Using the Fine-Tuned YOLO Model for Object Detection on Traffic Signs on TT100K Datasets

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***Abstract*—With the increase in the reliance on the transportation that is intelligent and with the high accuracy detection of traffic signs and scenes in the autonomous vehicles system ensures the operational efficiency. With different road environments like light and weather variation as well as small or partially obscured signs, the traditonal model and approches feels to fall behind. Different real time deep learning models like YOU ONLY LOOK ONCE or YOLO, gained immense importance and popularity for their ability to detect with high accuracy at high speed. But those models that are pretrained on the datasets like COCO which is a general purpose datasets, face challenges to adapt effectively on a domain specific traffic signs datasets. Our research focus is YOLOv8 model on TT100K Datasets which is a large scale datasets containing real world traffic sign images. At first, the pretrained YOLO model applied directly on the TT100K Datasets to form a baseline capability and model exhibited weak performance.To solve this problem, model was fine tuned that allows it to learn domain specific features. The methodology involved training with consistent image size, learning rate and batch settings. which is optimized for dataset's characteristics.Post training evalution revelead significant improvements in both detection accuracy and visual performance. The fine tuned model enhanced the ability in order to identify and classify traffic signs in real world. On the whole, the study showcases the importance of the transfer learning in orer to familiarize with object detection model. Results confirms that targeted fine tuning on models like YOLO can be suitable for time sensitive tasks.**

***Index Terms*—YOLO, Deep Learning, Traffic Sign, accuracy**

I. Introduction

With the advancements in the field of autonomous driving vehicles and technologies, accurate detection of the traffic signs and scenes becomes critically important.As we all know that traffic signs plays very important role in the regulation of the traffic flow, ensures that roads should be safe and also provide information that are essential to human drivers as well as that of Automatic or self driving vehicles, but it also plays role in the intelligent transportation systems. Modern studies have showed that robust traffic signs integrations plays key role in contributing the reduce traffic accidents and also enhanced the navigation systems.

In order to address the challenges facing the detection of traffic signs, that involves the leveraging state-of-art detection of objects algorithms that accurately identify and classify traffic signs in complex environments. "YOU ONLY LOOK ONCE (YOLO)" models has gained spotlight due to its ability of real time detection of objects, that makes it capable to be suitable for the traffic sign task. The latest version of YOLO (YOLOv8) has provides the improved accuracy with improved speed. This is essential for the as traffic signs detections have dynamic nature. Fine tuning the YOLOv8 on complex datasets like TT100K, has adapt the unique characteristics of traffic sign detection and it also improved the detection performance.

But the traffic sign detection task is not an easy task. Traffic sign detection faces several challenges. Sometimes traffic signs are so small that it will be difficult to detect a sign and also difficult to detect a sign which is far away. Also sometimes weather condition and complex backgrounds can become obstacle in sign detection. It increases the complications of sign detection. In addition to that, imbalances in traffic sign classes also poses serious problems as model becomes biased towards the sign which is occurring more frequently.

Different approaches have been taken to overcome these challenges. Some of them add attention mechanims in order to enhance the feature extraction capability. This will enable the model to focus on the relevent region of the images. Some researchers introduce the detection ;ayers to capture the samll objects . These techniques addresses the difficulties in traffic sign detection and refine the model architecture and training procedures.

In this research, following methodologies have been used.

- YOLOv8 model has been used as the architecture model for detection of traffic signs and scenes.
- TT100K Datasets has been used and model was fine tuned on it. It provides better adaptation to some specific features of traffic signs
- Model evalution has been using metrics.

- After fine-tuning, the data was analyzed on the basis of detection of small traffic signs.
- Results were compared with existing methods.

II. Literature Review

Traffic sign and traffic vehicle detection field gained a lot of attention because of its growing need in the automation industry and for effective transport. Many researchers have study different methods that can enhance the detection accuracy and which is found to be more useful under different challenging conditions such as that of small sized objects and severe weather condition.

