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Investigating The Relationship Between Vehicle Speed and Pothole Detection by Using Mobile Phone

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Cep Telefonu Kullanılarak Araç Hızı ile Çukur Tespiti Arasındaki İlişkinin Araştırılması

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Abstract

It is known that road pavements are damaged due to time, climatic conditions and construction errors. Considering these damages, the most important road defect that reduces road safety and comfort is potholes. Especially as the width and depth of the pothole increases, driving safety is also endangered. In addition, the locations of these potholes, especially on urban roads, are determined manually in many regions. This process causes delays in the maintenance and repair of the potholes. To this end, the authors plan an in-vehicle integrated system consisting of multiple stages to automatically detect potholes occurring in the road network. The main purpose of the planned system is to identify potholes with high accuracy. However, the effect of vehicle speed on pothole detection in this system is unknown. In order to solve this complex situation, real-time video recordings were made on the same road and pothole at different vehicle speeds. Then, the pothole detection process was realized through these videos with the single-stage detector YOLOv7 vs YOLOv8. When the results obtained were examined, exact relationship could not be determined between vehicle speed and pothole detection. This situation may vary according to various parameters such as camera angle, image quality, sunlight condition. In addition, when both models are compared according to the performance criteria, YOLOv7 has a partial superiority over YOLOv8 in mAP0.5, precision, recall and F1 score values. It is especially significant that these criteria are close to 1. Finally, the perception results obtained from the images obtained from the video showed that there was no overfitting in the models.

***Anahtar Kelimeler**: Road damage; Pothole; Automatic Detection; Speed; Intelligent Transportation Systems.*

Öz

Yol kaplamalarının zaman, iklim koşulları ve inşaat hatalarından dolayı bozulduğu bilinmektedir. Bu hasarlar dikkate alındığında yol güvenliğini ve konforunu azaltan en önemli yol kusurlarından biri çukurlardır. Özellikle çukurun genişliği ve derinliği arttıkça sürüş güvenliğini de tehlikeye atmaktadır. Özellikle şehir içi yollarda bu çukurların konumları birçok bölgede manuel olarak belirlenmektedir. Bu süreç çukurların bakım ve onarımında gecikmelere neden olmaktadır. Bu amaçla yazarlar, yol ağında meydana gelen çukurları otomatik olarak tespit etmek için birden fazla aşamadan oluşan araç içi entegre bir sistem planlıyorlar. Bu sistemin ilk aşaması, yüksek doğrulukta nesne algılama yöntemleri ile çukurların belirlenmesidir. Ancak bu sistemde araç hızının çukur tespiti üzerindeki etkisi bilinmemektedir. Bu karmaşık durumu çözmek için aynı yol ve çukur üzerinde farklı araç hızlarında gerçek zamanlı video kayıtları yapılmıştır. Daha sonra YOLOv7 ve YOLOv8 tek aşamalı detektör ile bu videolar üzerinden çukur tespit işlemi gerçekleştirilmiştir. Elde edilen sonuçlar incelendiğinde araç hızı ile çukur tespiti arasında kesin bir ilişki tespit edilememiştir. Bu durum kamera açısı, görüntü kalitesi, güneş ışığı durumu gibi çeşitli parametrelere göre değişiklik gösterebilmektedir. Ayrıca her iki model performans kriterlerine göre karşılaştırıldığında YOLOv7'nin mAP0.5, hassasiyet, geri çağırma ve F1 skoru değerlerinde YOLOv8'e kısmi üstünlüğü bulunmaktadır. Bu kriterlerin 1'e yakın olması anlamlıdır. Son olarak videodan elde edilen görsellerden elde edilen algılama sonuçları, modellerde aşırı uyumun olmadığını göstermiştir.

***Keywords:** Yol Hasarı; Çukur; Otomatik Algılama; Hız; Akıllı Ulaşım Sistemleri.*

1.Introduction

It is an undeniable fact that the material and spiritual demands of people have increased in recent years. The fact that Z and Y generations have excessive consumption habits has caused changes in the structures of societies. In fact, 75 percent of the world's population consists of people under the age of 65, and 25 percent of this proportion consists of people under the age of 14 (Int. Ref. 1). In addition to consumption habits, excessive

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mobility desires and the search for easy solutions to problems give rise to different approaches. Therefore, researchers and some companies in recent years have been offering open-source opportunities. This situation is considered as a policy of obtaining the highest efficiency from the existing young potential. To summarize, the artificial intelligence-based solutions used in recent years are not only related to the development of technology. It is shown as a success of the young people's community that supports this development and wants a quick, simple, cheap solution. One of the biggest steps of this success is image processing based on convolutional neural networks (CNN) (Zaidi et al. 2022). Image processing is frequently used to solve many existing problems (image enhancement (Huang and Su 2021), object detection (Wu et al. 2023), health sector (Pi et al. 2021), defence industry (Kim et al. 2021)) today. It is developing day by day and is used in different fields.

