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Comparison of Potential Road Accident Detection Algorithms for Modern Machine Vision System

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***Abstract*. Nowadays the robotics is relevant development industry. Robots are becoming more sophisticated, and this requires more sophisticated technologies. One of them is robot vision. This is needed for robots which communicate with the environment using vision instead of a batch of sensors. These data are utilized to analyze the situation at hand and develop a real-time action plan for the given scenario. This article explores the most suitable algorithm for detecting potential road accidents, specifically focusing on the scenario of turning left across one or more oncoming lanes. The selection of the optimal algorithm is based on a comparative analysis of evaluation and testing results, including metrics such as maximum frames per second for video processing during detection using robot's hardware. The study categorises potential accidents into two classes: danger and not-danger. The Yolov7 and Detectron2 algorithms are compared, and the article aims to create simple models with the potential for future refinement. Also, this article provides conclusions and recommendations regarding the practical implementation of the proposed models and algorithm.**

Keywords: Machine learning, machine vision, object detection, road accidents, CNN.

I. INTRODUCTION

Road accidents have become a prevalent problem due to the increase in both the number of vehicles and their speed, resulting in a higher number of victims and injuries [1-3]. Current methods of preventing dangerous situations on the roads primarily focus on the safety of individual vehicles, without considering other road users outside of their built-in safety mechanisms [4, 5].

There is a need to develop methods that can detect and notify drivers of potential dangers in areas that are currently beyond the capabilities of existing ADAS systems to scan for obstacles of varying types [6-8].

Taking in consideration the current tendencies in the tech world, the automotive safety systems should be developed using data analysis systems [9-11].

Additionally, an important factor for road safety is the driver's ability to respond appropriately to changes in traffic and information received while driving [12, 13].

The most dangerous in terms of road behavior are bicyclists and motorcyclists, which may rapidly change going trajectory [14, 15].

As a result, developing and researching new methods for monitoring driver behavior, predicting dangerous situations while driving, and notifying drivers about them is a crucial and relevant task [16-18].

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The key trends in terms of road safety research are:

- improvement of data mining approaches for extracting essential for road safety information from the data outdoor cameras [19, 20];
- investigation of methods for complex analysis of data mentioned before [21, 22].

Current research aims to estimate an algorithm that has the smallest prediction time, smallest size, and good accuracy for identifying and preventing road accidents based on outdoor video streams. Also, the usage of this model in robotic vision systems is one of the main points, because of surely high progress in development in this way.

The main goal of this research is defining the possibility of determining possible road accidents in a quick way, using machine learning algorithms and clarify the effectiveness and which algorithm is more applicable for explained problem for quick prediction and usage in robotic vision system.

II. Materials and Methods

The computer vision technologies are very rich and takes fast development. The most recent and valuable research there is Yolo [23] algorithm family which is developed to v7 and Detectron2 [24] with Faster R-CNN on backend, which has the Facebook origin. Those algorithms are very fast and efficient, so they were taken for investigation which one is more suitable for task of fast road accidents detection along with usage in robot vision system.

A. ML model metrics

The following metrics have been used to calculate trained models' performance: Time to train, Average Precision with IoU, Model size, Loss CLS, Used GPU memory, Loss box, Inference time.

The IoU formula is the following

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}, \quad (1)$$

The Loss Box formula is the following

$$L_{box}(t^U, v) = \sum_{i \in \{x,y,w,h\}} L_1^{smooth}(t_i^u - v_i), \quad (2)$$

The Loss cls (classification) formula is the following

$$L_{cls}(p,u) = -\log\log p_u\,, \quad (3)$$

The Precision has the following formula

$$P = \frac{TruePositive}{(TruePositive + FalsePositive)}, \quad (4)$$

B. Data Description

Current research uses aims to determine the danger situations on the road. As far as such video data is very hard to find, the own produced video stream is used. The only one danger case explained in current article – turning left across oncoming lanes, where at least one lane is stopped for skipping the car which turn left and at least one oncoming lane without cars. The Fig. 1 display mentioned case.