An approach was proposed where a small target detection was done with YOLO-Based layer model. This was used in order to improve the identification of small or far away traffic signs in a complex environment. Advanced feature extraction mechanisms were incorporated like residual blocks and attention mechanism and hence the accuracy detection has been significantly improves. [1]

More advancement in the field have focused on the improvements of the YOLO-Model performance. The model was studied under different weather conditions. different techniques like enhanced feature detection and the modules like small object detection has been integrated in order to address specific challenges faced by automated self driving cars. that was due to small object in complex area of environment. This achieve the notable goals in term of precision and recall. [2]

Some researchers focus on the real time detection. To do this, they optimize the model parameters that can work efficiently but also maintaining the high accuracy while monitoring the applicability of YOLO Models to check either they can fit in the real world environment or not. It was seen that when detection speed and precision is balanced, the models work efficiently in the diverse traffic sign environments. [3]

In addition to that, some researchers have proposed new techniques by leveraging the new and latest YOLOv8 models and incorporate them in the Bidirectional Feature Pyramid Networks in order to increase the multiple object detection all at once. This method, by detecting the small traffic signs, is particularly efficient on larger datasets has achieved great results [4] [5]

Hence these recent advancements showcases the importance of the recent and ongoing progress in the field of object detection, that emphasizes the importance of the optimization of the model architecture and training of models for efficient traffic sign detection.

III. Methodology

In this assignment, object detection system has been developed using YOLOv8. For this specific assignment, road signs and traffic of different vehicles have to detected. It is very important for the development of autonomous vehicles system in which high accuracy is crucial in order to avoid accidents or any other mishaps. For this assignments, TT100K Datasets has been used with over 45,000 images. The TT100K Datasets contains the wide variety of traffic signs that has been captured under different weather conditions and under different traffic size condition. Original datasets contains over 100,000 images. A subset of 45,000 to 50,000 images have been used for object detection.

For implementations to be done, YOLOv8 has been imported from ultralytics library of Python. This model has been pretrained on COCO Dataset originally and hence has its own pretrained weights. This pretrained model becomes very helpful for general object detection specifically on traffic signs domain. Other libraries such as torch with cuda121, open-cv and matplot lib has been installed for training and visualization of datasets training and testing.

After setting up the mode, object detection was done on the sample image using the pretrained weights. The YOLO model identify the different traffic signs and vehicles accurately, drawing the bounding boxes around object. It also labels them with related class names and also provide confidence score around the box. This set to be the base line for the fine tuning images.

After performing the pretrained model of YOLO on sample images, a fine tuning process was carried outon the selected TT100K Datasets. Images annotated in the YOLO Format. After that images have been prepared for training purposes. During fine tuning process, hyperparameters like learning rate, batch size and number of epochs were adjusted in order to improve the model performance. Training of model allowed it to learn features that are domain specific, more accurately. This improves the precision of detection. Some other performance metrics such as Precision, recall, mAP(mean average precision) has been calculated before and after fine tuning to find the improvements in results.

Hence this methodology makes ensures that model leverages the strengths of pretrained weights as well as adapts properly to a specialized datasets. transfer learning and domain specific fine tuning combines together in order to contribute to give more accurate results and perform efficient object detection that is well suited for intelligent traffic monitoring systems and for autonomuos navigation applications.

IV. Results and Discussion

After training the dataset of TT100K on YOLOv8 model, the preformance have been improved which was observed through evalution metrices. As the model pretrained on the COCO dataset which is not focus on the traffic signs or scenes, it results in lower detection at first but after fine-tuning, the detection accuracy has been increase.

The performance of YOLO on TT100K dataset has been done in two phases. first phase is before fine tuning and second phase is after fine tuning. Before fine tuning, the results shows the very poor performance of model with precision is 0.000774, recall is 0.031, mAP at threshold of 0.5 is 0.000478 and average mAP from 0.5 to 0,95 is 0.000311. this difference shows that there is domain gap between COCO Datasets and TT100K datasets. Model didn't detect and classify most of the traffic signs. Also output images shows highlighted many detection that were missed causing false positives and incorrect bounding boxes.

