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Farklı Coğrafyalardan Elde Edilen Verilerle Yol Hasarlarının Makine Öğrenmesi Yöntemleri Kullanılarak Tespiti: Türkiye Üzerine Bir İnceleme

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Öz

Karayolu hasarı, özellikle sürücülerin konforunu ve güvenliğini ciddi şekilde etkilemektedir. Yollardaki hasarların tespiti, sadece ulaşım güvenliği açısından değil, aynı zamanda maliyet açısından da büyük önem taşımaktadır. Yol hasarlarının tespiti, erken müdahale ve onarımı sağlamak açısından kritik öneme sahiptir. Bu çalışmada, YOLO (You Only Look Once) v8 algoritmasının yol hasar tespit performansı, Çekya-Türkiye, Hindistan-Türkiye, ABD-Türkiye ve Japonya-Türkiye dahil olmak üzere farklı coğrafyalardan elde edilen veri setleri kullanılarak değerlendirildi. Bulgular, algoritmanın hasar tespit konusundaki yeteneklerini ve belirli hasar türlerini ayırt etmede karşılaştığı zorlukları ortaya koydu. Türkiye veri setinin oluşturulması için Hatay ilindeki yolların görüntüleri kaydedildi. Bu görüntüler, Microsoft'un VoTT uygulaması kullanılarak etiketlendi. Geliştirilen modeller arasında karşılaştırmalar ve değerlendirmeler yapıldı. Bu modeller arasında en iyi sonuçları Japonya-Türkiye modeli, 0.55 mAP ve 0.54 F1 skoru ile verdi. Modellerin sonuçları, hasarın görünümünün coğrafi konuma ve yol verilerinin kalitesine göre değiştiğini gösterdi. Yerel görüntülerden ve belirsiz hasar türlerinden oluşan verilerin eğitimde önemli olduğu gözlemlendi.

Anahtar kelimeler: Yol hasar tespiti, YOLO algoritması, Makine öğrenmesi, Nesne tespiti, RDD2022

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Fırat Üniversitesi Deneysel ve Hesaplamalı Mühendislik Dergisi

Detection of Road Damages Using Machine Learning Methods with Data Collected from Various Geographies: A Study on Türkiye

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Abstract

Road damage seriously affects the comfort and safety of drivers. The detection of road damage is of great importance not only for transportation safety, but also in terms of cost. The detection of road damage is critical for enabling early intervention and repair. In this study, the road damage detection performance of the YOLO (You Only Look Once) v8 algorithm was evaluated using datasets obtained from different geographies, including Czechia -Türkiye, India-Türkiye, USA-Türkiye, and Japan-Türkiye. The findings revealed both the capabilities of the algorithm in damage detection and the challenges it faced in distinguishing certain types of damage. For the creation of the Türkiye dataset, images of roads in the province of Hatay were recorded. These images were labeled using Microsoft's VoTT application. Comparisons and evaluations were made among the developed models. Among these models, the Japan-Türkiye model yielded the best results with a 0.55 mAP and 0.54 F1 score. The results of the models indicated that the appearance of damage varies according to the geographical location and the quality of road data. It was observed that data consisting of local images and uncertain damage types were important in training.

Keywords: Road damage detection, YOLO algorithm, Machine learning, Object detection, RDD2022

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1. Introduction

Currently, monitoring and maintenance of road infrastructure are largely conducted through physical observations. However, this method not only leads to delays in identifying damages, but is also notably time-consuming. Manual road surveillance faces challenges in keeping pace with the rapid deterioration of roads due to factors such as rising traffic density, environmental effects, and wear over time. In Türkiye, there has been a significant rise in the number of vehicles over the years due to an increasing population and per capita gross national income. In Figure 1, the red-colored histogram depicts the country's population, while the black line demonstrates the number of vehicles.

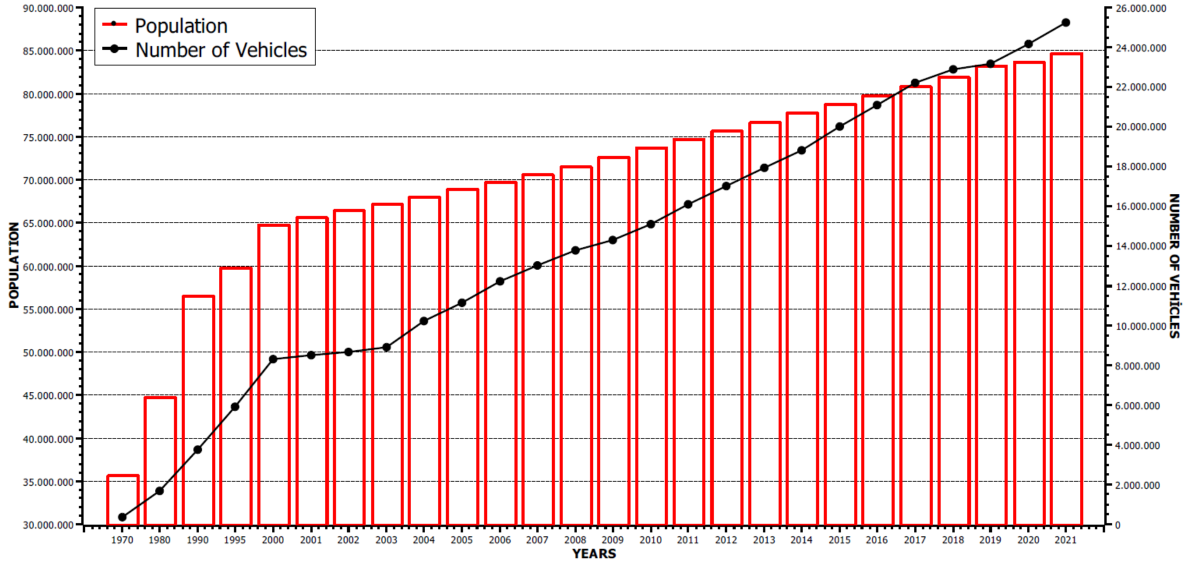

Figure 1. Distribution of population and number of vehicles in Türkiye by years [1]

Concomitant with the increase in the number of vehicles, as seen in Figure 2, road networks have undergone expansion and their quality has been enhanced. In Figure 2, the line graphs depict different types of roads; in particular, the augmentation in bituminous roads, represented by red and black, has elevated the significance of road maintenance and administration. To administer the expanding road networks, the highways within the country have been segmented into regions, and these regions further subdivided into administrative units.

