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RECOGNITION OF TRAFFIC SIGN USING DEEP LEARNING

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Abstract: This paper presents an approach to recognition of traffic signs using Convolutional Neutral Networks (CNNs) and You Only Look Once (YOLOv4) networks. Traffic sign recognition is a crucial aspect of autonomous driving systems, aiding in navigation, safety, and compliance with traffic regulations. In this project, we propose a novel approach to traffic sign recognition utilizing a combination of Convolutional Neural Networks (CNNs) and the You Only Look Once version 4 (YOLOv4) object detection framework. The integration of YOLOv4 allows for efficient real-time detection of traffic signs in complex scenes, while CNNs enable accurate classification of detected signs. The proposed system involves preprocessing input images, followed by training the YOLOv4 framework to detect traffic signs. Subsequently, the detected signs are extracted and classified using a CNN model trained on a labeled dataset of traffic signs. The synergy between YOLOv4 and CNNs enhances the robustness and accuracy of traffic sign recognition, even in challenging scenarios with varying lighting conditions and occlusions. Experimental evaluations on benchmark datasets demonstrate the effectiveness and efficiency of the proposed approach compared to existing methods. The developed system holds significant promise for integration into autonomous vehicles and intelligent transportation systems, contributing to enhanced road safety and traffic management.

***Index Terms* – traffic sign recognition, deep learning, convolution neural network, tensor flow, keras, YOLO v4.**

I. INTRODUCTION

Traffic sign recognition plays a pivotal role in modern transportation systems, facilitating safer and more efficient navigation on roadways. With the rapid advancement of autonomous vehicles and intelligent transportation systems, the need for robust and accurate traffic sign detection and classification algorithms has become increasingly pressing. Traditional methods relying on handcrafted features and rule-based classifiers often struggle to handle the complexities and variability of real-world traffic sign scenarios. In recent years, deep learning techniques have emerged as a powerful tool for computer vision tasks, offering superior performance in object detection and classification. In this project, we propose a novel approach to traffic sign recognition leveraging the capabilities of Convolutional Neural Networks (CNNs) and the You Only Look Once version 4 (YOLOv4) object detection framework. The integration of these two state-of-the-art techniques aims to address the challenges associated with real-time detection and classification of traffic signs in diverse and dynamic environments.

The primary objective of this project is to design and develop a robust system capable of accurately detecting and classifying traffic signs in real-time scenarios. By combining the strengths of CNNs for fine-grained classification and YOLOv4 for efficient object detection, we aim to achieve superior performance in terms of accuracy, speed, and scalability.

The remainder of this report will detail the methodology, experimental setup, results, and discussion, ultimately demonstrating the effectiveness and practical applicability of the proposed approach in the domain of traffic sign recognition. Through this project, we aim to contribute to the advancement of autonomous driving technologies and intelligent transportation systems, ultimately enhancing road safety and traffic management.

RELATIVE WORK

Currently, two main categories of deep-learning-based object detection methods exist: One-stage and Two-stage approaches. The RCNN family, including RCNN, Fast RCNN, and Faster RCNN, exemplifies a traditional two-stage algorithm. In a two-stage detection algorithm, the process involves separately determining the traffic sign recognition and its type. For instance, the Faster RCNN's Region Proposal Networks (RPN) assist in generating candidate boxes that may contain the traffic sign. Following this, another network discerns the category of the traffic sign within the selected candidate box. While Traffic sign recognition employing a two-stage approach offers high-precision results, it comes with the drawback of increased computational cost, leading to longer processing times and making real-time detection challenging.

The one-stage detection algorithm involves simultaneously positioning and identifying different traffic signs. Prominent algorithms in this category include SSD and the YOLO series (YOLO, YOLOv2, YOLOv3, and YOLOv4).

In general, when comparing different versions of YOLO, newer versions often aim to address limitations, improve accuracy, and enhance performance. Developers typically iterate on the models to make them more robust and suitable for a wider range of applications.