In this study, the automatic detection process of potholes, which is one of the most dangerous road damages occurring in the road network, is examined in detail. It causes material and moral damage to traffic components, especially when compared to other road damages. In addition, the wheel sizes and inadequate suspension systems of micro-multiplier vehicles increase the damage caused by potholes. Different types of road damage such as potholes, longitudinal, alligator and lateral cracks occur in the road network (Maeda et al. 2018a). The road covering where these damages occur is covered with asphalt concrete. Lifespan of flexible pavements used in the road network; It is directly proportional to the type of construction, the quality and size of the aggregate used, the quality and ratio of bitumen, the quality of workmanship, the ambient temperature and the traffic load passing over it. If one of them is not designed properly, damage to the road surface occurs. The occurrence of these damages is actually a traffic safety problem and poses a danger to human life. We just state a few facts from related studies worldwide. While 3597 people died due to potholes in India, 50 cyclists were seriously injured due to bad road conditions in the UK (Int.Ref. 2-3). The size of the pothole is very important in the severity of accidents. While the advanced safety and suspension systems of the new generation vehicles overcome small potholes, small wheeled vehicles such as bicycles and scooters are seriously damaged. There are studies and products for the detection of existing road damage on the road network. In particular, it is possible to obtain high-resolution coating status from coating surfaces with vehicles with laser line-scan cameras and three-dimensional cameras. In addition, the depth defects existing in road surface are determined by the scan process. However, such imaging equipment mounted on dedicated vehicles is expensive and is often unaffordable for local agencies with limited budgets. Developing countries have entered economically more difficult periods with the recent cases (pandemic process). Therefore, simple but effective object detection-based smartphone applications are a solution to some problems. Moreover, road maintenance plays a vital role in the socio-economic development of a country. Institutions generally carry out road maintenance through notification or manual observations. This situation should until be done automatically and data flow should be provided from the problematic places.

The importance of the automatic detection system for the maintenance and repair of potholes in the road network for all components using the road network is increasing day by day. The authors plan to design an embedded system integrated into the vehicles. However, there are some research questions (RQ) in this process, which consists of different stages. The answer to the first question was answered within the scope of this study.

RQ-How does the accuracy rate of the object detection methods used change in detecting potholes in the road network at different vehicle speeds?

The authors wanted to bring the answer to this question to the literature. Because this system, which is planned to be designed, is intended to detect urban road defects. Therefore, object detection accuracy at different vehicle speeds is the key part of the system. It is thought that this system will be an intelligent transportation system product that will increase traffic comfort and safety in urban transportation. As the first step of this in this study, the pothole detection process based on the YOLOv7 (Wang et al. 2022) and YOLOv8 (Ultralytics 2023) object detection algorithm was performed. It has been investigated with what accuracy rates the potholes was detected automatically via real-time video.

The paper is divided into five sections following this introductory section. In the next section, a brief overview of the identification processes of road defects occurring in road networks and the contribution of this study to the subject is presented, while in the 3rd section, brief material information about the study and information about the method used are given. Chapter 4 includes the analysis results obtained about the pothole and vehicle speed and discussion of the results. Finally, the last section summarizes the main results of this study.

2. Literature Review

In addition to the increase in success criteria in object detection models in recent years, the importance of object detection has increased because it can provide solutions to problems existing in many sectors. The trend and need for autonomy occurring in vehicles has greatly contributed to the object detection process. In this section, brief information about object detection in the literature, road damage in the road network and the studies carried out in the field of pothole detection are given. In this section, no comparisons about object detection methods be presented. Because object detection methods are constantly being updated and improved. However, readers can review (Sultana et al. 2019, Zaidi et al. 2022) for detailed information about these models.

With object detection models, many things such as people, animals, goods, disabled roads, pedestrian crossings, defects in the road network, vehicle license plates, cancerous cells are detected

(Everingham et al. 2010, Russakovsky et al. 2015, Tsung-Yi et al. 2014). The purpose and detection method of each detection process is different. The object detection process, which started with AlexNet (Krizhevsky and Hinton 2012) in 2012, continues to improve every passing year.

Nowadays, object detection studies are usually based on R-CNN (Hoang Ngan Le et al. 2016) and YOLO (Redmon et al. 2016). The latest updated versions of these two basic detection methods are quite state-of-the-art products in terms of speed and accuracy. In order for the readers to understand more clearly, some studies were given in the form of tables.