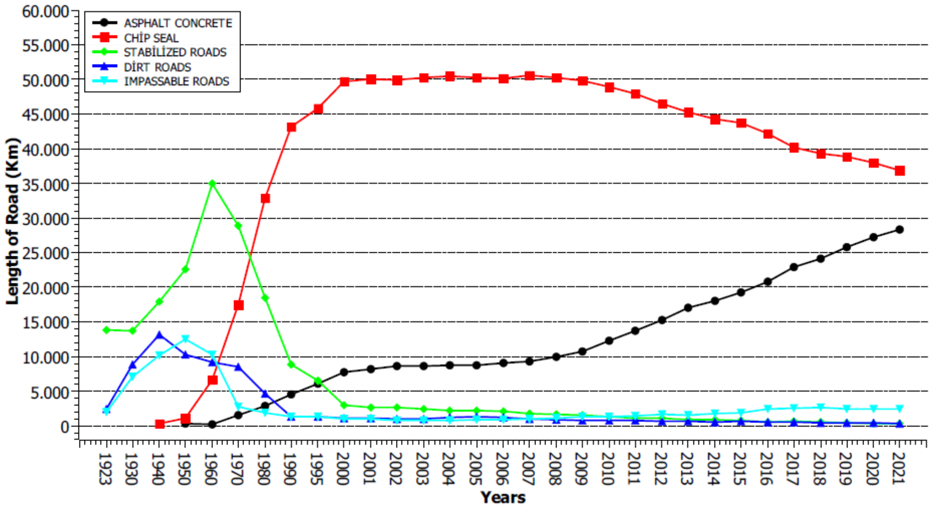

Figure 2. Lengths of road types in Türkiye by year [1]

The regional directorates and administrative divisions in Türkiye are given in Figure 3. Delays in detecting and repairing road damage not only amplify the extent of the damage but also lead to higher repair costs and constitute serious safety risks to drivers. The detection of road damage is crucial for early intervention and repair. Therefore, numerous studies are being conducted using machine learning techniques to detect, discern, and classify road damages.

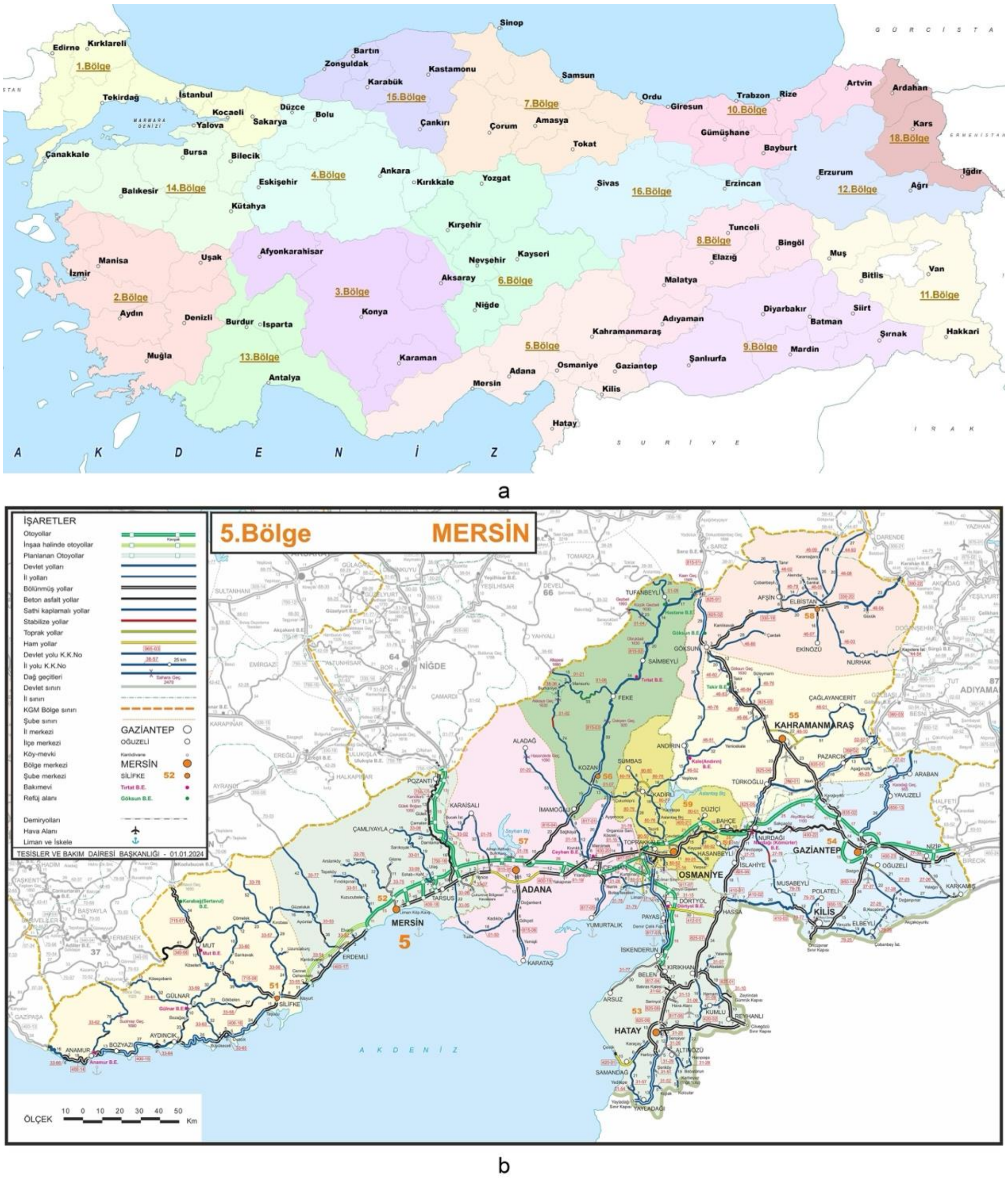

Figure 3. Highways (a) regional directorates (b) branches of the 5th region [2, 3].