Here is a brief history of the YOLO Algorithm

- YOLO (You Only Look Once), a seminal model for object detection and image segmentation, originated from the collaborative efforts of Joseph Redmon and Ali Farhadi at the University of Washington in 2015.
- YOLOv2, released in 2016, improved upon the original model by incorporating characteristics like like batch normalization, anchor boxes, and fine-grained feature maps for better localization.
- YOLOv3, released in 2018**,** Further boosted both speed and accuracy through a more powerful Darknet-53 backbone, residual connections, and multi-scale outputs for varying object sizes.
- YOLOv4, released in 2020, brought innovations like Mosaic data augmentation, a detection head devoid of anchors, along with a new loss function.
- YOLOv5 leverages the pre-trained YOLOv3 models and offers a well-documented API, making it accessible for developers seeking a fast and easy-to-use real-time object detection solution.
- YOLOv6, open-sourced by Meituan in 2022, is utilized in the company's autonomous delivery robots.
- YOLOv7 (2022) refines real-time detection. Its custom YOLOv7-CSPDarknet53 backbone boosts accuracy, while the Focus module improves spatial information. This translates to significant accuracy gains over YOLOv4 without sacrificing real-time speed.
- YOLOv8, the most recent release by Ultralytics, succeeds YOLOv7, inheriting its accuracy improvements but with a focus on model size reduction. This makes YOLOv8 particularly attractive for applications with limited computational resources. The key to this efficiency lies in the YOLOv8-CSPDarknet53 backbone, which utilizes efficient building blocks for faster feature extraction during object detection. Additionally, YOLOv8 incorporates Bottleneck CSP, a technique that further reduces.

II. METHODOLOGY

A.CONVOLUTIONAL NEURAL NETWORK(CNN)

Convolutional Neural Networks (CNNs) serve as the backbone of the recognition system. CNNs are a class of deep neural networks designed to automatically and adaptively learn spatial hierarchies of features from input images. Here's how CNNs work and their role in this traffic sign recognition project:

Convolutional Layers: CNNs consist of multiple convolutional layers, where each layer applies a set of learnable filters (also known as kernels) to the input image. These filters convolve across the image, extracting local patterns or features such as edges, corners, and textures. The output of each convolutional operation forms a feature map, capturing increasingly complex representations of the input image.

Pooling Layers: Following the convolutional layers, pooling layers are often incorporated to down sample the feature maps, reducing their spatial dimensions while retaining important information. Max pooling or average pooling operations are commonly used to achieve this down sampling, helping to improve computational efficiency and reduce overfitting.

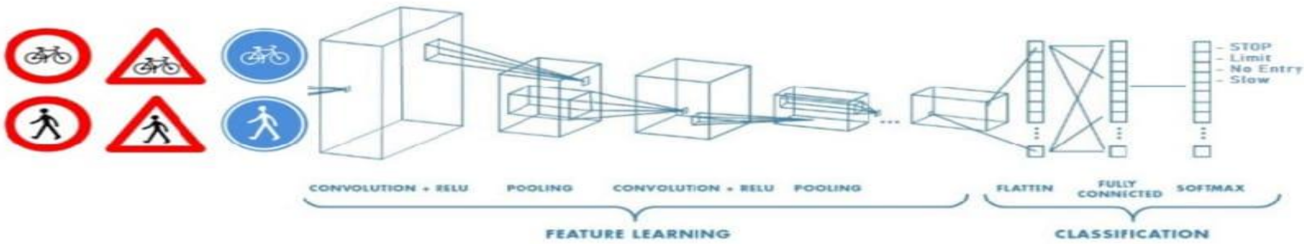


Figure 1: Convolutional neutral network architecture.

Activation Functions: Non-linear activation functions, such as ReLU (Rectified Linear Unit), are applied to the feature maps after each convolutional and pooling operation. These activation functions introduce non-linearity to the network, enabling it to learn complex relationships between features in the input data.

Fully Connected Layers: After several convolutional and pooling layers, the feature maps are flattened into a vector and fed into one or more fully connected layers. These layers act as traditional neural networks, learning high-level representations of the input features and making predictions based on learned parameters.

In the context of traffic sign recognition, CNNs are trained on a labeled dataset of traffic sign images. During the training process, CNN learns to automatically extract discriminative features from the input images and map them to corresponding traffic sign classes. Once trained, the CNN model can then be deployed to classify traffic signs in real-time scenarios, accurately identifying the type of sign present in the input image.