Table 1. Some studies conducted about road distress

Content of the studies	Applied method	Application Area / Data source	Ref.
In the study, an ensemble model was proposed for the efficient detection and classification of road damage. The proposed ensemble model has been extensively tested with different model versions. It was observed that the presented data set had two separate test sets and the F1 value for both cases was 0.628 and 0.6358, respectively.	YOLO-v4 / Region CNN	Experimental/ data set collected from Czech Republic-Japan-India was used.	(Doshi and Yilmaz 2020)
Since the road damage caused by the earthquake is constantly changing, it is necessary to monitor the road damage situation with remote sensing. For this purpose, the study proposes an automated approach to quickly determine road damage using high resolution satellite images and road maps. It is used to show the status of damage change by reference to roadside lines. If there is a change in the roadside line after the earthquake, this is the biggest proof that the road has been damaged. Damaged road sections are determined by comparing before / after the earthquake.	Remote Sensing, Edge Detector with Embedded Confidence (EDEC), Hough transformation	Wenchuan	(Ma et al. 2013)
This study introduced a YOLOv5x based solution to detect various road damages. Model training was carried out on four main damage types and 26620 images. The number of data used after data pre-processing was updated to 12195. The F1 values are 0.568 for test1 and 0.571 for test2, respectively.	YOLO-v5 / Deep learning	Experimental/ data set collected from Czech Republic-Japan-India was used.	(Jeong 2020)

In this study, a new system has been developed that detects road damage with a camera installed in the vehicle. Road damage detection with the CNN model has been successfully performed with 96% accuracy.	CNN-AlexNet	It was not mentioned exactly from which area the data were obtained.	(Aşcı and Karslıgil 2020)
With the help of high-resolution images obtained by remote sensing, road damage extraction based on road vector data and change detection method was performed. The road line is determined before the earthquake and the damaged road sections are determined by comparing the same road line after the earthquake. The damage in this study should not be confused with other types of damage. Earthquakes cause structural rupture and separation damage to the road network.	Remote sensing	Wenchuan	(Gong et al. 2012)
The authors created a complementary system for detecting road surface anomalies using two different methods. A smartphone-based system has been developed that can take images of problematic sections on the road surface and measure the acceleration of the vehicle. A comparative analysis was made by classifying the obtained images according to the road surface abnormality and transferring the changes in acceleration to histogram graphs. The detection process was carried out via the image.	Fully CNN / Three-axis acceleration	Goyang City	(Lee et al. 2021)
Deep learning algorithms based on different network backbones are used for automatic detection and classification of coating defects. CSPDarknet53, Hourglass-104 and EfficientNet models were used to evaluate their classification performance. These models were trained with 21041 images. According to different algorithms, YOLO-CSPDarknet53, (test1=F1score:0.5714 and test2=F1score:0.5751), which gave the best F1 score in two test sets, respectively, was obtained.	YOLO / CNN (CenterNet / EfficientDet)	Experimental/ data set collected from Czech Republic-Japan-India was used.	(Mandal et al. 2020)
A virtual road network inspector is proposed in this study to detect potholes in the road network and to monitor road conditions continuously. With this system, maintenance costs reduced, service quality and road safety increased. The results show that the road damage status is determined with an accuracy rate of 97.5%.	Machine Learning (support vector machines)	New South Wales, Australia	(Anaissi et al. 2019)
The authors used the YOLOv4 model in this study to automatically identify road damage. In addition, proportional-integral-differential (PID) optimization and YOLOv4 are used together to increase the efficiency of the model and the efficiency has been doubled.	YOLO-V4 / Proportional-integral-differential	The data set of Japan and another study was used.	(Guo et al. 2021)
In order to increase the accuracy of the study, images were collected in different weather and light conditions such as sunny, cloudy and sunset. While the aim of this study is to detect road damage, its main purpose is to establish a generalized model for monitoring road conditions in more than one country. As a generalized model, four cracks classes and pothole damage were taken into account. Training and evaluation processes were carried out with 30 scenarios and 16 deep neural network models by creating training and test sets in different variations of the data sets of three countries.	CNN	Experimental/ data set collected from Czech Republic-Japan-India was used.	(Arya et al. 2021)
Damage datasets for the model were obtained from Microsoft CoCo as 7240 images. Multi-level Feature Pyramids, YOLOv3 and RetinaNet, which are object detection models for road damage detection, are discussed. When the AP and mAP values were examined, it was determined by the authors that the Multi-level Feature Pyramids object detection model gave better values. However, it was stated by the authors that the detection speed of the model is not sufficient to use this model in real time.	Multi-level Feature Pyramids / YOLOv3 / RetinaNet	Microsoft COCO	(Yin et al. 2021)