The literature on road damage detection has experienced significant advancements in recent years, particularly with the utilization of deep neural networks and deep learning models. Maeda et al. introduced a method for road damage detection and classification using deep neural networks with smartphone images, highlighting the importance of utilizing smartphone technology for data collection [4]. Wang et al. focused on adjusting relevant parameters of the model based on analyses of aspect ratios and sizes of damaged areas in the training dataset. As a result of this approach, they obtained an F1 score of 0.62 [5]. Additionally, Maeda et al. emphasized the lack of a uniform road damage dataset and made their experimental results and smartphone application publicly available [4]. Cao et al. conducted a comprehensive evaluation of deep learning models for road damage detection using multiple dashcam images and highlighted the importance of increasing the diversity of image sources to improve model performance [6]. Arya et al. discussed transfer learning-based road damage detection for multiple countries and highlighted the need for effective solutions in countries struggling with road damage detection [7]. Furthermore, Arya et al. summarized the Global Road Damage Detection Challenge (GRDDC), which aimed to propose methods for automatically detecting road damages in countries like India, Japan, and the Czechia [8]. Arya et al. presented a labeled image dataset (RDD2020) for road damage detection using deep learning, providing a valuable resource for developing and testing road damage detection models [9].

Jeong and Kim explored the use of image tiling techniques to effectively use high-resolution road damage images captured in Norway in combination with other images of similar resolution. This approach was used to train twelve YOLO (You Only Look Once) v5x models for the detection of four distinct types of road damage. The study achieved an impressive average F1 score of 0.6744, demonstrating the effectiveness of the proposed methodology [10]. Wang and colleagues addressed the need for efficient road damage detection as an alternative to traditional, time-consuming manual methods. They proposed an automated, image-based approach utilizing a consensus model based on the YOLOv5 network and attention modules specifically designed for road-focused imaging. This innovative model combines ensemble learning with increased test duration to enhance detection performance. When evaluated across five test datasets in the CRDDC2022, the method attained an average F1 score of 0.65177, showcasing its potential for real-world applications [11].

Lu and colleagues presented an improved YOLOv5-based model for road condition and vehicle detection. The model aims to address the challenges related to the uneven distribution of samples and the presence of small objects in the dataset. Experimental results demonstrated that the improved model maintained real-time performance while achieving a mean average precision (mAP) of 64.5%, surpassing the original YOLOv5 model's mAP of 62% [12]. Xie and Liang explored the use of deep learning-based models, namely YOLOv5 and Nanodet, which are renowned for their high-speed detection capabilities, in the context of road damage detection. The models were trained using a dataset of 21,041 images and subsequently adapted for mobile Android devices. A comparative analysis of the models' performance revealed that the YOLOv5s model achieved a mAP of 51% on a PC [13]. Madarapu Sathvik and his team, the YOLOv7 algorithm was employed to detect potholes on road surfaces. The authors reported an F1 score of 0.51, indicating promising results for this application [14].

Overall, the literature review highlights the progress made in road damage detection through the use of deep learning models, smartphone technology, and innovative algorithms. The availability of datasets and challenges like the GRDDC have further contributed to advancements in this field, paving the way for more efficient and accurate road damage detection and classification methods.

These studies indicate that machine learning techniques are efficacious in detecting road damage. These methods can aid in early intervention, thereby reducing repair times and costs. Considering the growing number of vehicles and expansion of road networks in Türkiye, there is a demand for automatic and effective methods for road damage detection. This study will explore the application of machine learning techniques for the detection of road damage.

2. Data Set and Methodology

2.1. Dataset

The availability of a standardized road damage dataset is crucial for the development and evaluation of road damage detection systems. Maeda et al. highlighted the absence of a benchmark dataset for road damage detection, in collaboration with seven municipalities in Japan, created a dataset for road damage detection by recording images of roads spanning over 1,500 km and spending over 40 hours, thereby making them processable for analysis [4]. In the dataset, each type of damage was labeled with class tags such as 'D00', 'D10'. Figure 4 shows sample images from the RDD2018 dataset. Arya et al. introduced the RDD2020 dataset, comprising 26,336 road images with over 31,000 instances of road damage, intended for developing deep learning-based methods for automatic detection and classification of road damage [9]. Arya et al. further expanded on the road damage dataset with RDD2022, which includes images from six countries and was released as part of the Crowd sensing-based Road Damage Detection Challenge [15].