The CNN component of the project focuses on learning and fine-tuning the parameters of the neural network to optimize its performance in recognizing traffic signs with high accuracy and reliability. Additionally, techniques such as data augmentation, regularization, and transfer learning may be employed to further enhance the robustness and generalization capabilities of the CNN model.

B. YOU ONLY LOOK ONCE(YOLOv4)

In the context of traffic sign recognition, the You Only Look Once version 4 (YOLOv4) object detection framework plays a crucial role in efficiently detecting traffic signs within input images or video streams. Here's an explanation of how YOLOv4 works and its role in this project:

Single Shot Detection: YOLOv4 follows the principle of single-shot object detection, meaning it processes the entire image in a single forward pass of the neural network. This approach enables YOLOv4 to achieve real-time inference speeds, making it suitable for applications requiring fast and efficient object detection.

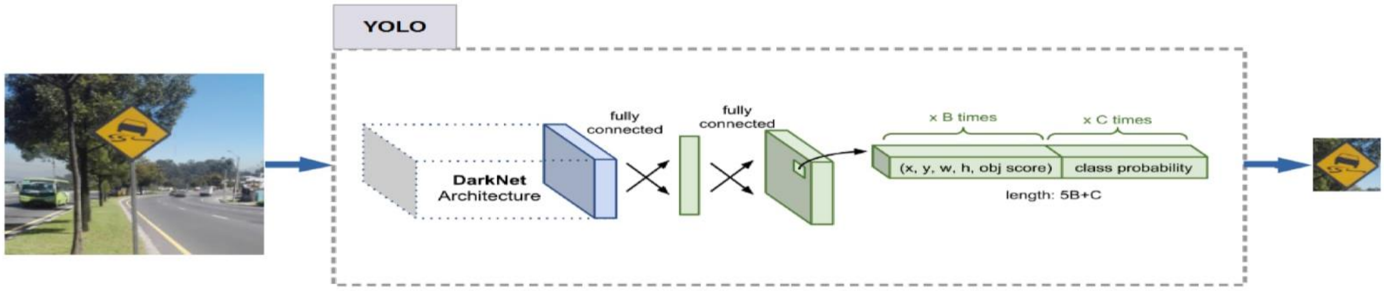


Figure 2. You only look once architecture.

C. MODEL DEPLOYMENT FLOWCHART

Figure 3 illustrates the standard approach used in model deployment. It starts with gathering the required dataset

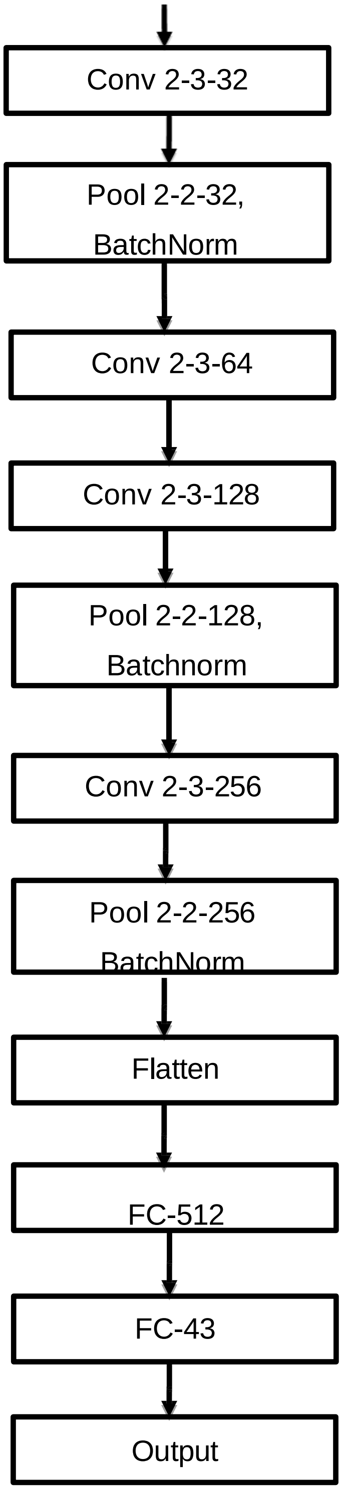


Figure 3. Architecture used

D. ASSEMBLING THE DATASET, ANNOTATING AND PREPARING THE DATASET

A Dataset is a set or collection of data. This set is normally presented in a tabular pattern. Every column describes a particular variable. Each row corresponds to a given number of the data set, as per the given question. This is a part of **DATA MANAGEMENT.**

Some types of Datasets are: Numerical,Bivariate,Multivariate,Correlational,Categorical.