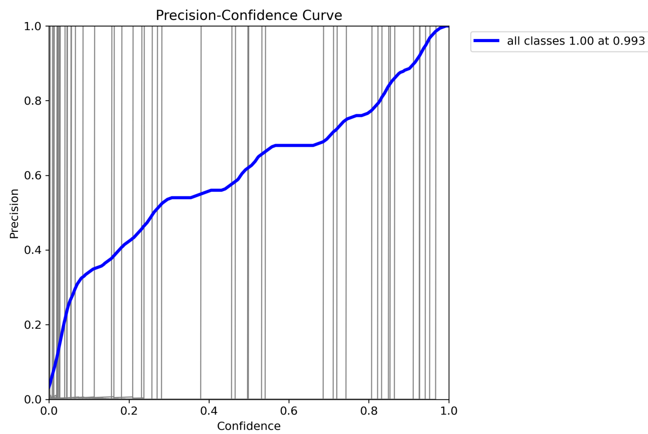

Fig. 1. Precision Curve Before Tuning

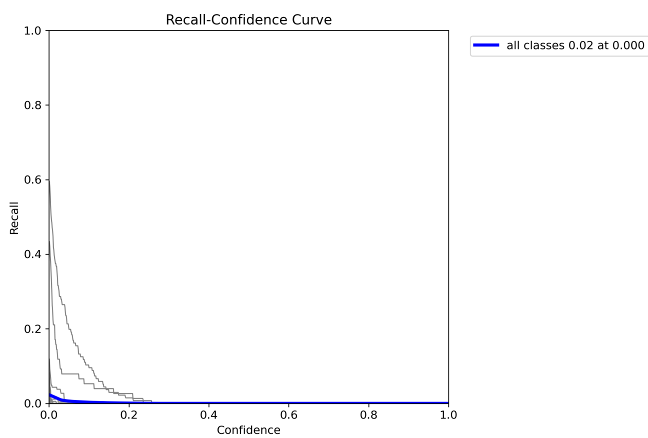

Fig. 2. Recall Curve Before Tuning

To solve this problem, model was fine tuned using TT100K training data for 50 epochs, with learning rate of 0.01 and batch size 8. During this process, a consistent image size of 640x640 pixels has been maintained. After performing the fine tuning process, the model shows the improvement . Accuracy for detecting objects has been increasing and model classify the objects correctly.

Resulting images also shows the difference between before fine tuning the model and after fine tuning the model. Hence, a fine tuning process enhance the detection ability f model significantly in real time enviornment. The results confirms