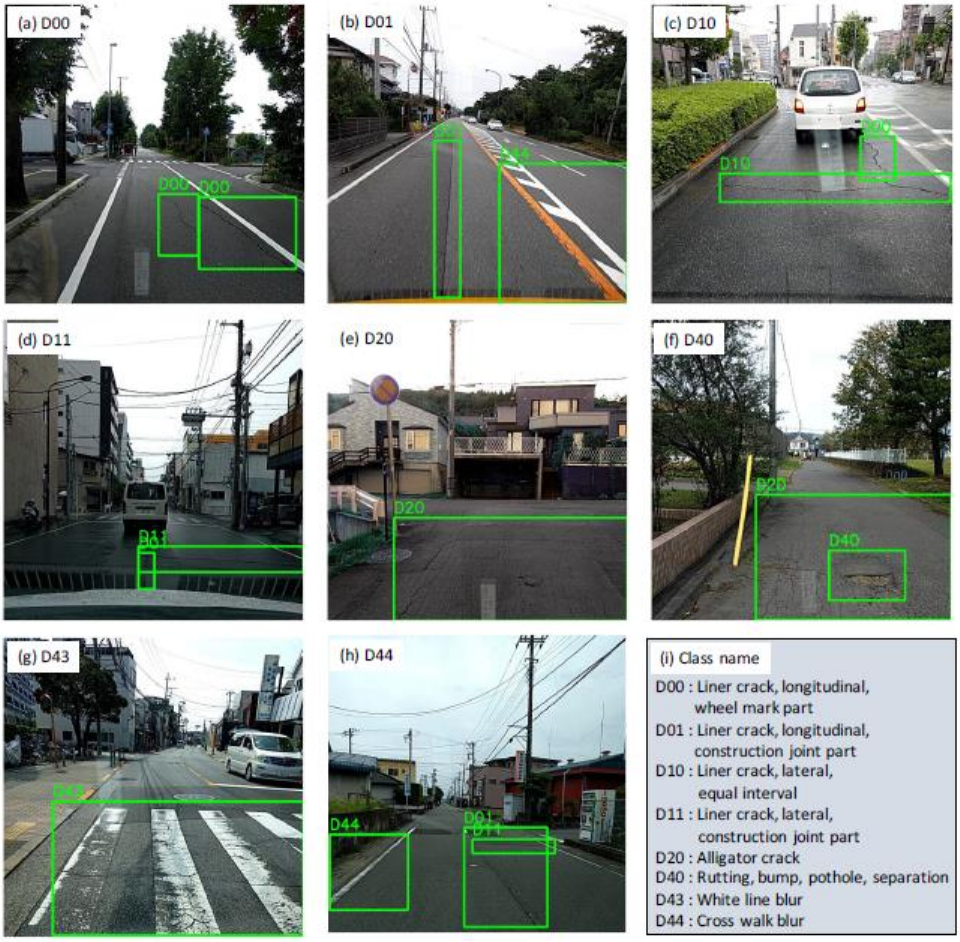

Figure 4. Damage types and sample photos in the RDD2018 dataset [4]

Within the scope of the study, addition to the RDD2022 dataset, a dataset comprising images of Hatay's highways has been created to be recognized by models employing the Convolutional Neural Networks (CNN) algorithm in Türkiye. For the creation of the dataset, the use of a 70mai Dash Cam 4K A800S camera, featuring a 140-degree field of view and a resolution of 2848 x 1600 pixels, was employed (as shown in Figure 5) [16]. To record the roads, image recording was carried out starting from the center of Iskenderun and traveling through the surrounding districts.

Figure 5. 70mai Dash Cam 4K A800S and vehicle integration

It was configured to produce an output in mp4 format every 3 minutes. The purpose of the video recording was to capture the entire road without any loss of image. The recorded images were transformed into photographs at a rate of one frame for every 50 frames. The created dataset consisted of a total of 2209 photographs with a resolution of 2848x1600. The acquired photographs were assessed by an expert in the field of transportation. Images that would technically not be worth labeling, such as blurriness, noise, or photos that did not show the road, were cleaned up. Types of damage were identified among the selected, high-quality images.

Table 1. Types and details of road damage in RDD2022 and the created dataset.

Type of Damage	Class Name
Longitudinal Liner Crack	D00
Lateral Liner Crack	D10
Alligator Crack	D20
Rutting, Bump, Pothole, Separation	D40

2.2. Method

The collected images were labeled according to the types of damage and prepared for model training using the VoTT (Visual Object Tagging Tool) toolbox [17]. The labeling process and bounding boxes are shown in Figure 6. The gathered dataset was labeled using VoTT, an open-source image labeling program. The labels of the data obtained from RDD2022 and the Hatay highways were converted from Pascal-VOC format to YOLO format, making them suitable for the YOLOv8 algorithm. Models were developed on datasets obtained from various geographies, such as Czechia-Türkiye, India-Türkiye, USA-Türkiye, and Japan-Türkiye. These models and their labeling processes are displayed in Figure 7.

Figure 6. The ultimate annotated image comprises of bounding boxes and a class label, which in this instance is denoted as D00

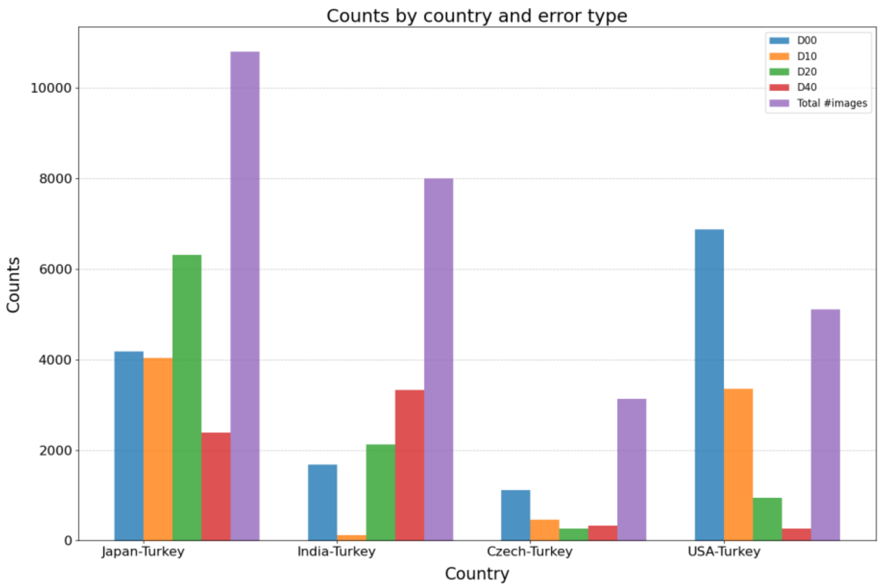

Figure 7. The content of the models and their label classes

The YOLO algorithm operates faster than other algorithms by processing the image through the neural network in a single pass. The introduction of the YOLO algorithm by Redmon and colleagues has created a fundamental change in the field by providing a faster and more efficient alternative for real-time object detection [18].

YOLOv8, the eighth iteration of the algorithm, offers faster and more accurate results compared to its previous versions [19]. Equipped with a deep learning-based structure, YOLOv8 typically operates in conjunction with convolutional neural networks. This algorithm scans the image in a single pass, determining which object each pixel belongs to. Consequently, unlike traditional methods, it integrates the steps of region detection and classification into a single process.