We have Collected traffic sign datasets from **KAGGLE.COM**. Our Datasets consist of 42 classes that consist of both train and test images. Some of those images we used are keep right,general caution,different speed limits etc.

Some of the images are shown below:

D1. Classes in the traffic sign dataset:

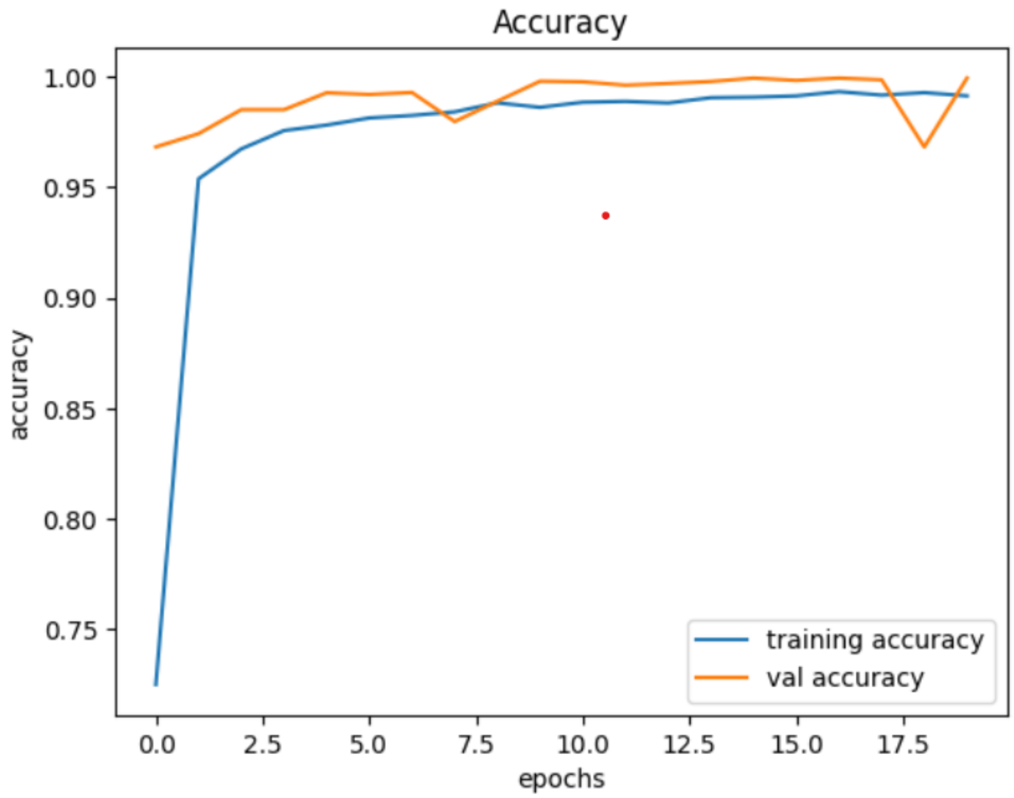
Some of the categories within the real-time detection dataset are as follows**:**

- Speed limit (20km/h)
- Speed limit (30km/h)
- Speed limit (50km/h)
- Speed limit (70km/h)
- Speed limit (80km/h)
- End of speed limit (80km/h)
- Speed limit (100km/h)
- Speed limit (120km/h)
- No passing
- No passing vehicle over 3.5 tons
- Right -of- way at intersection
- Priority road
- Yield
- Stop
- No vehicles

Data quality is crucial for effective machine learning models. Preprocessing, which includes cleaning, standardization, and feature extraction, is vital. It involves steps like image scaling and data augmentation.