Five damage types out of 16165 road damage samples were taken into consideration in this study. By using SSD and R-CNN with MobileNet, Inception and ResNet in different scenarios, the successful model in road damage detection was determined. At the end of the study, the authors determined that R-CNN-based models were more successful than SSD-based models. However, the biggest disadvantage of the models created on both bases is the very low success rate in damage with small objects.	SSD / R-CNN / MobileNet / Inception / ResNet	Japan	(Cao et al. 2020)
The authors aimed to better train the model by creating new synthetic data. In this context, they removed the pitted parts of the images with PG-NAT and placed them professionally on the undamaged road image with Poisson blending. As a result of this process, they provided the opportunity to create a new dataset by providing new synthetic data. With the obtained dataset, detection and classification processes were performed for each class using SSD MobileNet and SSD Resnet50.	PG-NAT / SSD MobileNet / SSD Resnet50	Experimental/ data set collected from Czech Republic-Japan-India was used.	(Maeda et al. 2018b)
The main purpose of this study is to develop a new large-scale data set for road damage detection and classification of this damage. Then, a damage assessment model based on the state-of-the-art CNN method was trained and evaluated. In addition, the authors believe that a simple method of road inspection using only a smartphone would be beneficial in regions where experts and financial resources are scarce.	Inception V2 / MobileNet	Japan	(Maeda et al. 2021)

When the studies in the literature are examined, the detection process of road damage over the collected data has been carried out with different detection methods in many studies. Detection results were also checked over the image. However, real-life is quite different from this situation. These systems have to be used in real time to solve problems. In particular, automation is critical in detecting road defects. How pothole detection accuracy varies at different vehicle speeds is a gap in the literature. In addition, vehicle speeds were never taken into account in the studies. Because the detection processes are done on the image.

This study aims to eliminate the uncertainty between vehicle speed and pothole detection in the literature. To the best our knowledge, real-time detection of potholes in the road network with YOLOv7 and YOLOv8 was performed for the first time, taking into account the vehicle speed. YOLOv7 and YOLOV8, which are single-stage detectors, were chosen because of real-time detection. The contribution and innovation of the current study to the literature are mentioned below:

I. Potholes occurring in the road network of six different countries were used as a dataset in a study for the first time. A global scale pothole detection system has been obtained. Obtaining pothole damage images from different countries increases the robustness of the detection model.

II. As a result of the dataset labelling process, a comparative analysis of the pothole detection was performed using the YOLOv7 and YOLOv8 models.

III. Real-time video recording of the pothole in the road network was performed at 25-35-50-70 km/h speeds. Pothole detection was performed on this process with YOLOv7 and YOLOv8.

IV. Performance analysis of the pothole detection process was performed in real time at different vehicle speeds. In terms of traffic safety, no speed test was conducted below 25 km/h. According to the speed limits published by the General Directorate of Highways of Turkey, the highest speed of construction machines is determined as 20 km/h. In addition, the speed limit for the automobile on the road network where the testing was carried out is 90 km/h. Considering these two situations, the authors chose the lowest test speed of 25 km/h (Int.Ref. 4).

3. Materials and Methods

3.1 Network Architecture

This section will provide information about object detection models that automatically detect potholes. Recently, models with high object detection speed and accuracy have been presented to the literature by researchers. The last members of the YOLO family, YOLOv7 and YOLOv8, have preferred in this study. Because in this study, the test process performed via a real-time video. Therefore, it has been stated by (Zaidi et al. 2022) that single-stage detectors are suitable for this process. The flowchart of the study is given in Figure 1. All stages are explained in detail in other sections.

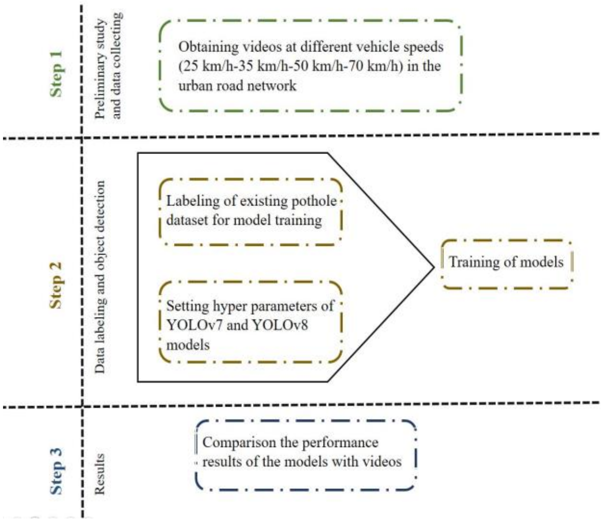

Figure 1. The workplan of the study.

3.2 Base Models

The critical point in object detection has been AlexNet, which emerged in 2012. The critical point in detecting and classifying road defects was the Global Road Damage Detection Challenge 2020 (GRDDC) competition organized by Institute of Electrical and Electronics Engineers (IEEE) in 2020 (Int.Ref. 5). 121 teams from different countries competed in this competition. Road damage data collected from India, Czech Republic and Japan were given to the competitors. The detection performance evaluation of the teams was made over the F1 score. The IMSC team, which came first in the competition, preferred YOLO as the detection model.

The YOLO family was first introduced in 2016 by Redmon et al. (Redmon et al. 2016). YOLO is a one-stage network model that estimates class probabilities and bounding boxes directly from the input image using a simple CNN network. Since 2016, many YOLO versions have been brought to the literature by different developers. In this study, the authors preferred the YOLOv7 and YOLOv8 object detection models, which are the last members of the YOLO family. The network structure and working principle of the YOLOv7 model are shown in Figure 2.