The structure of the YOLOv8 algorithm is illustrated in Figure 8. The sequential definition of this structure encompasses three main components: the backbone, neck, and head. The backbone, often represented by a convolutional neural network, serves the purpose of extracting noteworthy characteristics from the image at different scales. The neck component processes these extracted features, thereby augmenting the spatial and semantic information. Ultimately, the head component utilizes these enhanced features to generate predictions for the task of object detection.

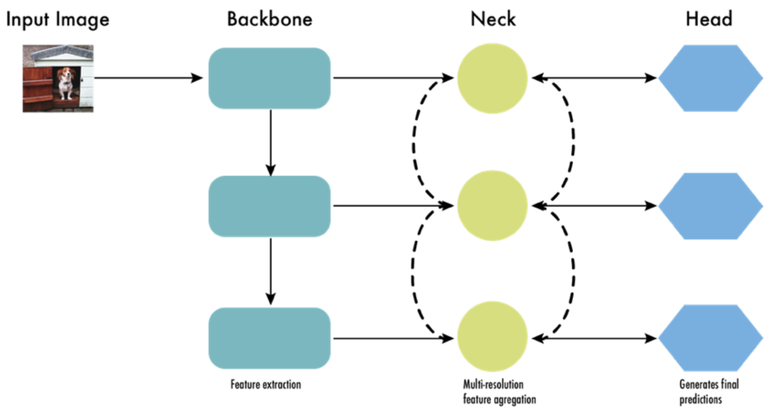

Figure 8. Structure of the YOLOv8 algorithm [20]

3. Results

3.1. Experiment Environment and Metrics

The data that has been compiled for the purpose of identifying road damage has been categorized into four main types of damage: D20, D40, D00 and D10. These were then divided into training and testing datasets. The developed models were trained and tested on Colab using an A100 graphics card [21]. This GPU features 6,912 cores, 40 GB of memory capacity, and a power of 19.49 TFLOPS. Various metrics have been examined to evaluate models with different image and label counts from different countries. The most commonly preferred metrics in object detection evaluation, such as the mAP (Mean Average Precision) and F1 score, were used. Additionally, the results of the method have been presented in a confusion matrix. The customized matrix for this study is displayed in Table 2, while the formulas for each metric are given below.

Precision is the likelihood of correctly guessing a positive instance from all predicted positive instances, and recall is the likelihood of guessing a positive instance from true positive instances. The formulas for precision and recall are shown in equations (1), (2).

$$P = \frac{TP}{TP + FP} \tag{1}$$

$$R = \frac{TP}{TP + FN} \tag{2}$$

Table 2. Confusion Matrix Explanation.

Terms	Results
True Positive (TP)	Cases where the model predicts damage and there is indeed damage.
True Negative (TN)	Cases where the model predicts no damage and there is indeed no damage.
False Positive (FP)	Cases where the model predicts damage but there is no damage.
False Negative (FN)	Cases where the model predicts no damage but there is actually damage.

In the field of object detection, Precision and Recall are interdependent metrics that are not suitable for direct assessment of the detection process. Consequently, the introduction of Average Precision (AP) serves to characterize the precision of detection, while the F1-Score acts as a holistic measure to assess the model comprehensively. Increasing values of AP and F1-Score indicate high accuracy of the network, while mAP reflects the average accuracy in n defect categories. The mathematical formulations for AP, mAP, and F1-Score are delineated in equations (3), (4), and (5).

$$AP = \int_0^1 P(R)dR \tag{3}$$

$$mAP = \frac{1}{n}\sum_{i=1}^{m} AP^i \tag{4}$$

$$F1 - Score = 2 \times \frac{P \times R}{P + R} \tag{5}$$

mAP, or Mean Average Precision, serves as a measure employed to assess the efficacy of object detection systems. It represents the average accuracy of all predictions made by the system. Typically, it is calculated by taking the average of AP (Average Precision) values for different IoU (Intersection over Union) thresholds. The accuracy of the predicted bounding boxes in AP is evaluated through the utilization of IoU. IoU is a metric that represents the proportion of the intersecting area to the combined area of the actual and predicted bounding boxes, as depicted in Figure 9. It measures how closely the actual and predicted bounding boxes overlap. In this study, the IoU threshold is set at 0.5, meaning a prediction must have an IoU of at least 0.5 to be considered accurate.

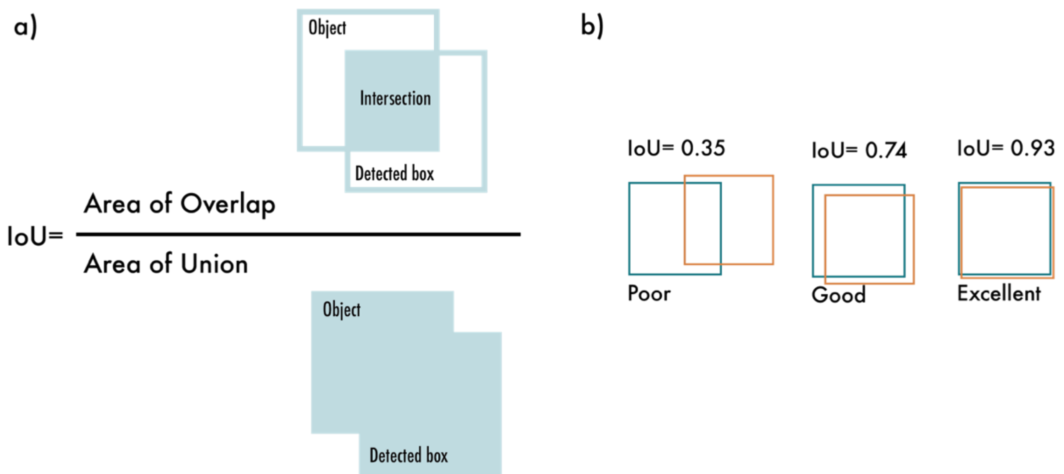

Figure 9. Intersection over Union (IoU). (a) The intersection area of two bounding boxes divided by their total area yields the IoU value; (b) three distinct IoU values for boxes placed differently are given as examples [20]

3.2. Experimental Results

In this section, we delve into the empirical outcomes obtained from the conducted experiments. The results are systematically organized and displayed in Table 3. The table encapsulates a comparative analysis of detection performance metrics across diffrent bilateral model configurations, with a particular emphasis on the collaborative models between Türkiye and various other countries. It is noteworthy that the Japan-Türkiye model configuration stands out, exhibiting superior performance as evidenced by the quantitative measures.