III. RESULTS AND ANALYSIS

In our project, we have successfully identified various types of traffic signs. To achieve this, we employed YOLO v4, a state-of-the-art model, to train on diverse datasets encompassing multiple classes. Our evaluation of the model's performance has been comprehensive, incorporating analyses such as confusion matrix assessments and the examination of different loss curves. These metrics provide valuable observations and perspectives into the model's ability to accurately classify and localize traffic signs of interest within the input images. By leveraging advanced techniques and rigorous evaluations, we have been able to achieve robust performance in detecting and categorizing a wide range of traffic signs than APT


Accuracy
accuracy
1.00
0.95
0.90
0.85
0.80
0.75
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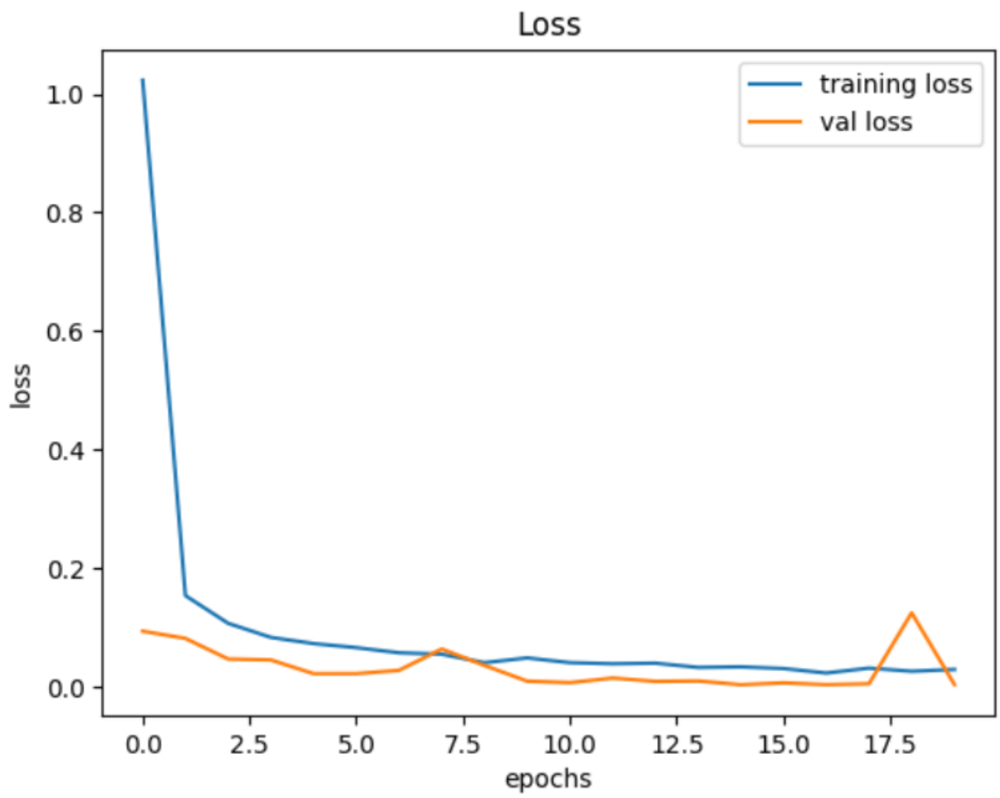
5.0
7.5
10.0
12.5
15.0
17.5
epochs
training accuracy
val accuracy


Loss
loss
1.0
0.8
0.6
0.4
0.2
0.0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
epochs
training loss
val loss

