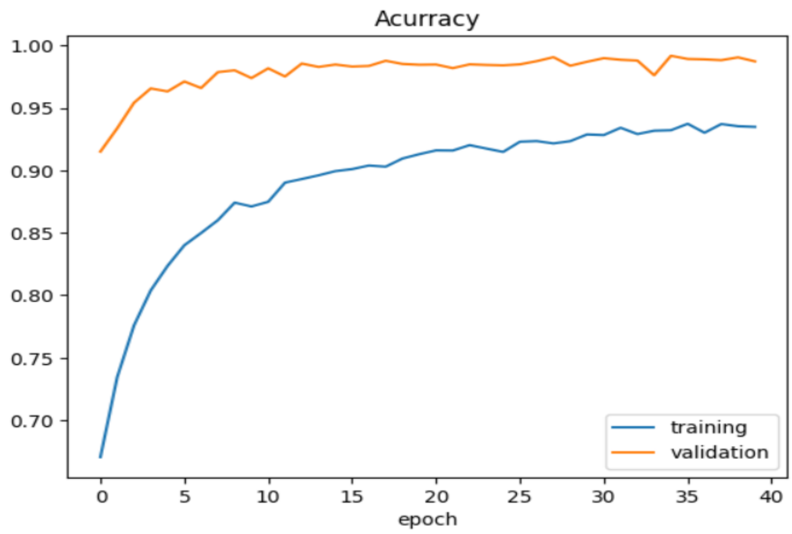

Figure 4 Accuracy graph

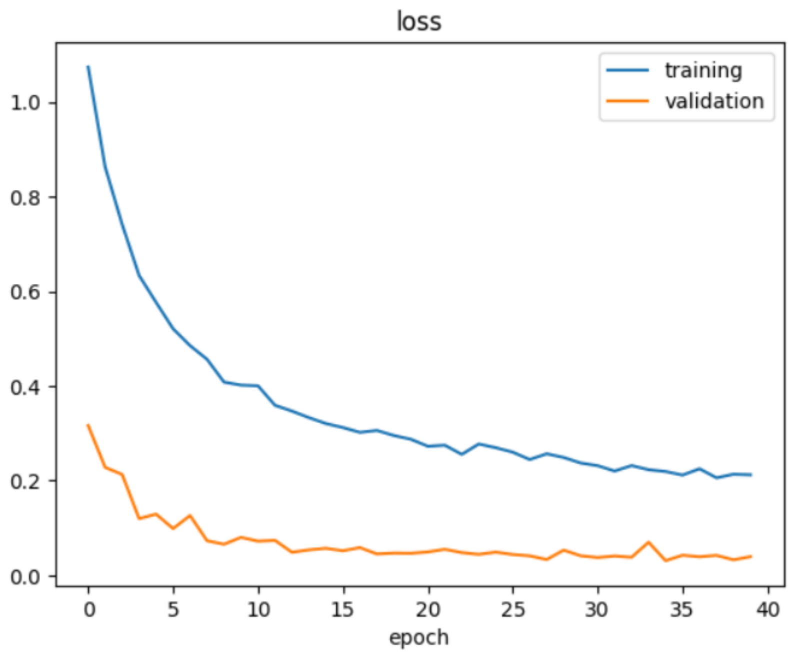

Figure 5 Loss graph

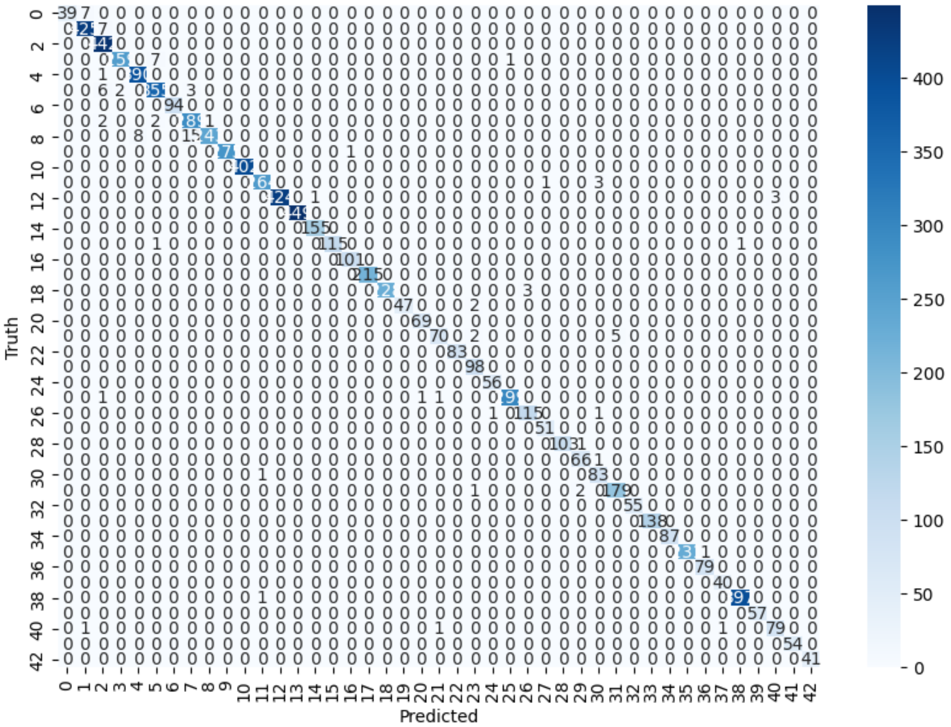

Figure 6 confusion matrix

The principal metrics of performance analysis for evaluating CNN-based traffic sign detection involve a set of parameters that define the effectiveness of a model concerning recognition and classification capacity for the different traffic signs. The primary metric involves accuracy, which refers to the capability of the CNN in correctly identifying different types of traffic signs from a given set of input images. High accuracy implies that the model can classify various types of traffic signs, which is one of the important requirements for real-time applications such as autonomous driving. Precision and recall are two others, which capture the ability of the model to only correctly identify true traffic signs without false positives and, therefore, recall all the relevant signs without any miss.

Important performance metric yet is the processing speed, specifically when the detection of traffic signs is used in real-world scenarios. Thus, the CNN with the least latency and inference time was necessary to ensure real-time detection and therefore can be deployed on the vehicles, but faster models usually degrade the accuracy, so trade-off must be considered.

The other important requirement is robustness of the model in different conditions, such as lighting, occlusion, or different angles of view. Well-performing CNN should generalize to learn across variations from the real world: the signs may or may not be present, etc, and detect them reliably. Techniques like data augmentation and transfer learning often tend to improve performance in these areas by letting the model learn to better handle variability in the real world.

CHAPTER 5
Outline and Future Scope

Traffic Sign Detection (TSD) is crucial in autonomous driving and Advanced Driver Assistance Systems (ADAS). The seminar will cover the introduction, explaining the importance of detecting traffic signs for improving road safety and enabling self-driving vehicles. It will then focus on existing methods, starting with traditional techniques like color-based segmentation and shape recognition. This will lead into more advanced methods using machine learning and deep learning, such as Convolutional Neural Networks (CNNs) and real-time object detection frameworks like YOLO.