Table 3. Comparison of Detection Performance of the Models

Country	F1 Score	mAP@0.5
Czechia-Türkiye	0.34	0.31
India-Türkiye	0.41	0.367
USA-Türkiye	0.51	0.52
Japan-Türkiye	0.54	0.55

Upon examining the tabulated data, it becomes apparent that the Japan-Türkiye collaboration yields the most commendable results with an F1 Score of 0.54 and an mAP@0.5 of 0.55. These figures not only surpass the other country pairs but also suggest a robust model performance in detecting the objects of interest with high accuracy and reliability.

The results from the Czechia-Türkiye pair indicate a relatively lower detection performance, with an F1 Score of 0.34 and an mAP@0.5 of 0.31. Similarly, the India-Türkiye configuration demonstrates moderate performance improvements with an F1 Score of 0.41 and an mAP@0.5 of 0.367. The USA-Türkiye model shows further enhancement in detection capabilities, achieving an F1 Score of 0.51 and an mAP@0.5 of 0.52, which is indicative of a well-tuned model that balances precision and recall effectively.

Table 4. Summary of comparison with methods in other studies using road damage detection

	F1 Score	mAP
Sathvik et al. [14]	0.51	-
Wang et al. [11]	0.65	-
Xie and Liang [13]	-	0.64
Our method (Japan-Türkiye)	0.54	0.55

Designated as Table 4, this summary ranks each method according to their F1 score and mean Average Precision (mAP) values. According to the table, the method developed by Sathvik et al. [14] has been evaluated with an F1 score of 0.51, but the mAP value has not been provided. The study by Wang et al. [11] exhibits higher performance with an F1 score of 0.65. Xie and Liang [13] are represented solely by the mAP value and have achieved a considerably high value of 0.64. Lastly, the method referred to as Our method (Japan-Türkiye) shows a balanced performance with both F1 score (0.54) and mAP (0.55) values. This comparison table serves as a useful resource for analyzing the performance of road damage detection methods developed in different countries. Notably, the method developed through collaboration between Japan and Türkiye demonstrates a balanced performance in terms of both F1 score and mAP values, indicating it as an effective alternative for road damage detection. Let's take a closer look at the graphs presented below for a more detailed analysis and evaluation of our Japan-Türkiye model.

The F1-Confidence Curve illustrates how the F1 scores of a model's predictions vary within a certain confidence range. In the curve shown in Figure 10, the horizontal axis denotes the confidence level of the model's predictions, while the vertical axis indicates the F1 score. While the D40 class has low F1 scores, the

D20 class shows higher F1 scores. The best F1 score for all classes is the value of 0.54, obtained at approximately a 0.32 confidence threshold.

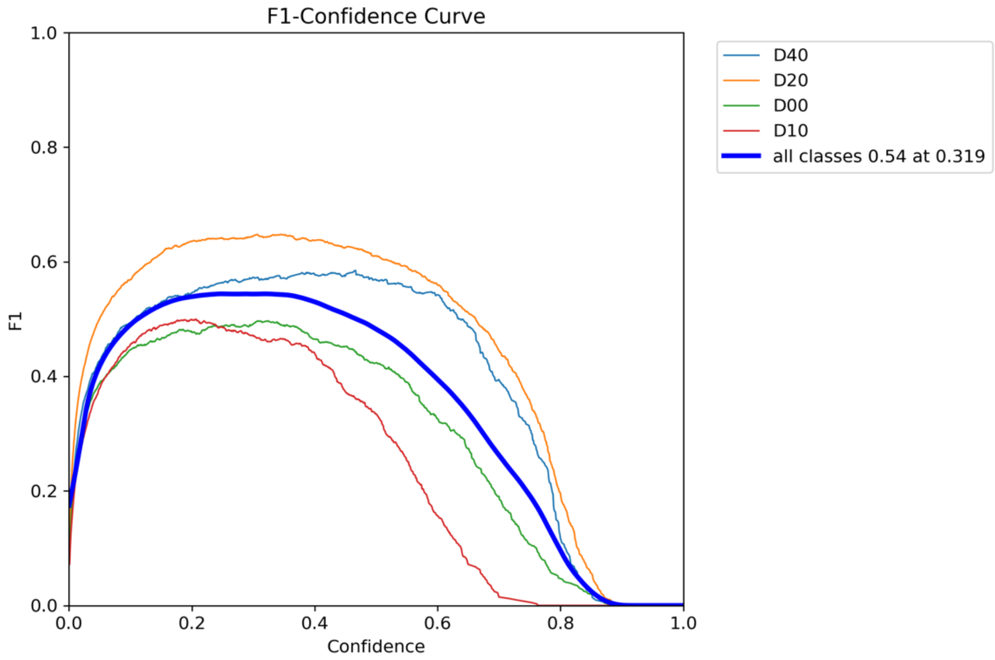

Figure 10. Japan-Türkiye F1-Confidence Curve

The Precision-Confidence Curve demonstrates the precision of a model's predictions within a certain confidence range. In the curve presented in Figure 11, the horizontal axis denotes confidence, reflecting how certain the model's predictions are, while the vertical axis indicates precision, which reflects how many of the selected items are indeed positive. The D20 class demonstrates higher precision compared to other classes, while the D40 class exhibits the lowest precision. The maximum precision for all classes is specified as 1.00 at a confidence threshold of 0.877.