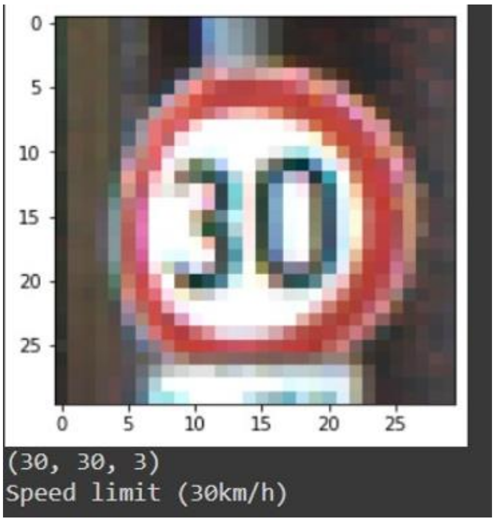
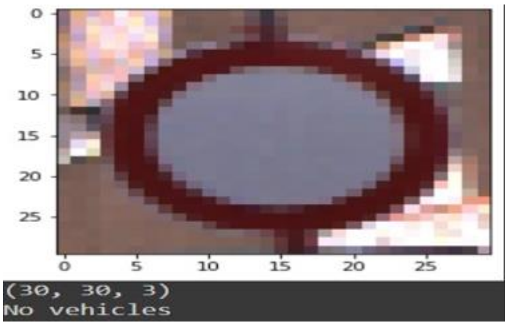
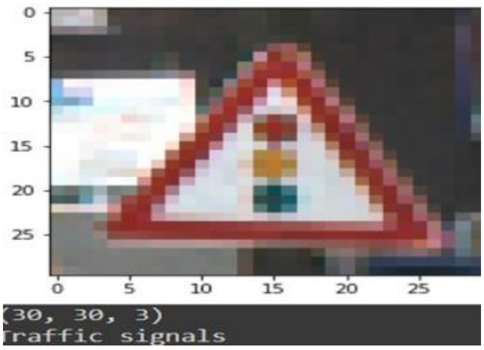
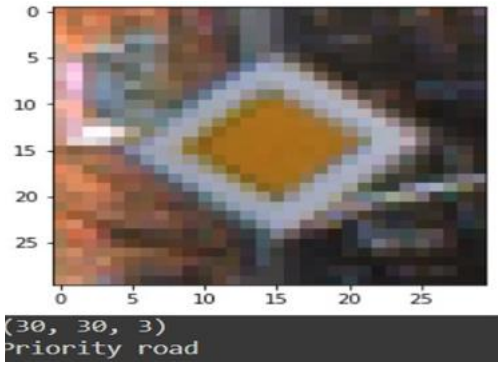