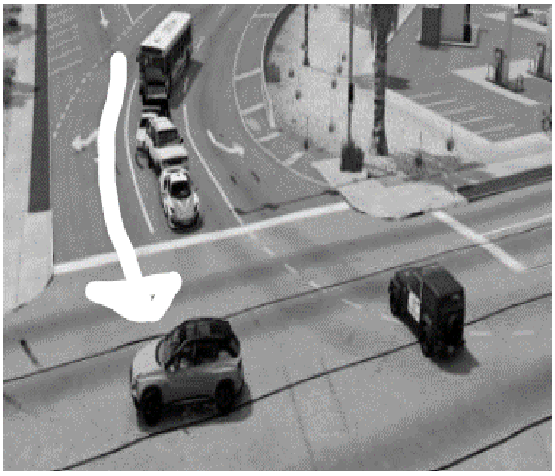

Fig. 1. Danger case explanation [25].

So, such cases can be simulated in BeamNG.drive [26] computer game and sliced in pictures. The strategy for creation of dataset for research was the following:

- Simulation of at least 5 different road crossing with different car setup, with different count of oncoming lanes.
- Do not consider night scenario, because infrared cameras are required.
- The only two classes should be explained: danger and non-danger.

The training dataset consists of 300 pictures, where 150 has danger class and 150 non-danger. The Fig.2 provides an example of dataset picture.

Fig. 2. Danger class example [25].

The resolution of pictures is 640x640.

C. ML ALGORITHMS ARHITECTURES

The developers of Yolov7 uses Extended ELAN architecture to control the shortest gradient path and a deeper network may learn effectively. The Detectron2 allows to use different algorithms under the hood. In current research the Faster R-CNN is used.

III. EXPERIMENT, RESULT AND DISCUSSIONS

The experiment includes the following steps:

- Experiment planning and code preparations;
- Model training;
- Evaluation and testing;
- Results comparison.

The Google Colab was considered as a platform to train and evaluate the models. The following code is used to train models [27-28].

The following environment specs are there: Python 3 Google Compute Engine backend (GPU: Tesla T4).

The models training consists of two steps: training of Yolov7 and training of Detectron2 model.

The Detectron2 model has batch size 64, image size = 640x640 and epoch count = 1500. The Yolov7 model has batch size = 16, image size = 640x640, epoch count = 55.

The table 1 display resource consumption during training of Detectron2 model.

TABLE 1 RESOURCE USAGE DURING DETECTRON2 MODEL TRAINING

Resource Name	Time, mins
System RAM	3.7 GB / 12.7 GB
GPU RAM	8.5 GB / 15 GB
SSD	25.9 GB / 78.2 GB

The table 2 display resource usage during training of Yolov7 model.

TABLE 2 RESOURCE USAGE DURING YOLOV7 MODEL TRAINING

Resource Name	Time, mins
System RAM	5.7 GB / 12.7 GB
GPU RAM	11.4 GB / 15 GB
SSD	24.9 GB / 78.2 GB

The table 3 displays time to train each model.

TABLE 3 TRAINING TIME

Algorithm	Time, mins
Detectron2	51
Yolov7	15.9

A. YOLOV7 RESULTS

The results of training are presented in table and chart view. The results of training and evaluation for Yolov7 model are present in Table 4.

TABLE 4 YOLOV7 RESULTS

Value	**Metric**
0.583	AP@.5:95
0.926	AP@.5
0.1916668 s / img per GPU	Inference time
74.8 MB	Model size

The accuracy of 58% is bad, but this was obtained on the 150 images per class. The next figures (Fig. 3, 4) represent loss metrics.

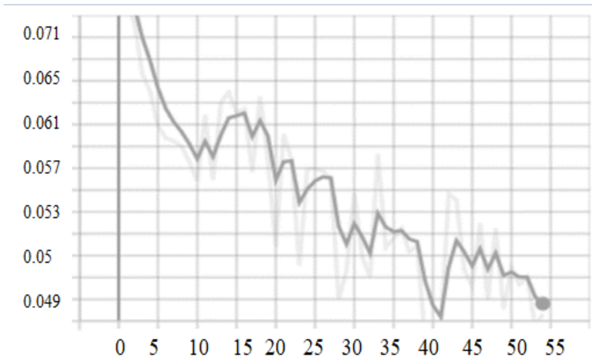

Fig. 3. The Loss box metric.