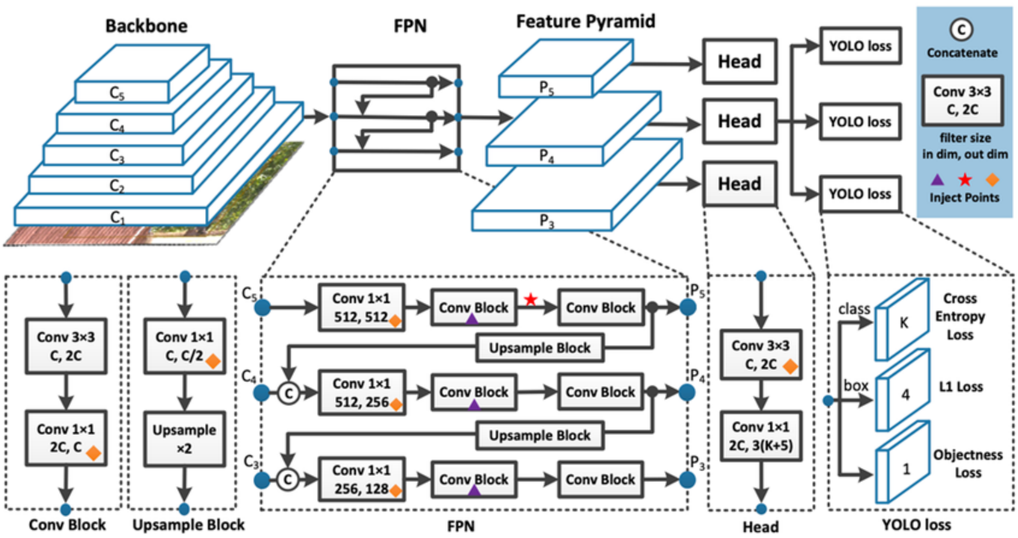

Figure 2. YOLOv7 network architecture (Wang et al, 2022)

A new trainable bag-of-freebies method was designed by Wang et al 2022. for problems derived from state-of-the-art methods. With the new version obtained, it surpassed all known object detectors in terms of both speed and accuracy. It has the highest accuracy (56.8% AP) of all real-time object detectors. This was valid until Ultralytics' YOLOv8 model was brought to the literature.

It should be remembered that the object detection process is always updated. YOLOv8 is a state-of-the-art model that builds on the success of previous YOLO versions and introduces new features and improvements to further increase performance and flexibility.YOLOv8 is designed to be fast, accurate and easy to use. This makes it an excellent choice for object detection, image segmentation and image classification tasks.The YOLOv8 network architecture is not presented in this section. Because Ultralytics did not visualize the network model. However, readers can look at the network architecture visualized by GitHub user RangeKing (Int.Ref. 6). The detailed comparison between both models is shown in Figure 3. As the number of parameters increases, the performance values get closer to each other. However, it is clearly seen that YOLOv8 is faster than YOLOv7. The biggest difference between the two models is the speed value over object detection.

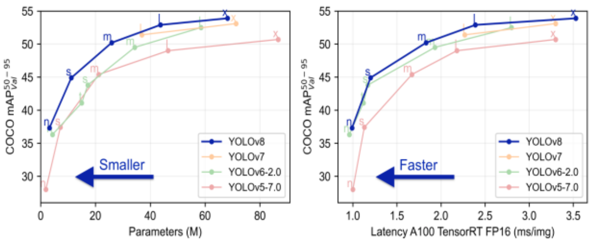

Figure 3. Comparative analysis of the latest models of the YOLO family (Int.Ref. 7)

In general, developers of object detection models offer users the opportunity to customize their models. This process is called configuration. Users' data quality, data size, hardware status and experience are effective considerations in this configuration process. There are also many hyper parameters in the configuration. It is almost impossible to try all these parameters in different configurations. However, both the literature and the author's experience are helpful in determining value ranges.

3.3 Data exploration and splits

Only the pothole data was obtained by extracting data from the approximately 13 thousand-road damage public dataset provided by GRDDC. This data set was obtained from India, Czech Republic and Japan, respectively. In addition, data for six countries (Japan, India, Czech Republic, Norway, United States, and China) included in the Crowdsensing-based Road Damage Detection Challenge (CRDDC2022) were also extracted. A total of 835 road images containing pothole damage were obtained. These images were photographed by researchers in different countries. No data augmentation was applied to the road images used. Some researchers cut the pothole image from a different image and add it to the other image to expand the data set. However, it has been determined that some data are the same or not used. The total number of data sets used for this study is 673. The data set consists of three parts: training, testing and validation set. Training set 539, test set 67 and validation 67 were divided into 80%, 10% and 10%, respectively. The limited number of road images, studies in the literature, and author experiences were effective in the separation rates of the dataset. In object detection, the quality and number of training data affect model accuracy. Example images of the public dataset are in Figure 4. These public datasets are very valuable in the field of road damage. Because creating a road damage dataset is both costly and time consuming. For readers who want to access the dataset: (Int.Ref. 8)