Figure 3. Recognition of traffic sign






(30, 30, 3)
Priority road


yield
speed limit
mandatory
other
00003.jpg
00346.jpg
00305.jpg
00290.jpg
00357.jpg
00341.jpg
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00275.jpg
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00334.jpg
00299.jpg
00272.jpg
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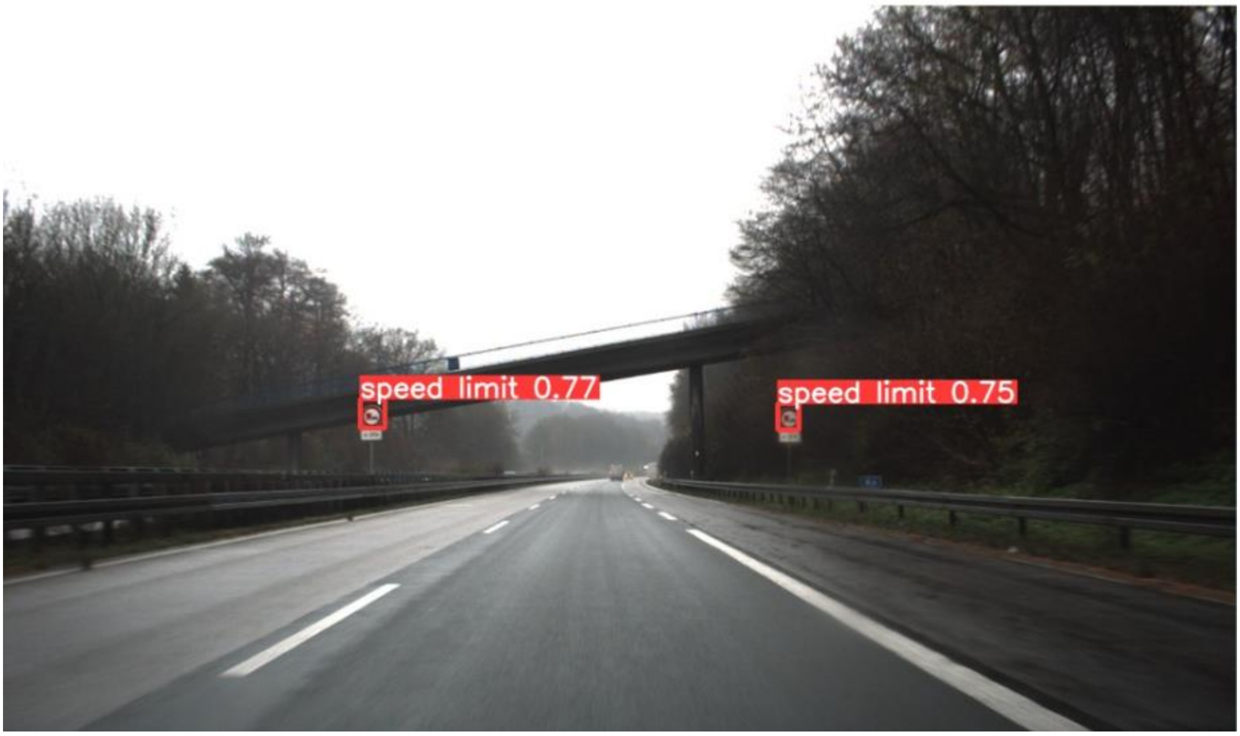
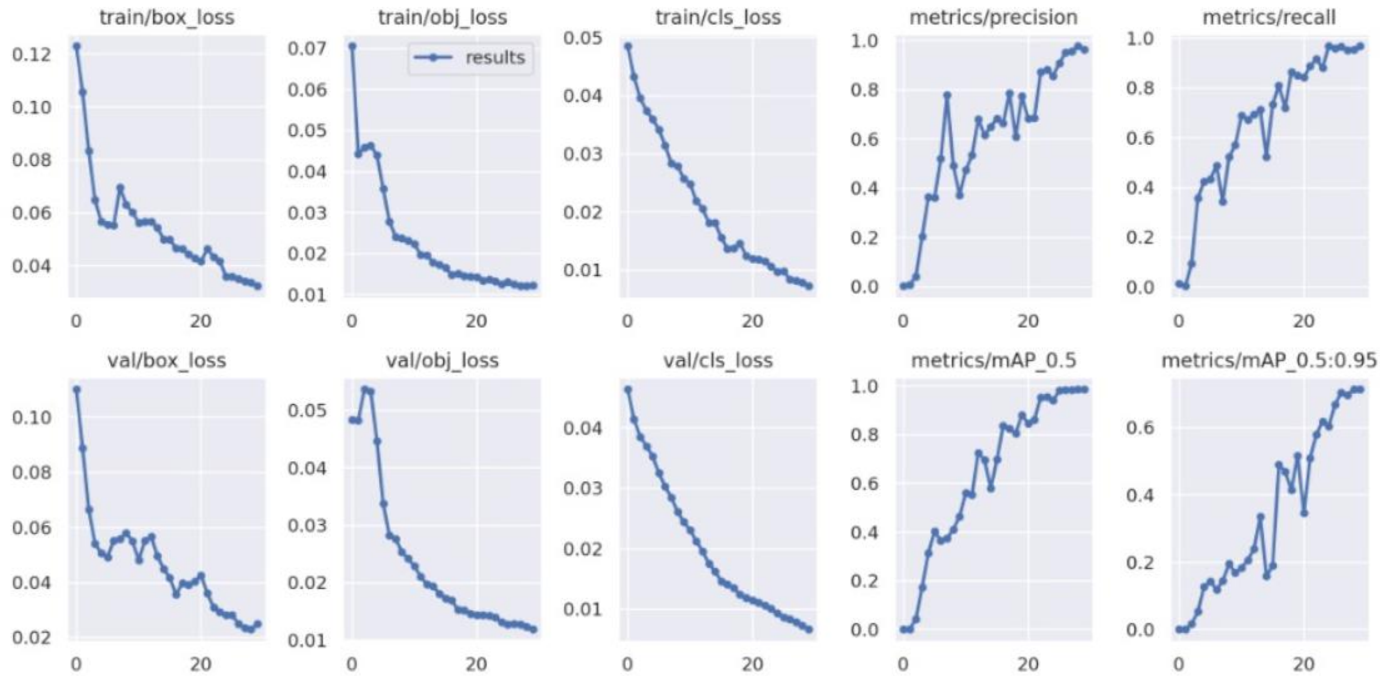

speed limit 0.77
speed limit 0.75


other 0.36
mandatory 0.39


train/box_loss
train/obj_loss
results
train/cls_loss
metrics/precision
metrics/recall
val/box_loss
val/obj_loss
val/cls_loss
metrics/mAP_0.5
metrics/mAP_0.5:0.95

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