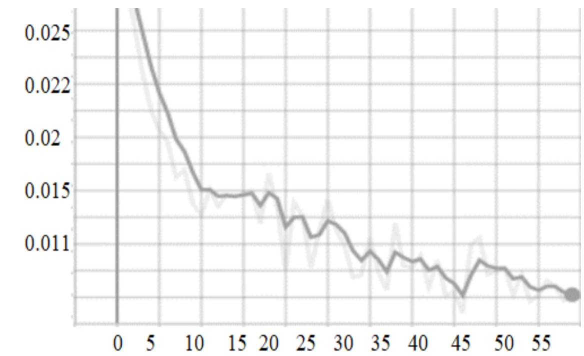

Fig. 4. The Loss classification metric.

The precision significantly decreased during ~42 epoch. The Fig. 5, 6 display that. But in case, if more pictures will be available for training, then higher precision may be for the same number of epochs.

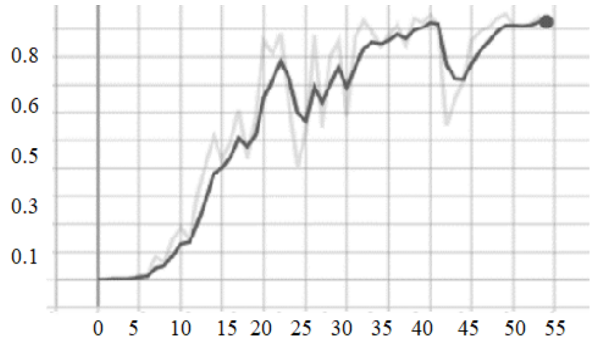

Fig. 5. AP@.5 metric of Yolov7.

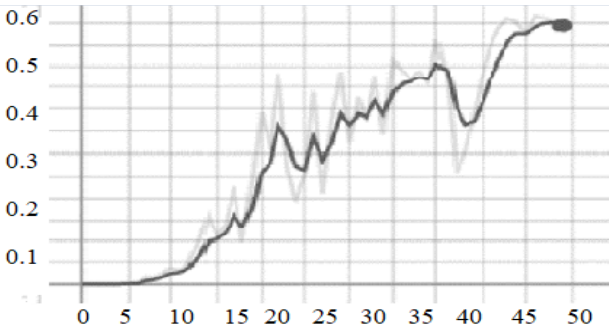

Fig. 6. Fig. 8 AP@.5:95 metric of Yolov7.

The inference results are on Fig. 7, 8. There are no mistakes or incorrect predictions was observed.

Fig. 7. Inference result of Yolov7 [25].

On the mentioned inference result the one oncoming lane presents and this is non-danger class. The model distinguish where the one oncoming lane and where two and more. This is very important in undestanding of dangerous situations. Because when the two or more lanes exist and only one lane is full and when one lane exist and it is full, these are different cases.

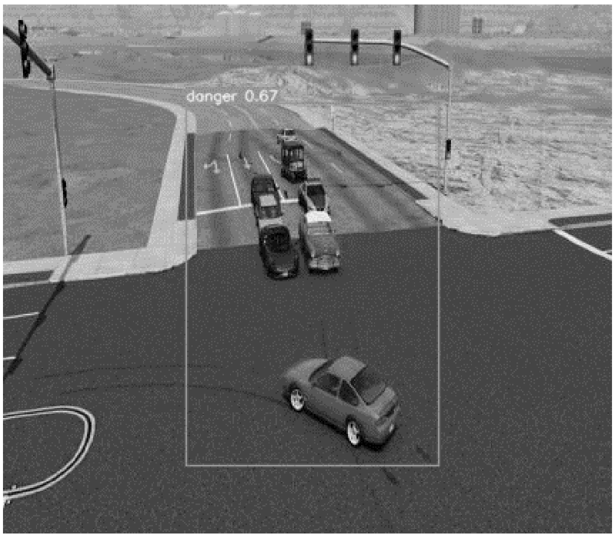

Fig. 8. Inference result of Yolov7 [25].

B. DETECTRON2 RESULTS

The Detectron2 model has the following results values (Table 5).