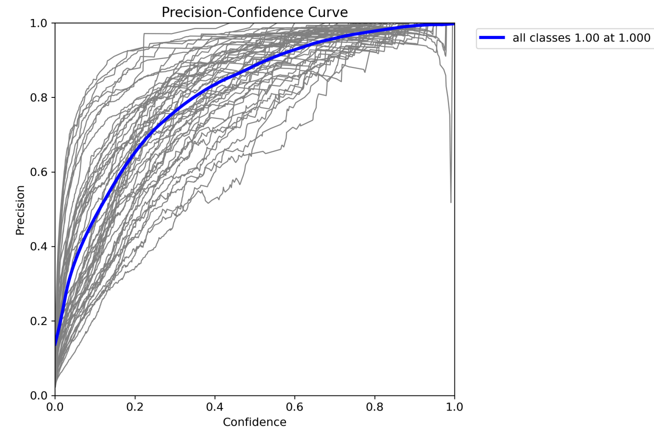

Fig. 3. Precision Curve After Tuning

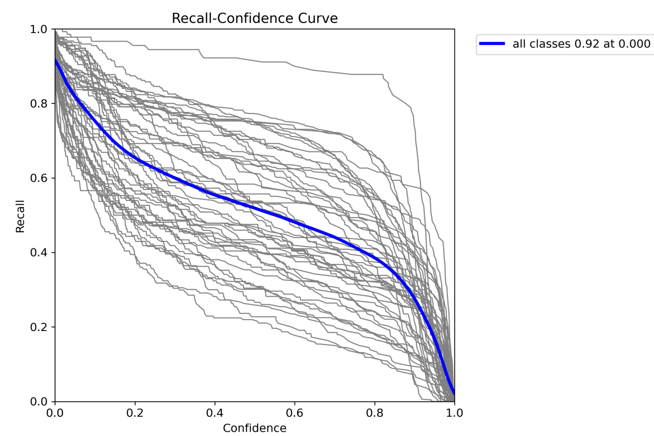

Fig. 4. Recall Curve After Tuning

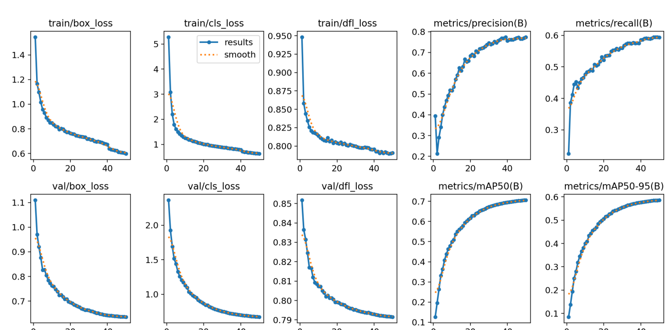

Fig. 5. Training Resuls

Fig. 6. Prediction in pictorial datasets

that YOLOv8, through fine tuning can achive better results. Hence increases the real time detection of accuracy with balanced speed.
The tabular results are as follows

TABLE I
PRETRAINED RESULTS BEFORE FINE TUNING.

Class	Images	Instances	P	R	mAP@0.5	mAP@0.5:0.95
all	3627	10823	0.000774	0.0310	0.000478	0.000311
person	235	264	0.000177	0.0758	9.59e-05	3.14e-05
bicycle	108	161	0	0	0	0
car	158	185	8.37e-05	0.119	4.81e-05	2.91e-05
motorcycle	402	495	0	0	0	0
airplane	38	91	0	0	0	0
bus	116	169	0	0	0	0
train	474	498	0.00018	0.00402	9.08e-05	7.72e-05
truck	89	142	1.9e-05	0.0141	9.66e-06	2.89e-06
boat	110	132	0	0	0	0
traffic light	131	136	0.000829	0.596	0.00208	0.00104
fire hydrant	149	209	0.00066	0.0239	0.00034	0.000142
stop sign	75	76	0.0026	0.434	0.00299	0.00195
parking meter	99	115	0.00162	0.0696	0.00092	0.000371
bench	591	594	0	0	0	0
bird	119	163	0	0	0	0
cat	319	353	0	0	0	0
dog	271	276	0	0	0	0
horse	610	640	0	0	0	0
sheep	131	136	0	0	0	0
cow	121	124	0	0	0	0
elephant	104	158	0	0	0	0
bear	198	253	0	0	0	0
zebra	104	104	0	0	0	0
giraffe	718	775	0	0	0	0

V. CONCLUSION

From the study above, we can say that the YOLOv8 object detection to detect the traffic signs using TT100K Dataset has found to be effective. Although pretrained model shows the poor performance, fine tuning the YOLO on specific datasets has shown significant improvement in detection accuracy. This also shows the importance of adaption of learning model to real time scenarios that varies significantly from the datasets. Results highlighted the model YOLO can achieve high accuracy when tuned appropriately. The bounding box has been improved with great precision and recall with better visualization. This model contributes in the growing field of traffic sign awareness deep learning models and future work perform this task with high YOLO Variants.

TABLE II
RESULTS AFTER FINE TUNING

Class	Images	Instances	P	R	mAP@0.5	mAP@0.5:0.95
all	3627	10823	0.772	0.594	0.706	0.595
pl80	235	264	0.641	0.436	0.550	0.478
p6	108	161	0.644	0.516	0.589	0.539
ph	158	185	0.827	0.686	0.783	0.613
w	402	495	0.892	0.788	0.876	0.576
pa	38	91	0.688	0.747	0.791	0.724
p27	116	169	0.919	0.692	0.815	0.698
i5	474	498	0.847	0.815	0.885	0.650
p1	89	142	0.945	0.600	0.770	0.688
il70	110	132	0.876	0.621	0.790	0.721
p5	131	136	0.849	0.529	0.656	0.538
pm	149	209	0.754	0.622	0.714	0.636
p19	75	76	0.717	0.487	0.571	0.509
ip	99	115	0.824	0.691	0.807	0.463
p11	591	594	0.756	0.650	0.740	0.564
p13	119	163	0.826	0.497	0.627	0.447
p26	319	353	0.843	0.777	0.864	0.722
i2	271	276	0.861	0.742	0.845	0.636
pn	610	640	0.878	0.795	0.856	0.605
p10	131	136	0.487	0.441	0.481	0.409
p23	121	124	0.795	0.484	0.652	0.547
pbp	104	158	0.744	0.588	0.693	0.626
p3	198	253	0.830	0.692	0.787	0.697
p12	104	104	0.632	0.462	0.549	0.487
pne	718	775	0.956	0.813	0.911	0.679

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