Figure 4. Some images and data labelling boxes in the training set

Roboflow (Int.Ref. 9) provides opportunities to researchers with the open resources it has provided in the field of image processing in recent years. The authors carried out the labelling process of the data set through Roboflow considering this situation. Readers who want to access the extracted and labelled data set can contact the authors. In addition, the road network and equipment layout of the videos obtained at different vehicle speeds in the study are presented in Figure 5. The mobile phone used is iPhone 11 64GB model. The approximate height of the rearview mirror on which the camera is fixed is 1.3 meters from the ground. The resolution is 1080 while the video dimensions are 1920x1080. Some camera features of the phone used are, respectively, extended dynamic range for video up to 60 fps, 120° field of view, dual 12MP wide and ultra-wide cameras.

Figure 5. Display of the route and equipment where speed data is collected

3.4 Evaluation indicators of model

Various criteria have been used in the literature to understand model performances from different perspectives and levels of detail. In this study, an object detection-based application was implemented instead of image classification or segmentation. There are basic evaluation factors in model evaluation in object detection. The IoU, also referred to as the Jaccard Index, facilitated similarity quantifications between the ground truth G_b and the predicted P_b bounding boxes, as shown in (1):

$$\text{IoU} = \frac{area\ (P_b \cap G_b)}{area\ (P_b \cup G_b)} \quad (1)$$

IoU is the area of overlap divided by the area of union value. In this case, if IoU >= 0.5, then it is a match, and it is not otherwise. mAP (mean average precision) value was preferred to understand the precision of the model.

In this study, Precision, Recall, mAP and F1 score values were taken into account in order to accurately and objectively evaluate the performance of the object detection model. Precision is the state that indicates success in a positively predicted situation. Recall indicates how successfully positive states were predicted. As the precision value increases, the model detection success also increases. However, high Precision alone does not make sense. Other values should also be considered for an accurate and comprehensive assessment. Precision, Recall, mAP, and F1 score were calculated as follows (Hussain et al. 2022, Patel et al. 2022, Wu et al. 2022):

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{F1 score} = 2\text{x}\frac{(\text{Precision x Recall})}{(\text{Precision+Recall})} \quad (4)$$

$$\text{mAP} = \frac{1}{n}\sum_{i=1}^{n} AP_i \quad (5)$$

where TP (True Positive) represents the number of potholes that are correctly detected; FP (False Positive) represents the number of other objects detected as potholes ; and FN (False Negative) represents the number of potholes that are undetected/missed.

3.5 Model training details

Before starting the training process of the pothole detection model, a number of hyper parameters need to be set. Also, this process has been implemented with GoogleColab with Pytorch. This process varies depending on many factors. Factors such as user knowledge and experience, the number and type of data set, the hardware of the computer used and the platform on which the model will run directly affect the selection of hyper parameters. Similar values are used for the YOLOv7 and YOLOv8 models. The defined hyper parameters for guiding the training process are presented in Table 2. The image sizes of the data used for training in both models are equal and 640x640. Considering the number of data used for training, it is sufficient for the batch size and epochs numbers to be 16 and 32, respectively. Initial learning rate is a tuning parameter that determines the step size in each iteration while moving towards the minimum loss function.

Table 2. Training hyper parameters

Models	Input Image Size	Initial Learning Rate	Batch Size
YOLOv7	640 x 640	0.01	16
YOLOv8	640 x 640	0.01	16
Models	**Momentum**	**Weight Decay**	**Total Epochs**
YOLOv7	0.937	0.0005	32
YOLOv8	0.937	0.0005	32

4. Results and Discussion

It is vital that potholes that occur on road networks are detected automatically and that the repair process is carried out quickly. Because this road defect dangerously affects traffic safety and comfort according to its width and depth. The biggest example of this negative situation is in India. In 2019, 3597 deaths occurred due to road potholes. Another issue that should be taken out of this information is that the severity of small wheeled vehicles being affected by potholes is quite high. In recent years, it is planned to prevent traffic congestion under the name of micro-mobility. The increase in the number of e-scooters in Türkiye in recent years causes many problems in some regions. In the province of Istanbul, there are problems between many local municipalities and e-scooter service providers. E-scooter users often use sidewalks for parking and driving. Considering that the vehicles will use the same road network with the legal regulation in the future, it is foreseen that the potholes will cause great material and moral losses. Therefore, this situation is only one of the reasons for the automatic detection of potholes.

In this study, YOLOv7 and YOLOv8, which are single-stage detectors, are preferred among object detection methods. The main reason for this is that the model aims to obtain a real-time pothole detection system as well as object detection and speed. In addition, these models have been brought to the literature as the newest object detection models. The authors think that these models will be more suitable for the in-vehicle integrated system, which is the second phase of this study.