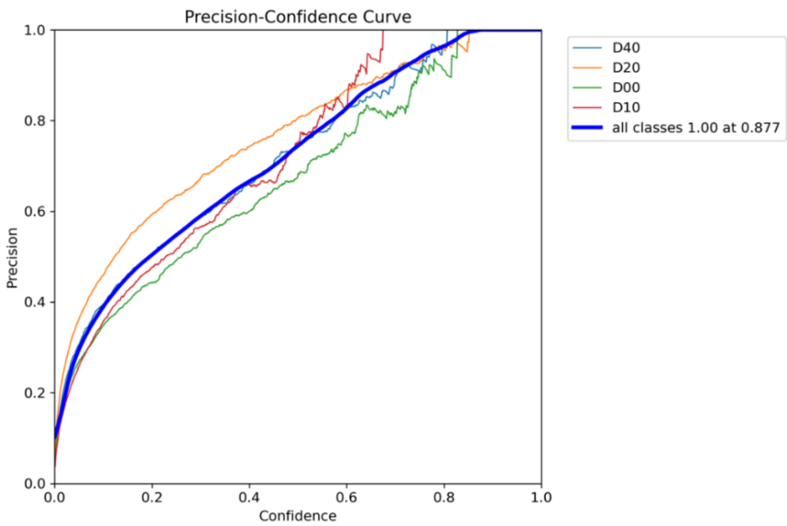

Figure 11. Japan-Türkiye Precision-Confidence Curve

The Recall-Confidence Curve illustrates how well the model detects true positives at a certain level of confidence. In the curve presented in Figure 12, the horizontal axis denotes the confidence level, while the vertical axis indicates recall, which is the proportion of true positives that have been correctly identified. The D20 class exhibits high recall, while the D40 class shows the lowest recall. The maximum recall for all classes is shown as 0.87, but this is achieved at a 0.00 confidence threshold, which may not be practical to use.

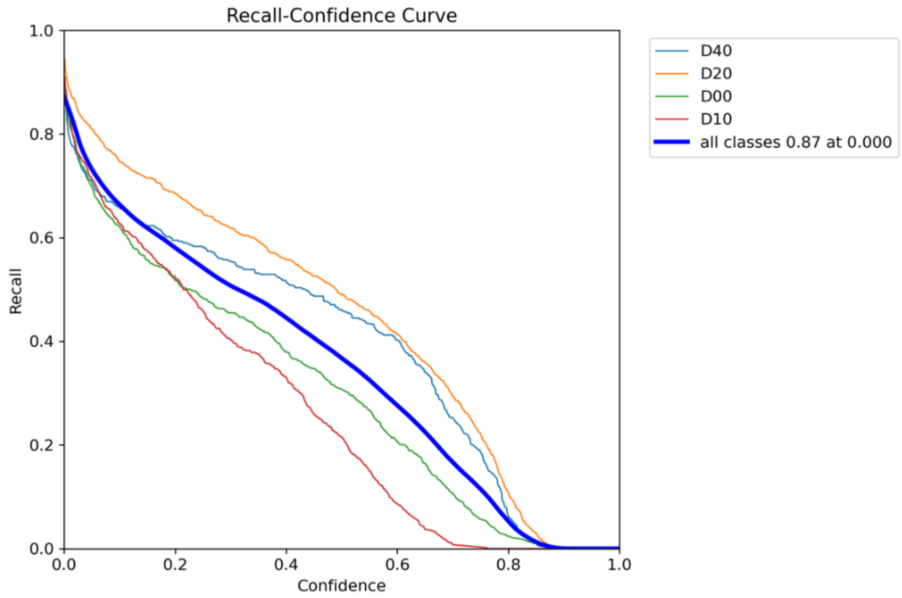

Figure 12. Japan-Türkiye Recall-Confidence Curve

The Confusion Matrix demonstrates the accurate and erroneous predictions generated by the model for every category. The normalized confusion matrix expresses these values as percentages of the total number of samples, providing a clearer indication of the model's performance. This is useful for comparing the model's performance across different classes. The normalized confusion matrix is presented in Figure 13. The high accuracy rate (0.66) of the D20 class is notable, but it seems that the D00 and D10 classes tend to be confused with the background (0.46 and 0.48, respectively).

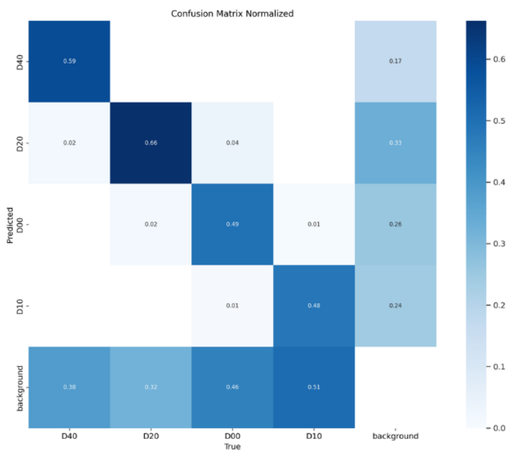

Figure 13. Japan-Türkiye Normalized confusion matrix

The Precision-Recall Curve displays the precision and recall values of the model at different threshold levels. The larger the area under the curve presented in Figure 14, the better the performance of the model. Here, the D20 class has the highest mAP@0.5 value (0.678), indicating better classification performance compared to other classes.