The challenges section will discuss issues like varying lighting conditions, occlusion, and real-time computational requirements. A comparative study will evaluate the performance of different models based on accuracy, speed, and robustness, along with current state-of-the-art technologies. The report will also highlight the applications of TSD, particularly its integration into autonomous vehicles and its contribution to traffic management systems.

The future scope will explore advancements in deep learning and lightweight models to enhance real-time detection. Additionally, data augmentation and synthetic datasets will be emphasized to improve training and handling of diverse conditions. The scope will include the development of adaptive systems capable of recognizing new or damaged traffic signs and integrating multimodal data from sensors like LiDAR and GPS to enhance detection reliability. Lastly, edge computing advancements will be discussed for deploying efficient models on low-power devices.

This seminar will provide a comprehensive understanding of TSD, its current state, and its future directions.

CHAPTER 6

CONCLUSION

Traffic sign detection is one of the most important aspects of road safety enhancement and support to the development of self-driving vehicles. A system for efficient and accurate identification of traffic signs enables ADAS significantly to reduce the accident rate and improve traffic management. The introduction of deep learning techniques has dramatically improved detection accuracy as well as the robustness of detection in varying environments and conditions. Future research directions would be into real-time processing, adaptability to various scenarios of operation and, in particular, smooth integrations into other vehicular systems. Such research and innovation in this field would be to the best interest of safety and efficiency in intelligent transportation systems.

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