TABLE 5 DETECTRON2 RESULTS

Value	**Metric**
0.651	AP@.5:95
0.909	AP@.5
0.198093 s / img per GPU	Inference time
815 MB	Model size

The Loss box chart is on the Fig. 9.

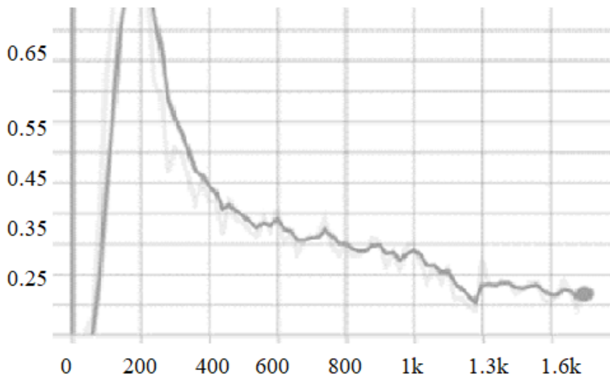

Fig. 9. Loss Box for Detectron2.

The Loss classification chart is on the Fig. 10.

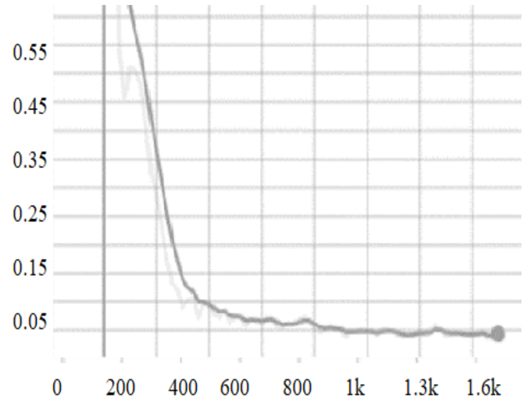

Fig. 10 Loss CLS for Detectron2.

The inference results are on the Fig. 11, 12.

Fig. 11 Inference result of Detectron2 [25].

Fig. 12 Inference result of Detectron2 [25].

IV. DISCUSSIONS

The discussion section entails a comparison of the model's results and identification of the most appropriate algorithm for the problem of usage it in robotic vision system. Table 6 presents the compilation results for the aforementioned algorithms.

TABLE 6 COMPILATION RESULTS

Value	Detectron2	Yolov7
AP@.5:95	0.651	0.583
AP@.5	0.909	0.926
Inference time	0.198093 s / img per GPU	0.191668 s / img per GPU
Model size	815 MB	74.8 MB
GPU RAM	8.5 Gb	11.4 GB
Time to train	51 mins	15.9 Mins
Epoch	1500	55

The results indicate that while there is only a slight improvement in accuracy, Yolov7 outperforms Detectron2 in other parameters. This is likely due to the fact that achieving similar accuracy with Detectron2 requires even greater amounts of time and resources. It is possible that a larger dataset may yield better results as using only 300 images is not sufficient for creating a high-performing model. Also, the small amount of size is better in terms of usage by autonomous system, where hardware size has big value.

V. CONCLUSIONS

This study presents insights into the most effective image detection and tracking algorithm for quickly identifying dangerous situations on the road. Given the alarming statistics on road accidents resulting in injuries and deaths, it is imperative to address this problem. Previous studies have focused on statistical approaches for predicting road accidents and using regression algorithms to make predictions based on various factors such as weather, road conditions, time of day, day of the week, season, speed, and car condition.

To prepare the dataset, 300 images with different road intersections, outdoor settings, and car setups were captured and labeled using the Roboflow service, which also allows for image resizing and dataset splitting. The research evaluated the performance of two algorithms, Detectron2 (with Faster R-CNN) and Yolov7, using various metrics, such as Average Precision, Inference time, Time for training, Model size, and GPU RAM usage. The research found that Yolov7 outperformed Detectron2 in terms of performance metrics.

The study also explores the potential for applying these approaches to a single-board computer or robot vision systems and provides a starting point for researchers conducting similar two-class classification research. Overall, this study offers valuable insights into improving road safety through effective image detection and tracking algorithms.

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