Firstly, screenshots over the videos obtained at different speeds are presented in Figures 6 and 7 to show and compare the detection results of both models. Although the differences between both models are small, it has been observed that YOLOv8 detects it with higher detection accuracy.

Figure 6. Detection performance of YOLOv7 on the same road and pothole at 25-35-50-70 km/h

Figure 7. Detection performance of YOLOv8 on the same road and pothole at 25-35-50-70 km/h

The detection accuracy of the YOLOv8 at three different speeds other than 35 km/h is higher than that of the YOLOv7. The authors thought that there would be a correlation between object detection accuracy and vehicle speed. However, the experimental results obtained showed that there is no exact relationship between vehicle speed and detection accuracy. There may be different reasons for this situation. Many parameters such as camera location, camera resolution quality, weather conditions, sun light angle have an effect on object detection. It can also be expressed that the models have the power to overcome such difficulties. It is intended that all parameters been the same by making video recordings within a 30-minute time frame. There are some values that prove the validity of these models as a result of the trained data set.

First, the mAP, Precision, Recall, F1 score values of the YOLOv7 and YOLOv8 models trained to detect the potholes were examined. These values of YOLOv7 and YOLOv8 are given in Table 3.

Table 3. Comparative experiments

Models	mAP0.5	mAP0.5:0.95	Precision
YOLOv7	0.995	0.635	0.996
YOLOv8	0.978	0.572	0.951
Models	**Recall**	**F1 score**	-
YOLOv7	0.995	1	-
YOLOv8	0.9	0.924	-

It is observed that the performance values between the two models are close to each other.

While the detection values of YOLOv7 are higher in experimental comparisons obtained over real-time video, the detection accuracy of YOLOv8 is higher. The complex network structures of object detection models are shown as the reason for this situation. In addition, the results obtained from real-time videos and image data may vary. This is the success of the internal structure of the models. As a result, it is observed that both models work with high accuracy performance. F1 score and PR curve graphs are presented in Figure 8 to understand the accuracy of the model more clearly.

The F1 score value of the YOLOv7 model was observed to be 1. In some cases, a value of 1 may indicate that the model is overfitting. However, pothole detection was successfully achieved in the images obtained from the video. The situation is similar for the test set, which includes images other than the images used for the model training set. If the difference between the detection accuracies made with YOLOv7 and YOLOv8 was large, overfitting could be mentioned. However, when Figures 6 and 7 are examined, the pattern detection accuracy rates are quite close. The lowest detection rate was measured as 51%. This value is especially sufficient for pothole detection whose shape varies. In particular, the variable situation of damage to road networks challenges researchers in perceiving it. It is possible to increase the accuracy rate in both models. As data heterogeneity, data number and quality are increased, model detection performance will also increase.

Both PR and F1 score charts of both models are acceptable. It is understood from the graphics that the models work correctly or even perfectly. In YOLOv7, the highest F1 value is reached within the confidence interval of 0.461.