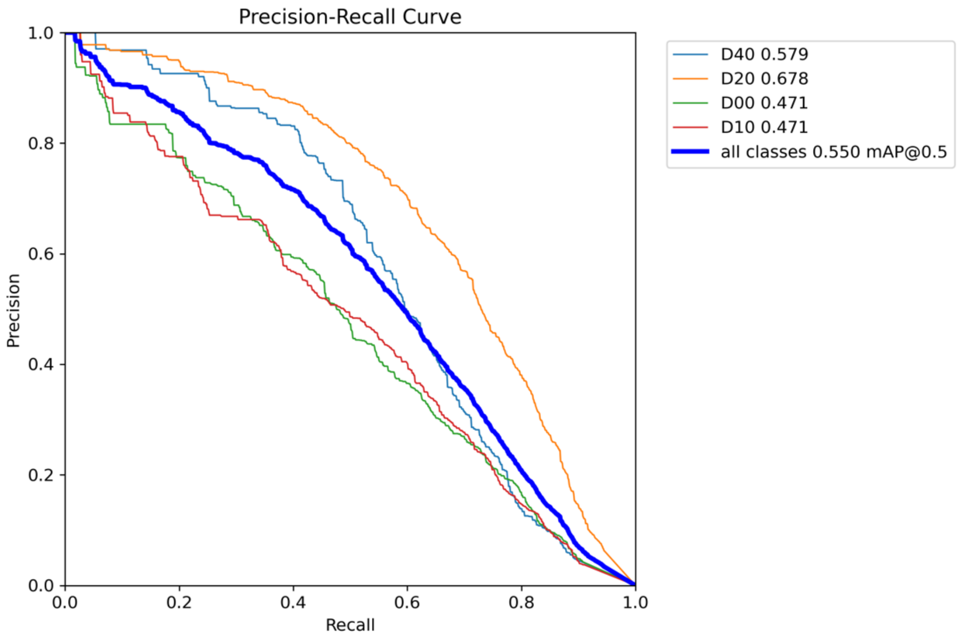

Figure 14. Japan-Türkiye Precision-Recall Curve

Figure 15 shows the curves of the metrics showing the epochs and their changes during the training of the model. A decrease in losses over time indicates that the model is learning from the data. Training losses have significantly dropped, while validation losses have decreased in a somewhat slower but steady manner. The increase in precision and recall metrics also indicates an improvement in the model's performance.

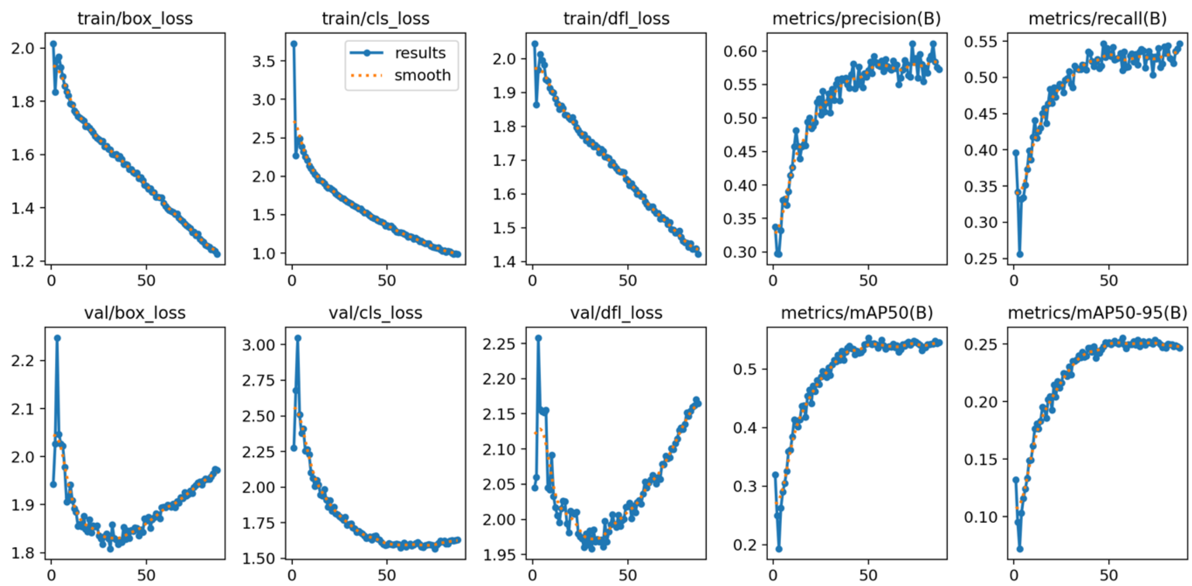

Figure 15. Japan-Türkiye model training curves

4. Conclusion

The study embarked on an exploration of road damage detection using the YOLOv8 algorithm, leveraging datasets from diverse geographical contexts, including collaborations between Türkiye and other countries such as Czechia, India, the USA, and Japan. The primary objective was to assess the algorithm's efficacy in identifying road damages, a critical concern for transportation safety and maintenance cost optimization.

The methodological approach entailed the utilization of the VoTT Image Labeling Program for object labeling and the employment of Nvidia's A100 graphics card within Google's Colab service for the training process. The evaluation of the models was predicated on their mAP and F1 scores, with a particular focus on the Japan-Türkiye model, which demonstrated superior performance.

The results of the study are succinctly summarized as follows:
- The Japan-Türkiye model emerged as the most effective, achieving an mAP of 0.55 and an F1 score of 0.54.
- Comparative analysis revealed that this model outperformed other bilateral configurations, with notable proficiency in detecting specific types of road damage such as potholes and alligator cracks.
- The study highlighted the variability in damage appearance across different geographies and underscored the importance of training models on local datasets.

However, the study is not without its limitations. The detection of certain damage types, such as longitudinal and lateral cracks, proved challenging, often resulting in misclassification. Additionally, the model exhibited a tendency towards overfitting, as evidenced by fluctuations in validation losses. These insights pave the way for future research, emphasizing the refinement of detection algorithms and the exploration of more sophisticated training methodologies to enhance model generalizability and accuracy.

Based on the findings and insights from this study, several directions for future research have been identified for the development and improvement of road damage detection methodologies. Suggested areas for future work include:

- Algorithm Enhancement: Investigating the integration of advanced machine learning algorithms and exploring the potential of deep learning architectures beyond YOLOv8. This includes the examination of newer versions of YOLO or alternative frameworks that may offer improved detection capabilities, especially for less distinct types of road damage.

- Data Augmentation and Diversification: Expanding the dataset to include a wider array of geographical locations and road conditions. This would entail the collection and labeling of road damage images from varied climates and topographies to enhance the model's generalizability and robustness across different environments.

By pursuing these directions, future research can significantly contribute to the advancement of road damage detection technologies, ultimately enhancing road safety and maintenance efficiency.

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6. Author Contribution Statement

In the study, Author 1 contributed to the formation of the idea, design, literature review, evaluation of the results obtained, procurement of the materials used and examination of the results; Author 2 contributed to the formation of the idea and control of the article in terms of content.

7. Ethics Committee Approval and Conflict of Interest Statement

There is no need to obtain ethics committee permission for the prepared article. There is no conflict of interest with any person/institution in the prepared article

8. References

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