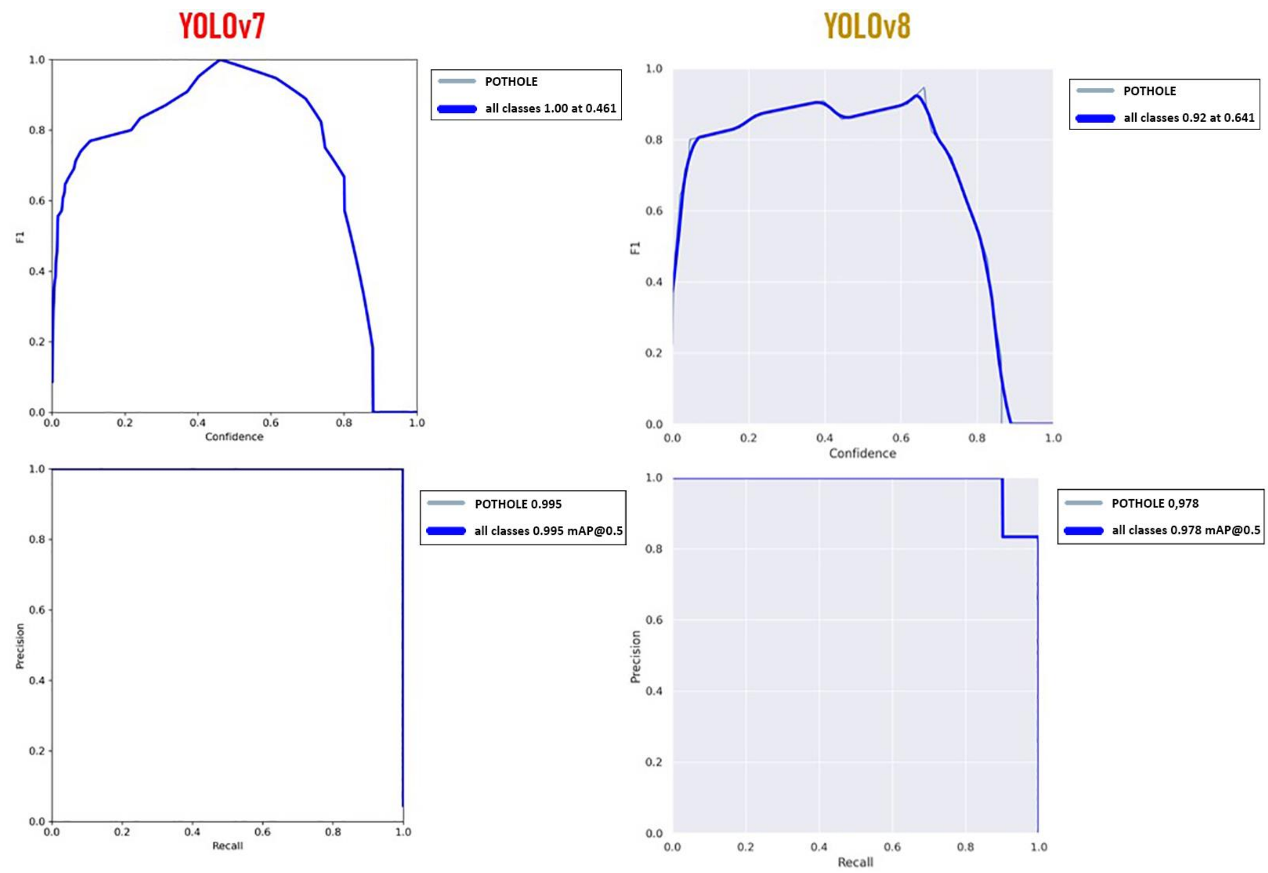

Figure 8. PR and F1 score graphs of YOLOv7 and YOLOv8

However, it can be seen that high F1 values are achieved up to the confidence interval of 0.8. It is seen that the model does not give almost accurate results, especially after the 0.8 confidence interval. In YOLOv8, the highest F1 value was obtained with a confidence interval of 0.641. Both models showed poor performance after the 0.8 confidence interval. This shows that the models generally do not have the ability to detect with the highest accuracy. Improvement in training data will increase these values. In addition, the highest and lowest F1 values obtained by the competitors in the first competition organized by IEEE are 0.662 and 0.4656, respectively. However, comparing these results with this study may not give completely accurate results. Because the status of the data used in object detection is very important. In order to ensure complete comparison, the test data must be the same in the studies carried out. The contribution of this study is important for researchers who want to use moving objects or moving object detection systems. However, since object detection processes depend on many parameters, different results are expected in different studies. Another situation that the authors noticed is that the models detect the potholes in the images with high accuracy. But the highest detection rate on video is 0.69. This is related to the angle of collection of training data. While the image of the potholes is clear and clear in the collected data, the camera angle is very shallow in the video recording process. This causes a decrease in the detection rate on the video.

5. Conclusion

Automatic detection of potholes that occur for different reasons in road networks is important for road safety and comfort. The integration of these systems into vehicles and the sharing of existing pothole locations on the road network to local municipalities will accelerate the road maintenance and repair processes. Accuracy performance of pothole detection at different vehicle speeds, which is the first stage of this embedded system, is investigated in depth in this study. Two different object detection models were analysed on the same road and pothole at four different speeds (25-35-50-70 km/h). The lowest accuracy rate belongs to YOLOv7 with 51%. While this rate was achieved at a speed of 50 km/h, YOLOV8 reached a value of 69% at the same speed. It is clear that the YOLOv7 and YOLOv8 models used in the pothole detection process are successful. In addition, precision, recall and F1 score values being close to one indicate that the models are working well. The lowest values of these evaluation criteria are 0.951, 0.9 and 0.924, respectively. These obtained values are considered successful in object detection processes. The authors expected a linear relationship between vehicle speeds and pothole detection before performing the analysis. However, in the analysis results obtained, exact relationship between speed and detection accuracy could not be determined. This situation showed that the system to be obtained could be used at high speeds on intercity roads. This will provide a great benefit to the literature. It will be a guide for researchers who want to obtain embedded systems in different fields about the effect of speed parameter on detection accuracy.

Declaration of Ethical Standards
The authors declare that they comply with all ethical standards.

Credit Authorship Contribution Statement
Author 1: Conceptualization, Methodology/Study design, Validation, Investigation, Resources, Data curation, Writing-original draft, Writing – review and editing, Visualization.
Author 2: Validation, Writing – review and editing, Visualization, Supervision

Declaration of Competing Interest
The Authors declare that there is no conflict of interest.

Data Availability Statement
The authors declare that the main data supporting the findings of this work are available within the article.

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